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IMPACT OF PUBLIC FUNDING ON THE DEVELOPMENT OF NANOTECHNOLOGY : A COMPARISON OF QUEBEC, CANADA AND THE US

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Cette thèse intitulée :

IMPACT OF PUBLIC FUNDING ON THE DEVELOPMENT OF NANOTECHNOLOGY : A COMPARISON OF QUEBEC, CANADA AND THE US

présentée par : TAHMOORESNEJAD Leila

en vue de l'obtention du diplôme de : Philosophiae Doctor

a été dûment acceptée par le jury d'examen constitué de :

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DEDICATION

I would like to dedicate this thesis to my husband, Naser, for all of his constant love, support and inspiration.

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I would first like to express my gratitude to Professor Catherine Beaudry for her invaluable guidance and advising. This thesis would have never happened without her continuous encouragement, sincere support and inspiration. I am also indebted to my research co-director Andrea Schiffauerova for her support during these years. The scientific intuition and experience of both these scholars was of paramount importance in placing this thesis on the right track.

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RÉSUMÉ

La nanotechnologie est la haute technologie la plus prometteuse de ce siècle. L'investissement mondial dans cette technologie a augmenté rapidement dans les deux dernières décennies. En outre, cet investissement va probablement contribuer de façon non négligeable à la croissance économique future. La recherche dans cette nouvelle technologie basée sur la science nécessite un financement public important pour faciliter la production de connaissances, réduire les incertitudes et les risques connexes, et assurer le succès du développement de la nanotechnologie. Compte tenu de son potentiel dans une large variété de domaines, les gouvernements et les décideurs politiques ont cherché à allouer efficacement des fonds, afin de maximiser les avantages économiques. Il est donc essentiel d'améliorer et d'approfondir notre compréhension concernant la façon dont les financements publics pourront influencer la performance de la recherche.

Le but principal de cette thèse consiste à analyser l'impact du financement public sur le développement de la nanotechnologie, avec un accent tout particulier sur les résultats de la recherche scientifique et technologique. Les objectifs de la recherche portent sur deux volets : Tout d'abord, nous cherchons à examiner l'influence du financement. Le deuxième volet consiste à explorer l'impact de la collaboration et des réseaux innovants sur le développement de la nanotechnologie.

Ensuite, notre but est de comparer l'impact du financement et des réseaux de collaboration de nanotechnologie entre le Canada et les États-Unis. Cette recherche porte sur les extrants importants de la recherche académique : les publications et les brevets. Elle permet de caractériser les réseaux de collaboration en utilisant les liens de co-publication et de co-invention entre les scientifiques et les inventeurs.

Cette thèse contribue de manière significative aux questions de recherche suivantes : Comment l'augmentation du financement public pour les scientifiques œuvrant en nanotechnologie peut améliorer les publications et les brevets liés aux nanotechnologies en terme de nombre (a) et en terme de qualité (b)? Est-ce que les chercheurs qui détiennent une position plus influente au sein des réseaux de co-publication/co-invention sont plus productifs et plus cités? Est-ce que l'influence du financement public sur les recherches en nanotechnologie est différente au Canada par rapport aux États-Unis?

Pour répondre à ces questions, des informations sur les articles de nanotechnologie, les brevets et le financement ont été extraites à partir de diverses bases de données au Canada et aux États-Unis. De plus, cette information a été utilisée pour construire les réseaux scientifiques et technologiques, et pour analyser l'influence du financement par des analyses économétriques.

En ce qui concerne la première question de recherche, nos résultats montrent que le financement public fait augmenter généralement le nombre et la qualité des publications et brevets. Toutefois, cet impact positif est plus important aux États-Unis. Le financement est également moins susceptible d'influencer les brevets de nanotechnologie au Canada. En ce qui concerne l'analyse du financement de l'industrie au Québec, les fonds privés sont moins susceptibles de faire augmenter la qualité des publications.

Quant à notre deuxième question de recherche, les études montrent que les résultats scientifiques et technologiques sont en corrélation avec la position des chercheurs dans les réseaux de collaboration. Les résultats de la recherche en nanotechnologie, particulièrement au Canada, montrent que le rendement est plus élevé au niveau des publications, des brevets et des réseaux de collaboration.

Enfin, bien que l'impact entre le Canada et les États-Unis soit légèrement différent, cette recherche suggère que le financement et les réseaux de collaboration jouent un rôle important dans la stimulation de la quantité ainsi que de la qualité de la recherche académique.

ABSTRACT

Nanotechnology is considered to be the most promising high technology of this century. Worldwide investment in this technology has rapidly increased in the past two decades, and it will likely drive future economic growth. Research in this new science-based technology requires significant public funding to facilitate knowledge production, reduce related uncertainties and risks, and ensure the success of nanotechnology development.

Given its potential in a wide range of domains, governments and policymakers have sought to efficiently allocate funding to maximize economic benefits. It is therefore essential to further our understanding of how public funding influences research performance.

The main purpose of this thesis is to analyze the impact of public funding on nanotechnology development, with a special focus on scientific and technological research outputs. The research objectives are twofold: we first seek to examine this funding influence, and second to explore the impact of collaboration and related scientific and innovative networks on nanotechnology development.

Afterwards, our goal is to compare the impact of funding and of nanotechnology collaborative networks between Canada and the US on scientific and technological research outputs. This research deals with the prominent outputs of academic research, publications and patents, and characterizes collaborative networks using the co-publication and co-invention links between scientists and inventors.

This thesis contributes significantly to the following research questions: how increased public funding to nanotechnology scientists enhances nanotechnology-related publications and patents in terms of (a) number and (b) quality? Are researchers who hold a more influential network position in co-publication/co-invention networks more productive and more cited? Is the influence of public funding on nanotechnology research different in Canada compared with the US?

To answer these questions, information about nanotechnology articles, patents and funding was extracted from various databases in Canada and in the US and was used to build the scientific and innovation networks, and to analyze the influence of funding by econometric analyses.

Regarding the first research question, our results show that public funding generally increases the number and quality of these outputs. However, this positive impact is more significant in the US and funding is less likely to influence nanotechnology patents in Canada. Regarding the analysis of industry funding in Quebec, private funds are less likely to increase the quality of publications.

Concerning our second research question, results show that scientific and technological outputs are correlated with the position of researchers in collaborative networks. Nanotechnology research outputs particularly in Canada show greater returns on publications and patents on network collaborations.

Finally, although the impacts are somewhat different between Canada and the US, this research suggests that both funding and collaborative networks play an important role in boosting the quantity and quality of academic research.

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LIST OF SIGNS AND ABBREVIATIONS

CIHR	Canadian Institutes of Health Research
CIPO	Canadian Intellectual Property Office
NIH	National Institutes of Health
NNI	National Nanotechnology Initiative
NSERC	Natural Sciences and Engineering Research Council
NSF	National Science Foundation
SIRU	Système d’Information sur la Recherche Universitaire
USPTO	United States Patent and Trademark Office

LIST OF APPENDICES

INTRODUCTION

Nanotechnology is a rapidly progressing field that has experienced dramatic growth in the past two decades. According to National Nanotechnology Initiative, “nanotechnology is science, engineering, and technology conducted at the nanoscale, which is about 1 to 100 nanometers” (NNI, 2014). This new technology could influence and improve efficiency in all aspects of manufacturing, energy, healthcare, pharmaceuticals, and agriculture. Given its applicability in various science and technology sectors, it holds considerable potential and may well be the most promising technology of the century that is expected to stimulate economic development. This has initiated national efforts to better understand how nanotechnology can induce fundamental technological changes and spark a new technological revolution (Canton, 2006; Roco and Bainbridge, 2005).

Although some debate exists on the degree to which nanotechnology impacts the economy and society, some believe it holds overwhelmingly positive benefits while others are more pessimistic, it is generally believed to reap significant economic benefits (Wood et al., 2003).

Future advances in nanotechnology and possible positive and negative impacts of this new technology encourage governments to fund research to understand the positive and negative impacts that they might expect to emerge. The potential market for nanotechnology products has motivated governments to foresee important future benefits of nanotechnology and to substantially increase funding in various nanoscience and nanotechnology sectors. Roco (2001; 2002; 2005) observes this trend, stating that global investment in nanotechnology has experienced rapid growth in the past decades particularly since 1997 and has provided fundamental insights into this emerging technology. Hullmann (2006) also highlights that nanotechnology’s economic benefits have continued to attract attention from government and industries worldwide. Many companies have shown their confidence in rapid growth of nanotechnology by investing substantial resources to the development of nanotechnology.

Similarly, an analysis of nanotechnology public funding (NSF funding) over two decades (1991-2010) by Chen et al. (2013), reveals that new application areas are emerging and the government and industry have substantially expanded investment to drive nanotechnology development.

Public funding can unleash the potential of nanotechnology and foster revolutionary change in almost all disciplines and areas of relevance in the short and long term. Given that the government mainly supports basic research, there is a growing need to analyze government research funding and its effectiveness in generating new scientific publications and patents (Wang and Shapira, 2011). These two outcomes are the most appropriate indicators to measure scientific performance of researchers and innovative activities, with the aim of boosting the efficiency and effectiveness of R&D in advancing knowledge.

To analyze the impact of government funding, two questions are investigated in the literature: the first is concerned with quantity of output and the second addresses research impact. The research impact is treated carefully by measuring the quality of these outcomes.

Nanotechnology is indeed an interdisciplinary field, hence partnerships and collaborative activities are rapidly increasing in the field. Researchers participate in collaborations to access a large pool of expertise and accelerate discoveries (Roco, 2001). Collaborative networks drive knowledge generation particularly in more complex fields given that these fields are more likely to be involved in scientific collaborations (Katz and Martin, 1997; Singh, 2007).

Collaborative activities affect research productivity and some scholars have found that scientific outputs are closely dependent on the frequency of collaboration between researchers (Carayol and Matt, 2004; Glänzel and Schubert, 2005; Landry et al., 1996). Given that funding is generally allocated to a group of researchers rather than individual scientists, the correlation between productivity and collaboration is of great importance.

Collaborative environments also draw researchers as they enable access to more facilities, equipment, special skills, unique materials, and the efficient use of experiences (Lee and Bozeman, 2005).

This thesis investigates the impact of public funding on nanotechnology development by narrowing the research in the academic realm through two specific academic outputs: scientific output and technological development. We determine whether public funding increases the effectiveness and efficiency of the scientific community in terms of publications and patenting activities.

Based on the fundamental role of knowledge and innovation in fostering economic development, we examine the role that governments play in the knowledge generation process through this thesis.

In addition, we are interested in the study of academic collaboration, which influences research activities. To investigate the efficiency of collaborative behaviour among scientists, we examine the impact of scientific and innovative networks on research output in the field of nanotechnology.

Few studies explore the impact of research financing on commercial interests within universities. We therefore focus our study on academic patents and on the influence of co-invention and co-publication collaborations in development of this high technology.

Due to the availability of industry funding data in our database from the Quebec government, we further investigate the effect of private funding on academic nanotechnology research as it is currently considered in only a few studies. To answer our research questions, we conduct econometric analyses of academic publication and patenting activity in the nanotechnology field in Canada and the US. We then compare the effects in these two countries with a special focus on nanotechnology development in Quebec.

The rest of the thesis is structured as follows: we review the literature in Chapter 1 concerning funding, collaborations and subsequent outcomes; Chapter 2 describes the research objectives, hypotheses and the methodology employed in this study; Chapters 3 and 5 compare the impact of public funding and collaboration between Canada and the US, while Chapters 5 and 6 concentrate on this impact in Quebec; and finally Chapter 7 discusses the findings and results obtained. We conclude with limitations of this study and suggest future work.

CHAPTER 1 ARTICLE 1: IMPACT OF FUNDING AND COLLABORATIONS ON SCIENTIFIC AND TECHNOLOGICAL PERFORMANCE IN UNIVERSITIES

A Review of the Literature

Leila Tahmooresnejad, Catherine Beaudry

1.1 Abstract

This paper reviews the literature concerning research performance in the academic realm, in particular the impact of funding and collaboration on scientific publications and academic patents. Mostly, funding is granted to research teams; hence there is a need to jointly study the collaboration and funding, and their joint impact on research outputs. We review the empirical studies on co-authorship, co-invention and their effects on research performance. Reviewing literature reveals that prior studies mostly consider publications as research outputs and that academic patents have recently attracted more attention. Research on the impact of funding mainly focuses on public funding, while little systematic research has been conducted on private funding of academic research. Despite various studies on the influence of government funding on academic research performance, positive effects are not always found and some contradictory results co-exist in the literature. In addition, the literature on the impact of collaboration on academic research output reveals that little structured research has been conducted on technological outputs and co-invention collaboration in universities. In conclusion, we identify gaps and suggest future empirical studies.

Keywords: Funding, Collaboration, Scientific papers, Academic patents

1.2 Introduction

Governments devote considerable amounts of funds towards basic and applied research and development (R&D). Given that academia accounts for a large proportion of research, it is important to study funding trends in universities and analyze the effectiveness of these government expenditures. It is thus essential for decision makers to understand how government investment can be effectively allocated to maximize academic outputs (Hagedoorn et al., 2004).

There has been a growing concern over recent years about the increasing research costs of university research. Governments fund are approximately 60% of university research in OECD countries (OECD, 2010). The impact of federal expenditures on university outcomes has become a challenging issue.

Over the last three decades, governments have sought ways to change funding methods to stimulate productive research processes in universities (Gwynne, 2010; Liefner, 2003;). Geuna and Martin (2003), for example, observed that governments in many countries across Europe and Asia-Pacific implemented performance-based funding, which evaluates the research and prompts universities to be more efficient and accountable with their research funding.

Given the central importance of publication in the scientific community, this can be an appropriate indicator to measure a researcher's scientific productivity and performance. According to Fox (1983), publication is the most fundamental research output of universities; it allows scientists to gain professional advancement, recognition and promotion. In recent years, academic technological output has come into the focus of governments, as universities have shown that their research is commercially valuable to industries (Czarnitzki et al., 2007). Since the early 1980s, the Bayh-Dole Act in the US has indeed facilitated the patenting of innovations derived from government-funded research and has dramatically increased the number of university patents (Jaffe, 1989; Henderson et al., 1998).

Because funding is generally allocated to research teams instead of sole scientists particularly in the field of nanotechnology and medical science, another important related issue is the role of research communities on university performance. Modern science is more interdisciplinary, complex and costly, which encourages researchers to participate in collaborative research communities and access a large pool of valuable ideas and resources (Adams et al., 2005; Lee and Bozeman, 2005; Pike, 2010). Righby and Edler (2005) note that public funding plays an important role in the growth of collaborative research by encouraging researchers to interact.

Collaborative research is supposed to help create new scientific knowledge and enhance research performance (Stokols et al., 2005). To maintain competitive advantage, it also becomes crucial for researchers to actively participate in innovation networks to exchange and rapidly access various kinds of knowledge (Gao et al., 2011). This contribution to knowledge networks helps to create and diffuse new ideas as these collaborations can bridge academic boundaries to stimulate inventions (Breschi et al., 2005).

This survey of the literature sheds light on the elements critical to enhancing academic research output. Although the existing literature mainly studies the impact of funding and collaboration on research performance, a positive effect of the two former on the patter is not confirmed in all studies. Some gaps are still observed in prior empirical investigations. In this paper, we identify findings and highlight the gaps where further research is required. The remainder of this paper is organized as follows. In Section 2, we review the importance of research funding and its impact on research output. Our focus for research output is scientific publications and technological innovations, which is synthesized from prior studies. In Section 3, we discuss the critical role of collaboration and their effects on academic research. We conclude, highlight research gaps, and propose further empirical studies in Section 4.

1.3 Research Funding

The role of universities dose not solely consist in producing new knowledge and training, it also aims to develop social and economic growth. Universities significantly contribute to economic development and their role goes beyond the production of new knowledge. Given the billions of dollars spent on funding every year to support new emerging technologies to speed economic development, university research is at the center of attention of federal agencies. These institutions play such a critical role in national innovation systems that research policies must have a thorough understanding of research funding and of its impact.

Blume-Kohout et al. (2009) study the causal effect of federal funding on non-federal funding and suggest that raising government funding is an indicator of quality, which incites non-federal funders to provide additional resources. Hence, even if public funding does not have a direct positive impact on research outputs, it may indirectly affect university research.

Adams and Griliches (1998) suggest dividing public and private funding when focusing on the research performance of universities. Some scholars (Diamond, 1999; Muscio et al., 2013; Payne, 2001; Perkmann and Walsh, 2009) provide evidence that researchers experience a corresponding increase in their private funding when they receive more funding from government sources. However, David et al. (2000) found contradictory results regarding whether public and private funding complement or substitute each other. Leyden et al. (1989) showed that the relationship is insignificant, while Toivanen and Niininen (1998) found substitutability and Lichetenbreg (1988) observed a mixed effect with different methods. Hence results are not entirely conclusive.

The links between government grants and academic research are complex. Despite the fact that economists have recently paid much attention to research productivity, the effect of research expenditures on research output is not trivial. Understanding these links, however, is essential to science policy. The existing literature allows us to illustrate the impact of funding on research, as depicted in Figure 1.1. Each relationship will be examined in turn.

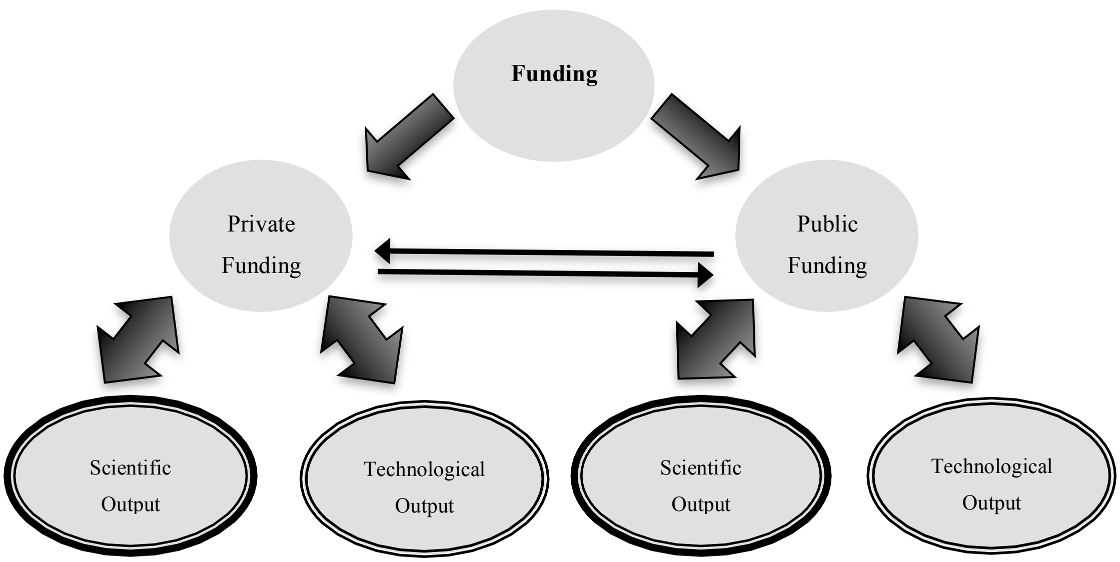

Figure 1.1: Impact of research funding on academic outputs

1.3.1 The impact of funding on scientific output

Arora and Gambardella (2005) studied the relationship between National Science Foundation (NSF) funding and the quality-adjusted number of publications and observed only a modest effect[1]. Jacob and Lefgren (2011) estimated the effect of National Institutes of Health (NIH) grants and showed that receiving a grant worth $1.7 million increases the number of publications

[1] The impact factor of the top 50 economic journals was used to adjust for quality in their research.

by one additional paper over the next five years, which implies a fairly limited impact. In contrast, empirical findings of Payne and Siow (2003) proved a strong positive correlation between research funding and the number of articles published. Although a comparison of successful and non-successful applicants in NIH career development awards by Carter et al. (1987) showed that these NIH awards have no effect on the research productivity.

Rigby's (2011) study on the relationship between funding and its impact on publications concluded that researchers publish articles based on a variety of research priorities. Grants, therefore, can indirectly generate multiple research outputs, such as working reports, theses, etc. Figure 1.2 shows the taxonomy of topics that influence scientific outcomes.

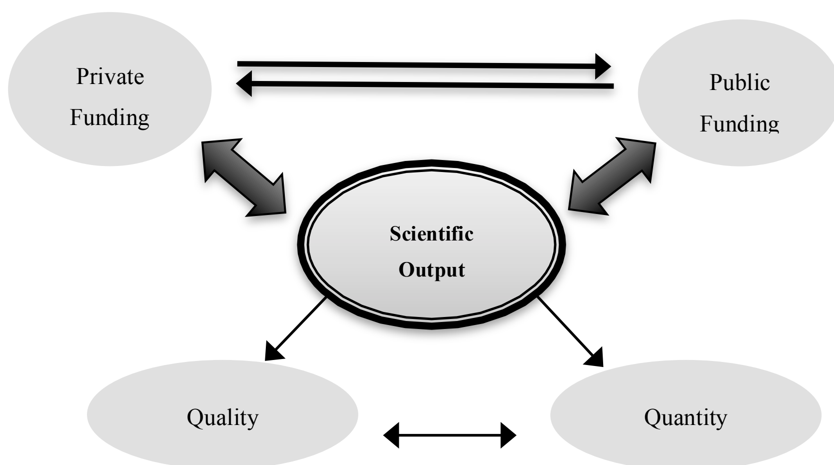

Figure 1.2: Impact of research funding on scientific outputs

Some studies found a link between researchers and grant attribution, which may cause a bias in analyzing the impact of funding on research performance. Arora et al. (1998) and Arora and Gambardella (2005) investigated the role of research institute quality and highlighted that there is a correlation between productivity of scientists and university quality with receiving grants. They also found that past research performance measured by the number of publications plays an important role in grant funding and consequently affects publication productivity. In a similar study, Adams and Griliches (1998) raised the point at the institutional level that differences across universities are important in order to evaluate the correlation between scientific outputs and funding, and that the results may be positive for only top universities.

Differences also exist between research fields: some are costly and require more funding or larger teams to conduct research (Rigby, 2011). For example, results from a study on biotechnology publications by Arora et al. (1998) imply that publication productivity may vary depending on the funding distribution within a research group. Any analysis on the role of grants in research productivity must therefore take into account the specific needs of diverse fields. Additionally, in the nanotechnology field, empirical studies by Shapira and Wang (2010) and Zucker et al. (2007) found a positive effect on knowledge productivity.

Various studies have questioned whether government funding influences the quality of publications. The results of Jacob and Lefgren (2011) on the effect of National Institutes of Health (NIH) grants seem to demonstrate that receiving NIH grants has at most a small positive effect on citations. Similarly, Payne and Siow (2003) observed an imprecise impact on the number of citations per articles following a $1 million increase in federal funding. Lewison and Dawson (1998) investigated the effects of multiple funding organizations on biomedical subfield publications. Using the number of citation as a performance measure, their results show that an increase in the number of funding organizations from which a researcher receives money can increase publication quality, particularly when the number of funding bodies changes from zero to one. In addition, these papers are more likely to be published in journals that have a higher citation impact. McAllister and Narin (1983) in an institutional level and Peritz (1990) found the same positive correlation between citation and funding respectively in biomedical and economic papers. In the nanotechnology field, Shapira and Wang (2010) attempted to measure the quality of publications across countries and found a mixed impact of government funding on citations.

Interestingly, and contrary to wide spread belief, Gingras (1996) discovered a strong correlation between quantity and quality of papers. According to his study, researchers with a large number of papers are more likely to publish in high impact journals and are likely to be the most productive researchers.

Increased university-industry collaboration has created a new form of knowledge production which fosters the direct commercialization of university research (Bloedon and Stokes, 1994; Starbuck, 2001). Empirical evidence on the impact of industry contracts on the scientific production are mixed: while it is scarce, there are concerns as to whether these interactions will decrease long-term research or change the culture of open science (Martin, 2003; Van Looy, 2004). According to Blumenthal et al. (1997), industry collaboration hinders the publication of research results due to concerns regarding intellectual property rights. Further, a survey-based study by Campbell et al. (2002) showed that industry funded researchers commonly receive requests to withhold the publication of results, which has a negative impact on their publication productivity.

On the contrary, Gulbrandsen and Smeby (2005) demonstrated that industry-funded researchers are more productive and generally tend to produce more applied research. Their results show that low levels of industry support increase the number of peer-reviewed articles while higher levels of industry funding are associated with decreasing numbers of academic publications. In a comparative study of productivity among faculty members, Blumenthal et al. (1996) found that the productivity of industry-funded researchers is the same if not higher than that of those who received no industry support. In another recent study that investigated the nanotechnology publications, Beaudry and Allaoui (2012) suggested neither a positive nor a negative impact of private funding on scientific productivity. Similarly, Kyvik (1991) only found a weak relationship between external funding and scientific papers.

Gulbrandsen and Smeby (2005) explained that the publishing profile of an industry-funded academic researcher may be different from that of a government-funded researcher. An industry-funded researcher likely publishes more reports or files more academic patents instead of journal articles. Additionally, Geuna and Nesta (2006) also suggested a possible substitution effect between paper publication and patent application for university scientists with industrial support: academic researchers must sometimes withhold research results for months due to intellectual property rights and thus experience a delay in publishing.

Empirical evidence is still mixed regarding the comparative efficiency of government funding and of industry support. Diamond (2006) counted the number of citations a paper received over a 7 year period and observed that privately funded research is more successful in that regard and that consequently, industry grants is positively correlated with higher quality research. Conversely, Boumahdi et al. (2003) weighted publications using the impact factor of their journals, which signals the quality of research, and found that the correlation between private funding and publication performance corrected for this impact is negative. They suggested that organizations that grant private funding may seek research that is closer to applications, while the research appearing in the higher impact journals is more likely to be fundamental.

In contrast, Behrens and Gray (2001) compared industry-sponsored projects with government-supported university projects and found no difference in the research quality of the resulting publications. Table 1.1 summarizes the prior studies regarding the impact of funding on scientific performance.

Table 1.1: Summary results of the studies on the impact of funding on scientific output

Author	Year	Data	Funding		Impact on scientific output		Results
			Public	Private	Productivity	Quality	
McAllister and Narin	1983	Biomedical publications for 120 U.S. medical school	✓		✓	✓	An increase of publication size and average citation per paper
Peritz	1990	The economic papers of 1978-1979	✓			✓	A tentatively positive effect
Blumenthal et al.	1996	Data from faculty members in life sciences at the 50 U.S. universities, 1994-1995	✓		✓		A possible decrease in academic activity
Lewison and Dawson	1998	Research papers in Biomedical subfield -UK papers, 1988-1994	✓			✓	A higher citation impact
Payne	2001	Data of private and public universities in the United States, 1972-1997	✓		✓		Greater growth for universities which historically received low levels of funding
Boumahdi et al.	2003	Research activity of 76 laboratories in Louis Pasteur University (ULP), 1993-2000		✓	✓	✓	A positive impact on publishing, a negative impact on research quality

Table 1.1: Summary results of the studies on the impact of funding on scientific output (continued)

Author	Year	Data	Funding		Impact on scientific output		Results
			Public	Private	Productivity	Quality	
Payne and Siow	2003	Receiving federal research funding on 74 research universities, 1972-1998	✓		✓	✓	An increase in the number of articles, but the increase in citation is small and imprecise
Arora & Gambardella	2005	Applications to the NSF in economics, 1985-1990	✓		✓		A modest effect on papers
Gulbrandsen and Smeby	2005	A questionnaire study of university Norwegian professors, 2001		✓	✓		A significant relationship between industry funding and publications
Diamond	2006	Chemistry articles by North American scientists, published in1985	✓	✓		✓	Private funding is more successful than government funding
Zucker et al.	2007	Data of the 179 U.S. in economic areas, 1981-2004	✓		✓		A large and robust impact on publication
Goldfarb	2008	Aerospace engineering publications, 1981-1988		✓	✓		A decrease in publications

Table 1.1: Summary results of the studies on the impact of funding on scientific output (continued)

Author	Year	Data	Funding		Impact on scientific output		Results
			Public	Private	Productivity	Quality	
Auranena and Nieminen	2010	Publications of eight countries, 2000s to the mid-2000s.	✓		✓		Best performers contribute to better performance
Shapira and Wang	2010	Nanotechnology published worldwide articles, 2008-2009	✓		✓	✓	Positive impact on quantity, mixed impacts on citations
Jacob and Lefgren	2011	Receiving an NIH grant on publications, 1980-2000	✓		✓	✓	A relatively small effect on the number of papers and citations
Beaudry and Allaoui	2012	Quebec publications and patents	✓	✓	✓		A positive impact of public funding, but no impact of private contracts
Chen et al.	2013	Web of Science (WoS) publications in nanoscale science and engineering (NSE), 1991-2012	✓			✓	An increase of scientific publications, a significant increase of citations

1.3.2 The impact of funding on technological output

Most previous research has focused on the impact of funding on scientific outputs, however a few investigations have measured the correlation between funding and commercial developments in universities. In recent decades, changes in the academic regulatory environment (i.e., Bayh-Dole Act of 1980 in the US) in the United States and some European countries, have given rise to technological innovations in universities. The growth of publicly funded academic patents and licenses after 1980s is therefore asserted to be a direct consequence of the Bayh-Dole Act although the tendency started prior to 1980s. This commercialization of university research has motivated academic researchers to seek economic returns from research, often in the form of patents (Mowery et al., 2001; Shane, 2004).

Henderson et al. (1998) suggested that an increase in the quantity of patents has been accompanied by a decrease in the quality of these commercial efforts. According to the literature, the recent trend towards increased university-industry collaboration implies a shift towards industrial funding and, more importantly, towards applied research in universities. Academic researchers with industrial funds are therefore more likely to contribute to patents rather than publications (Pavitt, 1998). Patents have been used as an indicator of innovation in literature starting with a study of Schmookler (1966). Figure 1.3 shows this influence on technological output.

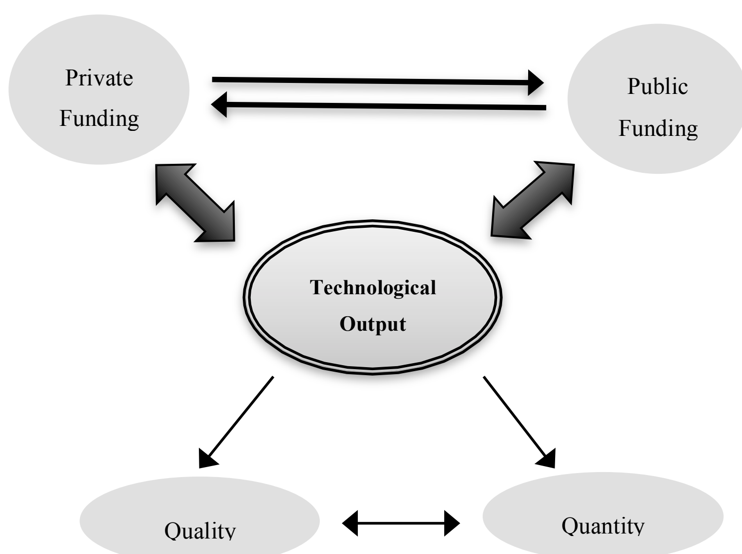

Figure 1.3: Impact of research funding on technological outputs

The econometric analysis of Foltz et al. (2000) on academic agricultural biotechnology patents suggests a positive relationship between patent production and government funding. In a later study, based on a panel of 561 observations of 127 U.S. universities, Foltz et al. (2001) separated the impact of federal and state funding and discovered a difference in their impact: only state funding is statistically positive and significant. Neither of these two econometric studies (Foltz et al., 2000; 2001) found a significant impact of industry funding on patent production.

Considering the sizable investment in academic applied research, it is not surprising that studies have sought to reveal convincing evidence of its effect. An extensive study by Payne and Siow (2001), for example, showed that $1 million in federal research funding yields 0.2 more patents.

Huang et al. (2005; 2006) analyzed the nanotechnology patents of NSF-funded researchers of 20 countries using citation map analysis to conduct a more direct study of technological innovations. Their findings denoted that these researchers and their corresponding patents have a higher impact than non-NSF funded recipients. A similar study of citation networks by Chen et al. (2013) showed that NSF funding has played an important role over the past two decades in developing nanotechnology patents in numerous subfields. According to their findings, NSF-funded researchers received a higher number of citations for their papers and patents. Furthermore, Azagra-Caro et al. (2003) found a positive impact of public and of private funding on university patents, distinguishing between university-owned and firm-owned patents. Their results illustrate that public funds are only weakly correlated with university-owned patents, implying that industrial partners are extremely effective in producing innovative outcomes. Table 1.2 summarizes the prior studies that measure the impact of funding on technological performance.

Table 1.2: Summary results of the studies on the impact of funding on technological output

Author	Year	Data	Funding		Impact on technological output		Results
			Public	Private	Productivity	Quality	
Foltz et al.	2000	Agricultural patents from USPTO, 1991-1998	✓	✓	✓		A positive and significant impact of public funding, industry funding is not significant
Foltz et al.	2001	Data from 127 universities, 1991-1998	✓		✓		State funding is positive and significant, but not federal funding,
Azagra-Caro et al.	2003	Data from research laboratories of University Louis Pasteur (ULP), 1993-2000	✓		✓		A weak impact of public funding on university-owned patents
Coupé	2003	WEBCASPAR-data of the National Science Foundation (NSF), based on a Survey	✓		✓		Funding on academic research leads to more academic patents
Payne and Siow	2003	Federal research funding on 74 research universities, 1972 - 1998	✓		✓		An Increase of $1million in federal funding results 0.2 more patents
Huang et al.	2005	Patents from 1991-2002	✓			✓	NSF-funded researchers and their patents have higher impact factors

Table 1.2: Summary results of the studies on the impact of funding on technological output (continued)

Author	Year	Data	Funding		Impact on technological output		Results
			Public	Private	Productivity	Quality	
Huang et al.	2006	Funding from NSF for nanoscale science and engineering (NSE) patents, 2001-2004	✓			✓	A significantly higher impact patents based on patent citation measures
Zucker et al.	2007	Observations for each of the 179 U.S. in economic areas, 1981-2004	✓		✓		An increase of patenting
Chen et al.	2013	United States Patent and Trade Office (USPTO) patents, 1991–2012	✓		✓	✓	An increased number of patents and citations

1.4 Research Collaborations

Collaborative networks stimulate knowledge diffusion and knowledge generation. Ideas and coded knowledge require scientists to collaborate effectively so that knowledge can flow easily across boundaries, universities and firms. However, the increasing complexity of knowledge over the past century has hindered scientists' ability to acquire all the necessary knowledge in various fields and leads them to participate in scientific collaboration (Chauvet et al., 2011; Katz and Martin, 1997; Lowrie and McKnight, 2004; Singh, 2007).

Recent studies have revealed that research networks play an important role in knowledge diffusion and economic growth as social networks recently have been much studied to uncover the impact of collaborative networks on research outcomes. This is especially true for academic researchers, who can more easily benefit from knowledge sharing across regional boundaries than individual researchers. Generally, scientific and technological outputs involve a number of authors since they usually represent outcomes from various projects and research is mainly conducted in teams. According to a study of Adams et al. (2005), the number of listed authors on scientific articles increased by 50% during the period between 1981 and 1999. Similarly, Frenken et al. (2005) raised the point that co-authored papers have increased in recent decades and can be an appropriate measure to examine the quality of research collaboration. These collaborations can enhance research productivity as well as contribute to the citation impact of collaborative research (Barabasi et al., 2002; Singh, 2004).

These studies have taken an important step towards investigation of the impact that co-publication and co-patent collaborative networks have on research outputs as shown in Figure 1.4. To understand the impact of collaboration, most studies have concentrated on the collaborative nature of knowledge production, geography, team size, etc. Lee and Bozeman (2005), however, challenge the underlying assumption that collaborative activities increase research productivity and quality. They highlighted the fact that all collaborations are not efficient and may have a negative impact on research productivity or that some collaborative research may have disappointing results. However, the effect of collaboration on research productivity may be influenced by numerous factors such as the age of scientists, success in receiving grants and contracts, the rank of university or the status of a researcher as faculty member, etc.

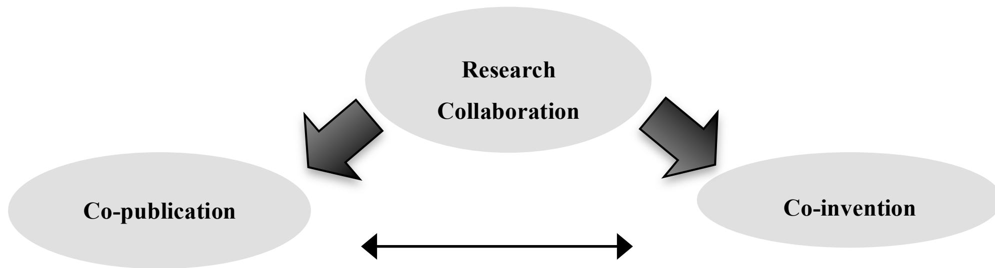

Figure 1.4: Two indicators to measure research collaboration in academia

1.4.1 The role of co-authorship collaborations in scientific performance

Apart from the inherent advantages of research collaboration as a means to channel knowledge, scientific collaboration may also increase the effectiveness of research and raise the quality of scientific outputs. It is assumed that co-publication is evidence of collaboration in academic research and that the resulting papers are the outcomes of a collaborative community. Co-publication is the most tangible form of scientific collaboration, which can be tracked to analyze the scientific networks and scientific output measured by the number of papers is closely associated with research collaboration (Glänzel and Schubert, 2005). Nevertheless, Melin and Persson (1996) raise two concerns in terms of using co-authorship as an indicator for research collaboration: first, co-authored publications can be the result of shared materials, equipment and not specifically of collaborative research; second, research collaborations do not always yield co-authored publications. Carayol and Matt (2004) analyzed the publication performance of researchers at the laboratory level and suggested that the combination of numerous researchers in labs is associated with higher publication productivity. Prior studies have generally focused on the number of authors as a measure of collaboration in co-authored publications. Figure 1.5 presents the factors that are important to study in assessing the impact of co-publication collaboration on academic research.

Pike (2010) suggested publication productivity and citation counts as means to examine scientific impact of a researcher, because the effectiveness of other metrics (e.g., size of citing community; measuring the extent of network integration) has not been clearly proven.

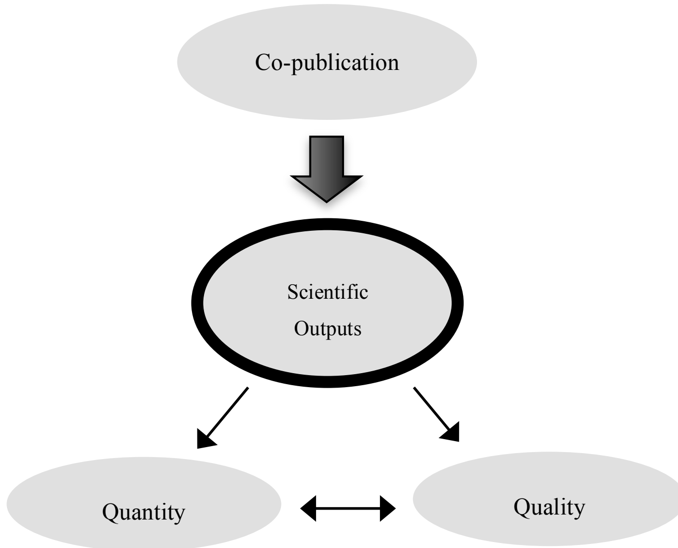

Figure 1.5: Impact of co-publication in academic research

According to a survey of academic researchers by Landry et al. (1996), collaboration increases the productivity of university researchers who collaborate with both other academic researchers and researchers from industries or institutions.

Singh (2007) further compared collaboration across national and organizational boundaries and found that scientists involved in external collaborations contribute to significantly more publications in the future. Hollis (2001) and Lee and Bozeman (2005) demonstrate that the simple number of peer-reviewed journal papers is significantly correlated with the number of collaborators, but when they implement a fractional count—where the number of papers is divided by the number of authors—the results are not confirmed. Hollis (2001) shows that the relationship between collaboration and publication quality also appears to be negative after adjusting for the number of authors per publication.

The findings of Frenken et al. (2005) show that the citation rate of papers is positively correlated with the number of authors. Wuchty et al. (2007) also highlighted that the process of knowledge creation has changed and that teams frequently produce more highly cited papers than individual researchers.

Similarly, Glänzel and Schubert (2005) shed light on giving and receiving citations and demonstrated that co-publication papers have more references than other papers and also receive more citations on average. Cross-national collaborations have been studied by a number of scholars (Katz, 1994; Glaenzel and De Lange, 1997) and geographical, historical and linguistic proximity, country size, and mobility of researchers, etc., are the subjects of numerous studies.

More specifically, Narin et al. (1991) observed that international collaborations are more effective given that internationally co-authored papers are cited twice as much as papers with authors from a single country. In contrast, He et al. (2007) addressed the difference between within-university collaboration, domestic collaboration and international collaboration on scientific outputs but could not find that internationally co-authored papers are of higher quality than within-university collaborative publications. They however observed that both collaboration undertaken within universities and across countries are strongly correlated with the quality of scientific papers whereas only collaboration within universities yields more publications in the future.

Nevertheless, according to He et al. (2009), the positive relationship between collaboration and research outcomes are more presumed than being investigated due to a belief that benefits of collaborated research is greater than the costs that are associated with this collaboration. Hence, the optimistic view that the benefits of collaborative research is more assumed than empirically verified. To test this assumption, Pike (2010) suggested to study collaborative research performance through networks, which provide important insight into scientist interaction in a research community. In particular, co-authorship can be used as a proxy for collaborative behaviour to assess how scientific collaboration enhances scientific research. The findings of Pike show that collaborations enhance scientists' scientific impact, measured by the h-index.

Katz and Marin (1997) also asserted that social networks built through collaboration provide valuable knowledge for future research outputs. Social network analysis can be used to further understand the performance of researchers in collaborative communities (Sonnenwald, 2007).

Related debates focused on how the network affects output of a researcher and whether a position of researcher within network or a more integrated network position incur better performance (Burt, 2004; Chung et al., 2007; Chung and Hossain, 2009). Newman (2004) constructed networks of scientists in biology, physics and mathematics to examine the collaborative patterns and the effect of these patterns on scientists' performance over time. He found differences among the fields, as biological scientists are more likely to publish co-authored papers than scientists in mathematics or physics. More recently, Abbasi et al. (2011; 2012) explored collaborative networks by using social network analysis measures in co-authorship networks. For instance, Abbasi et al. (2011) suggested that normalized eigenvector centrality has a negative impact on g-index as a citation-based performance, but normalized degree centrality, efficiency and average ties strength are positively correlated with this index. Their results also reveal that an author in the information systems discipline who has only one strong relationship with another may perform better than researchers who have many weak relationships.

However, collaboration does not always have a positive citation impact: Herbertz and Muller-Hill (1995) were unable to prove a substantial improvement through collaboration in the field of molecular biology. Another empirical study by Rigby and Elder (2005) analyzed the difference in research quality undertaken with and without collaboration, and observed that lower levels of collaboration can be associated with both higher and lower scientific outcomes. Hollis (2001) further highlighted that the capabilities of individual scientists determine the publishing quality of collaborative research.

1.4.2 The role of research collaborations in technological performance

Research collaboration in an innovation network can be measured by co-invention, in which multiple inventors apply for a patent together. A patent is a common indicator of research-driven invention given the fact that the information is freely available and can also be registered for a long time in patent offices (Frietsch and Grupp, 2006; Lo Storto, 2006).

Universities are generally dedicated to openly disseminating their results. Although major changes to U.S. federal law have dramatically increased the number of university patents, the Bayh-Dole Act of 1980 and the granting of IP rights to academic inventions derived from government funded research in 1984 (Jaffe et al., 1993), these changes have not increased the citation impact of academic patents (Henderson et al., 1998).

Figure 1.6 shows the issues in terms of studying the impact of co-inventions on academic research.

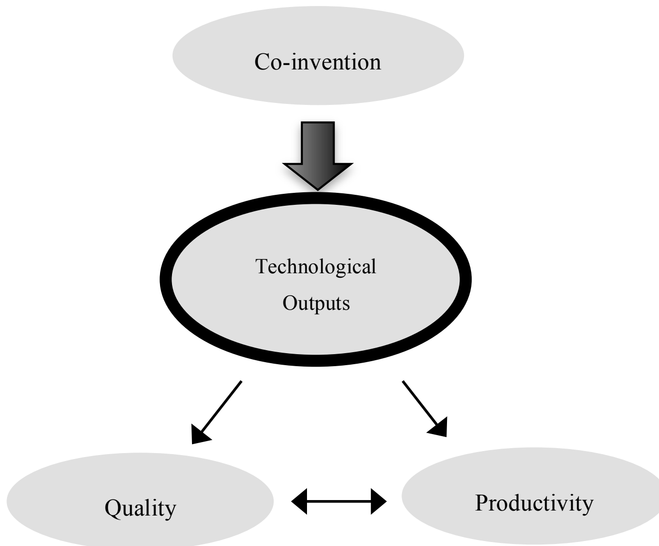

Figure 1.6: Impact of co-invention in academia

Very few papers have explored the role of collaboration in the technological performance of researchers. Despite the fact that university entrepreneurship is rapidly expanding (Rothaermel et al., 2007; Fernández-Pérez et al., 2014), the particular influence of collaborations on academic patents has rarely been studied. An empirical study of invention collaborations in China by Zhang et al. (2014) shows that the co-invention network only increases the productivity of inventors in provinces that are already productive and those that filed more patent applications.

Chen and Guan (2009) also investigated patent collaboration networks in 16 innovative countries during the period of 1975-2006 and discovered that research productivity is not positively related to the size of network as the positive effect is inversed after a specific range of network size. Contrarily to the growing argument that collaboration always enhances productivity, Fleming et al. (2007) observed no association of network collaboration on subsequent innovative productivity using U.S. patents granted between 1975-2002. In contrast, Schilling and Phelps (2007) support the consensus that the structure of innovative networks positively affects the knowledge creation and patent performance. Lecocq and Van Looy (2009) also generally found that Switzerland's research collaborations in biotechnology lead inventors to higher technological performance.

Using the network structure of Italian inventors, Balconi et al. (2004) suggested that not only are academic inventors better connected than non-academic inventors, they also occupy more central positions and play an important role in connecting inventors. Ma and Lee (2008) shed some light on innovative collaborations across the eight most inventive OECD countries between 1980 and 2005. Their results demonstrated that the collaborative efforts of inventive activities have experienced a consistent upward trend over this 25-year period. They revealed that the average size of inventive teams is approaching 2.5 inventors per patent, which suggests strong support for collaborations.

The study of a German innovation network by Canter and Graf (2006) also illustrates that the differential positions of new and existing inventors influence the technological performance of a network, and thus that a local network must contain a critical mass (including both types of innovators) to yield results. More recently, Beaudry and Kananian (2013) have investigated the collaboration network of Quebec academics in nanotechnology and biotechnology and found that the network position of researchers in their co-publication network is beneficial to their commercial activities and positively influences the number of patents of these inventors.

Few studies, however, directly focus on the impact of innovative networks on university patents. Previous studies have mostly analyzed the benefits of university-industry collaborations on commercial activities (see Barnes et al., 2002; D'Este and Patel, 2007; Hane, 1999; Lee, 2000; Perkmann and Walsh, 2007; Robb, 1991) or have extensively studied the influence of academic patenting efforts on open science publications (Balconi et al., 2004; Meyer, 2006; Van Looy et al., 2004).

Patent citations have been used to measure the impact of academic patents (Jaffe 1989). The number of citations that a patent receives is considered an appropriate proxy for the quality of a patent and shows the knowledge flow from the researcher who cited to the inventor of the citing patent. One main criticism of this measure is that patent office examiners also add some citations to the patent application, therefore skewing this proxy (Breschi et al., 2005). Beaudry and Schiffauerova (2011) used the number of claims as a proxy for quality to study the impact of co-inventorship network and found a positive influence of more central inventors on patent quality. Table 1.3 summarizes the impact of collaboration and networks on research performance in prior studies.

Table 1.3: Summary results of the studies on the impact of collaboration and networks on scientific and technological output

Author	**Year**	**Data**	**Type of collaboration**		**Impact on scientific output**		**Impact on technological output**		**Results**
			co-author	**co-inventor**	**Productivity**	**Quality**	**Productivity**	**Quality**	
Narin et al.	1991	Papers published in EC countries, 1977-1986	✓			✓			Collaborative papers were cited twice more
Herbertz and Müller-Hill	1995	Data from 13 research institutes in the field of molecular biology, 1980-1984	✓			✓			No difference in the average citation per paper with and without collaboration
Landry et al.	1996	A survey of academic researchers	✓		✓				Collaboration increases the productivity of researchers
Hollis	2001	Journal publications of 339 academic economists in 1981	✓		✓				Lower total output per author
Frenken et al.	2005	Knowledge production in European biotechnology, 1988–2002	✓			✓			Differences in citation impact can be related to the geographical scale of collaboration

Table 1.3: Summary results of the studies on the impact of collaboration and networks on scientific and technological output (continued)

Author	Year	Data	Type of collaboration		Impact on scientific output		Impact on technological output		Results
			co-author	co-inventor	Productivity	Quality	Productivity	Quality	
Lee and Bozeman	2005	Curricula vitae and survey responses of 443 academic scientists in the US	✓		✓				Publishing productivity is associated with the number of collaborators
Rigby and Elder	2005	22 scientific networks in Austria	✓			✓			Lower levels of collaborations are also associated with higher outputs
Fleming et al.	2007	Inventors and their patent co-authors from U.S. patents, 1975-2002		✓			✓		No evidence of positive impact of cohesive clusters on innovative productivity
Schilling and Phelps	2007	A panel of US firms for 11 high technology manufacturing, 1990-2000		✓				✓	Greater innovative output of firms embedded in alliance networks

Table 1.3: Summary results of the studies on the impact of collaboration and networks on scientific and technological output (continued)

Author	Year	Data	Type of collaboration		Impact on scientific output		Impact on technological output		Results
			co-author	**co-inventor**	**Productivity**	**Quality**	**Productivity**	**Quality**	
Wuchty et al.	2007	Papers over 5 decades for sciences and engineering, social sciences, humanities	✓			✓			More frequently cited research in teams than individuals
He et al.	2009	65 biomedical scientists from a New Zealand university	✓			✓			At article level, collaboration are positively related to an article's quality
Chena and Guan	2010	Patent collaboration networks of 16 main innovative countries, 1975-2006		✓			✓		Results cannot support the positive effects
Pike	2010	Published articles in the three behavioral journals, 1988-2007	✓			✓			A higher h-index is observed

Table 1.3: Summary results of the studies on the impact of collaboration and networks on scientific and technological output (continued)

Author	Year	Data	Type of collaboration		Impact on scientific output		Impact on technological output		Results
			co-author	co-inventor	Productivity	Quality	Productivity	Quality	
Abbasi et al.	2011	Data on the information schools of five universities	✓			✓			A positive significant influence of SNA measures on g-index
Beaudry and Kananian	2013	Quebec academics in nanotechnology and biotechnology, 1996 to 2005	✓				✓	✓	A positive influence of co-publication network
Zhang et al.	2014	Patent co-invention data from State Intellectual Property Office of China, 2011		✓			✓		Significant impact on patent productivity only in provinces with larger number of patents

1.5 Research Gaps and Conclusion

In this survey, we reviewed the literature on the effectiveness of funding and collaboration in universities. As funding is generally granted to research teams, funding and collaboration go hand in hand, but very little links are found in the literature regarding their joint impact on scientific and technological productivity and quality. It is critical to measure the impact of research funding on productivity and, more importantly, on research quality as specific financial investment does not necessarily yield higher quality. Two academic research outputs were identified: publications as scientific output and patents as technological output. The studies examined in this survey reveal that although government investment often enhances research productivity and quality, this positive effect has not been observed in all related studies.

Moreover, most of the studies considered only scientific publications as indicators of productive research, and often did not account for commercial activities of academic researchers. University research has increasingly turned to patenting and licensing activities in recent years even independently of the Bayh-Dole Act in the U.S. and similar rules in other countries. Depending on the purpose of some research projects, funded research however may lead to industrial outcomes instead of publications (Mowery et al. 2001). It is thus suggested to analyze the rise in academic inventions and marketing efforts. This is particularly important in new fields. The few studies conducted in this area generally suggest that commercial activities in universities increase research productivity and quality (Chen et al., 2013; Coupé, 2003; Payne and Siow, 2003; Huang et al., 2005; Huang et al., 2006; Zucker et al., 2007).

Similarly, we rarely found comprehensive studies on industry funding and its effects on academic research outputs. The findings we reviewed in this literature on the impact of private funding do not demonstrate that industry-funded research positively affects publications (Beaudry and Allaoui, 2012; Goldfarb, 2008). Despite the fact that the literature has focused on university-industry relations over the last few decades, industry funding appears to be less often studied than public funding in terms of these innovative outputs presumably because of the lack of reliable data on the subject. Nonetheless, empirical evidence on the direct effects of industry funding on academic outcomes is limited, and more investigations are required to measure its effectiveness and impact.

From an industry view, the benefits of collaborating with academia are found to be positive (see Lebeau et al. for a review), whereas the effects on academic research are not that clear. The limited findings we reviewed in this literature on the impact of private funding do not demonstrate that industry-funded research positively affects nor hinders publications. There is a need to examine various funding sources to precisely understand how research investments affect knowledge production: these analyses can prove beneficial to various funders and policy makers.

Furthermore, collaboration seems to have become a critical factor in research productivity. The impact of collaborations in the academic realm has frequently been measured by the number of co-authors, and generally researchers find a reinforcing effect of collaboration on research output. Other factors such as network determinants in social network analyses can provide more comprehensive measures to accurately evaluate the efficiency of these collaborations, but these measures are few and far between in the literature. As regards to network structures, a few studies (see Abbasi et al., 2011; Beaudry and Kananian, 2013) have shown that network measures can provide an accurate picture and valuable results to analyze the collaboration patterns.

In addition, most collaboration analyses consider the implications from a co-publication relationship while the growing attempt to commercialize interests can be represented in co-invention collaborations. We highlight two related needs: first, the need for a comprehensive study on how co-invention linkages affect the publication outcomes of researchers; and second, the need for integrated studies that assess the innovative productivity and quality of their publications. More research is required to comprehensively analyze whether scientific collaborations enhance the innovative outputs or only publication performance benefits from such collaborations. Figure 1.7 shows a conceptual framework of the gaps in empirical studies that merit attention to measure the impact of funding and collaboration on academic research. The dashed links show the lack of study on the impact of private funding on technological and scientific outputs. Also the influence of co-publication on technological outputs, and of co-invention on scientific outputs are the issues that are needed to be empirically verified. It is particularly important to analyze industry funding, as there exist certain concerns on the negative effect of industry collaborations on open science in academia.

Given the complex, costly and interdisciplinary nature of new and high technologies and of its funding limitations, further studies on this issue can advance our understanding of the key factors that enhance academic knowledge production and improve the effectiveness of funding, which will in turn enhance the productivity and quality of academic research.

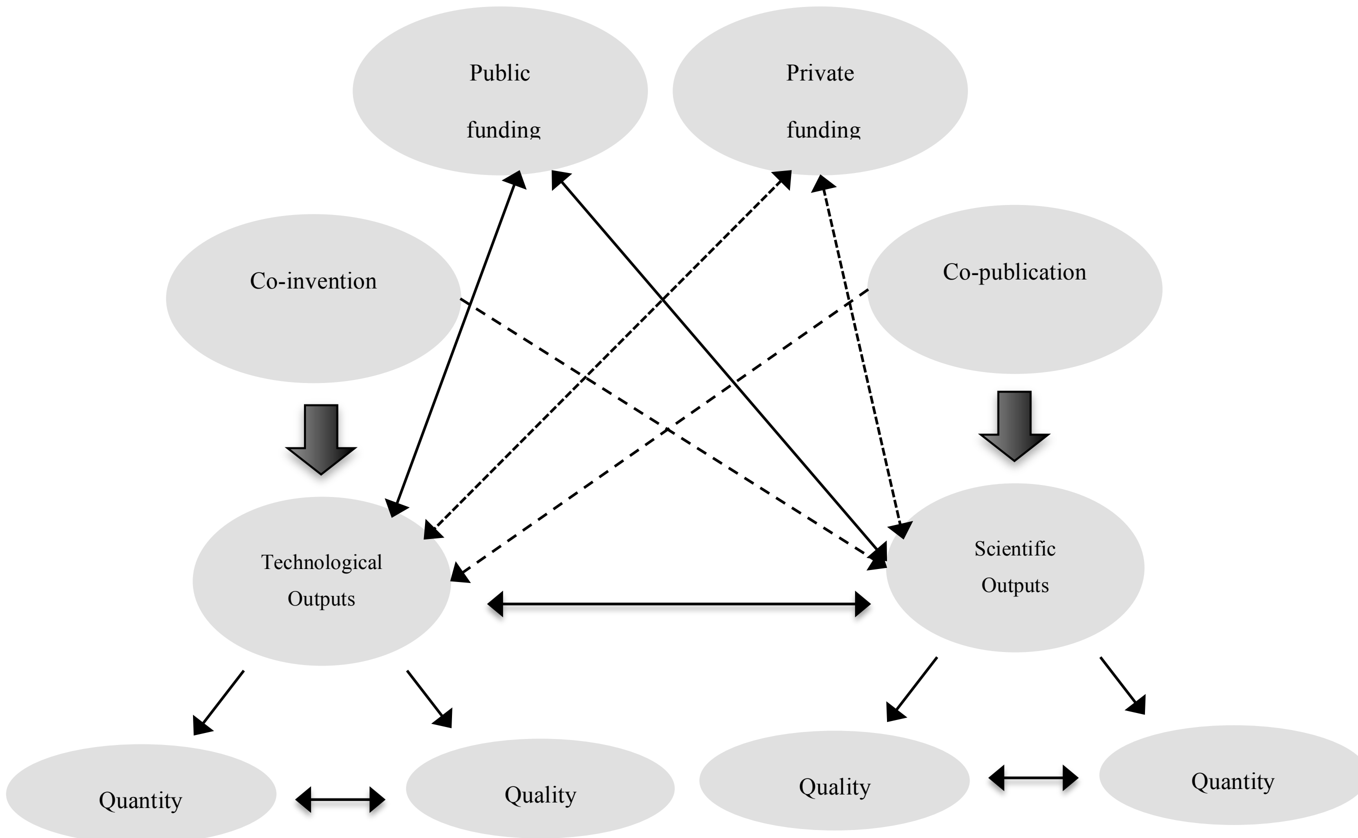

Figure 1.7: The gaps that require more attention in order to measure the impact of funding and collaborations on academic research

CHAPTER 2 RESEARCH APPROACH AND MAJOR HYPOTHESES

2.1 Research Objectives

This research focuses on two aspects of nanotechnology development: The impact of public funding, measured by the impact on productivity and efficiency of academic outputs; and collaborative networks of nanotechnology scientists in academia.

As we have seen in Chapter 1, prior studies do not clearly define the impact of government funding on academic output: some studies have found a positive effect, but other scholars have observed only a modest effect or no relationship. Regarding the influence of collaborative networks, some scholars highlight that the relationship between collaboration and research outcomes is more assumed than empirically proven.

Additionally, the existing literature focuses more on publications as the main academic output whereas entrepreneurial activity has recently increased within academia. Patents are important in promoting innovations and encouraging economic growth and development particularly in new high technologies, but the question of how public funding and collaboration can boost these outputs in universities remains unclear.

While there is a lack of study in emerging technologies, further, the ambiguous and unclear influence of government funding and collaboration on patents makes it difficult to develop policies that foster commercial activities in universities. Once we have validated (or refuted) the hypotheses presented later in the chapter, we should be able to suggest improvements science and technology policy in order to efficiently allocate grants to researchers for enhancing research output and quality.

Our first research objective is to identify the role that public funding plays in enhancing academic outputs. We examine publications, as universities highly value these outputs; and patents, as universities have recently increased commercial activities, specifically in high technologies. Our second research objective is to examine the influence that scientific and technological collaborations have on these academic outputs.

2.2 Hypotheses

We group our hypotheses into three categories: first, the impact of funding on research outputs; second, the impact of collaborations on research outputs; and third, the comparison between Canada and the US regarding this impact. The first set of hypotheses meets the first research objective in light of the impact of government financing on nanotechnology-related scientific and technological outputs. University research projects are mostly financed by the government and it is thus essential for decision makers to measure the effectiveness of such investments (Hagedoorn et al., 2004). Dramatic increases in research expenditures, particularly in high technologies, have caused growing concern over the effectiveness of research funding.

The links between government grants and academic research are complex. Despite the fact that economists have recently paid much attention to research productivity, the effect of research expenditures on research output is not trivial. Arora and Gambardella (2005) studied the relationship between National Science Foundation (NSF) funding and the quality-adjusted number of publications and observed only a modest effect[2]. Jacob and Lefgren (2011) estimated the effect of National Institutes of Health (NIH) grants and showed that receiving a grant worth $1.7 million increases the number of publications by one additional paper over the next five years, which implies a fairly limited impact. Their results on the effect of National Institutes of Health (NIH) grants on publication quality seem to demonstrate that receiving NIH grants has at most a small positive effect on citations. We thus purpose the following hypothesis:

Hypothesis 1.1*: Increased public funding to nanotechnology scientists is associated with (a)* ***more*** *nanotechnology-related* ***publications*** *and (b)* ***higher quality*** *nanotechnology-related* ***publications****.*

Most previous research has focused on the impact of funding on scientific outputs, however a few investigations have measured the correlation between funding and commercial developments in universities. Considering the sizable investment in academic applied research, it is not surprising that studies have sought to reveal convincing evidence of its effect. The econometric analysis of

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[2] The impact factor of the top 50 economic journals was used to adjust for quality in their research.

Foltz et al. (2000) on academic agricultural biotechnology patents suggests a positive relationship between patent production and government funding. An extensive study by Payne and Siow (2001), for example, showed that $1 million in federal research funding yields 0.2 more patents. Huang et al. (2005; 2006) analyzed the nanotechnology patents of NSF-funded researchers of 20 countries using citation map analysis to conduct a more direct study of technological innovations. Their findings denoted that these researchers and their corresponding patents have a higher impact than non-NSF funded recipients. In light of the evidence presented in the literature, we propose the following hypothesis:

Hypothesis 1.2: *Increased public funding to academic inventors is associated with (a)* ***more*** *nanotechnology-related* ***patents*** *and (b)* ***higher quality*** *nanotechnology-related* ***patents*** *than other academic inventors.*

Given our comprehensive data on industry funding in Quebec, we examine the influence of private funding on research outputs. However, prior studies have observed mixed effects on academic research when scientists receive industry funding (Adams and Griliches, 1998; David et al., 2000). Diamond (2006) counted the number of citations a paper received over a 7 year period and observed that privately funded research is more successful in that regard and that consequently, industry grants is positively correlated with higher quality research. Conversely, Boumahdi et al. (2003) weighted publications using the impact factor of their journals, which signals the quality of research, and found that the correlation between private funding and publication performance corrected for this impact is negative. In contrast, Behrens and Gray (2001) compared industry-sponsored projects with government-supported university projects and found no difference in the research quality of the resulting publications.

Thus, we suppose:

Hypothesis 1.3*: Nanotechnology scientists who receive more private funding is associated with* ***higher quality*** *nanotechnology-related* ***publications*** *compared with scientists who receive less or no private funding.*

Our second set of hypotheses addresses the impact of collaboration on academic outputs. Scientists generally work in research communities and publish their results and innovations in groups. Moreover, knowledge has become increasingly complex in the past century, which hinders scientists' ability to be knowledgeable in various fields and leads them to participate in scientific collaborations (Katz and Martin, 1997; Singh, 2007). Generally, scientific and technological outputs are associated with a number of authors and are the results of various research teams.

The question we address in this research is how evolving scientific and technological networks both affect the emergence of new publications and patents and boost the quality of these outputs. We therefore put forward the following hypotheses regarding the behaviour of academic inventors in co-invention and co-publications. Co-publication is the most tangible form of scientific collaboration, which can be tracked to analyze the scientific networks and scientific output measured by the number of papers is closely associated with research collaboration (Glänzel and Schubert 2005). According to a survey of academic researchers by Landry et al. (1996), collaboration increases the productivity of university researchers who collaborate with both other academic researchers and researchers from industries or institutions. Singh (2007) further compared collaboration across national and organizational boundaries and found that scientists involved in external collaborations contribute to significantly more publications in the future.

Similarly, Glänzel and Schubert (2005) shed light on giving and receiving citations and demonstrated that co-publication papers have more references than other papers and also receive more citations on average. Our hypotheses therefore go as follows:

Hypothesis 2.1*: A better network position of nanotechnology scientists within past* ***co-publication*** *networks has a positive effect on (a) the* ***number of publications*** *and (b) on the* ***quality of publications****.*

We also aim to investigate whether co-publication networks affects the academic patents:

Hypothesis 2.2*: The technological performance of academic inventors is (a)* ***higher*** *and (b) yields* ***better quality*** *in researchers who hold a more influential network position in past* ***co-publication*** *networks.*

Very few papers have explored the role of collaboration in the technological performance of researchers. Despite the fact that university entrepreneurship is rapidly expanding (Rothaermel et al. 2007), the particular influence of collaborations on academic patents has rarely been studied. An empirical study of invention collaborations in China by Zhang et al. (2014) shows that the co-invention network only increases the productivity of inventors in provinces that are already productive and those that filed more patent applications. Fleming et al. (2007) observed no association of network collaboration on subsequent innovative productivity using U.S. patents granted between 1975-2002. In contrast, Schilling and Phelps (2007) support the consensus that the structure of innovative networks positively affects the knowledge creation and patent performance. We therefore propose two hypotheses:

Hypothesis 2.3*: A better network position of nanotechnology scientists within past* ***co-invention*** *networks has a positive effect on (a) the* ***number of publications.***

Hypothesis 2.4*: The technological performance of academic inventors is (a)* ***higher*** *and (b) yields* ***better quality*** *in researchers who hold a more influential network position in past* ***co-invention*** *networks.*

We examine our research objectives for Canada and the US and finally, we compare the influence of financing on research performance in Canada and the US by defining a dummy variable for country. In Canada the proportion of government-funded R&D is high compared to industrial R&D (Niosi 2000). We therefore propose in our Hypothesis to test whether this government funding leads to scientific production of higher quality and quantity in Canada in comparison to the impact of public funding in the US. We suggest the following hypotheses:

Hypothesis 3.1: *Increased public funding to nanotechnology scientists in Canada is associated with (a)* ***more nanotechnology-related publications*** *and (b)* ***higher quality nanotechnology-related publications*** *in Canada compared to increased public funding to nanotechnology scientists in the US.*

Hypothesis 3.2: *Increased public funding to nanotechnology academic inventors in the US is associated with (a)* ***more patents*** *and (b)* ***higher quality patents*** *compared to Canadian academic* *inventors.*

These hypotheses will be tested in Chapters 3, 4, 5 and 6.

2.3 Data Description

Publications have been extensively used to measure the scientific productivity of researchers' performance. This is the most fundamental research outcome in universities that allows scientists to receive professional advancement, recognition and promotion (Fox, 1983). Correspondingly, in recent decades, governments have focused on technologically relevant outputs in academia (Czarnitzki et al., 2007; Jafe, 1989). Universities have played an important role in producing commercial research, which has proven crucial to various industries. Since the early 1980s, the Bayh-Dole Act has facilitated patenting of innovations derived from government-funded research and has dramatically increased the number of university patents (Jaffe, 1989; Jaffe et al., 1993).

In this thesis, such research outputs from various sources are employed to conduct this analysis.

2.3.1 Funding

The Canadian federal granting agencies database provides information on government research financing from the Natural Sciences and Engineering Research Council of Canada (NSERC) and the Canadian Institutes of Health Research (CIHR). Granting data on US researchers is gathered from Nanobank, which also includes National Science Foundation (NSF) and National Institute of Health (NIH) grants.

In Quebec, we have access to a unique and comprehensive granting database: the Système d'Information sur la Recherche Universitaire (SIRU) which contains information on government and industry funding awarded to researchers in the Quebec academic system and is managed by the Ministry of Education, Leisure and Sports (MELS). For the purpose of our analysis, we use data between the years 1985-2005. The reason for choosing this time period stems from the fact that we wanted to have enough citation years after 2005 (as an end date for the sample) because we examined three periods for citations, 3 years, 5 years and 7 years after publication and grant year for patents. 1985 is the start date in SIRU database but since the data is more reliable in the post-1996 period and there has been a considerable change in the quality of Scopus after 1996, and this timeframe seems too early for nanotechnology, we analyze the date between the years 1996-2005.

2.3.2 Publications

We extract publication and authorship data from Elsevier's Scopus, which provides more accurate and comprehensive metadata such as abstracts and citations from more than 18000 scientific journals. To gather such data in Canada, we extract articles in which at least one author is affiliated with a Canadian institution; this same methodology is applied to the U.S. data.

In order to complement and clean the large volume of US data, a combination of Scopus and Google Scholar was used to access the publications that contain nanotechnology-related keywords. We use the software "Publish and Perish" to filter the results in Google Scholar and match this data with data from Scopus, the latter enabled us to search the full text of publications.

2.3.3 Patents

Patenting data were extracted from the United States Patent and Trademark Office (USPTO) for both Canada and the US.

Due to the extensive commercial partnership between the US and Canada, Canadian inventors commonly register their patents with this entity to protect their innovations in a larger market (Beaudry and Schiffauerova, 2011). Hence, the USPTO is an acceptable substitute for the Canadian Intellectual Property Office (CIPO) as it contains much data on the affiliation of inventors.

2.3.4 Creating dataset

To extract the nanotechnology publications and patents, specific nanotechnology-related keywords are derived and combined from various keyword search strategies (Alencar et al., 2007; Fitzgibbons and McNiven, 2006; Mogoutov and Kahane, 2007; Noyons et al., 2003; Porter et al., 2008; Zucker and Darby, 2005; Zitt and Bassecoulard, 2006). Subsequently, keywords are investigated by consulting with nanotechnology experts. We then remove redundant keywords to obtain an appropriate representation of nanotechnology research outputs. Figure 2.1 shows the different data sources employed in our econometric analyses to compare nanotechnology research in Quebec, Canada and the US. We believe that the final set of keywords (see in Appendix E) is quite comprehensive and is able to effectively identify articles and patents directly related to nanotechnology.

In order to complement and clean the large dataset, we extracted data using a combination of Scopus and Google Scholar since the latter enabled us to search the full text of publications for nanotechnology-related keywords. We used the ‘‘Publish or Perish’’ software to filter the results in Google Scholar and then matched each identified article with the data from Scopus. This methodology allowed us to combine an in-depth full-text search of Google Scholar with well-structured data from Scopus.

We then merged our data from different sources defining a unique ID for each individual scientist. A considerable amount of work was required to perform the disambiguation of scientists' names in merging different publishing, patenting and funding databases. Matching was not trivial; our approach involved matching data using scientists' names. This process is likely to result in possible errors in uniquely identifying scientists having similar names (synonymy) or assigning different IDs to the same scientist whose name is written differently in various databases (homonymy). To circumvent these common problems, we utilize a variety of other information about scientists to define a unique ID for each academic researcher and thus to minimize the incidence of wrong matches. The main information was provided by the affiliation of scientists in both Scopus and SIRU in addition to the address of academic inventors in the USPTO database.

A large amount of manual work and careful examination was however necessary to clean the data. This check of individuals' name helps avoid ambiguity and bias in our data. We then created a panel dataset in which we compiled yearly information for each individual scientist/inventor over a 20-year period (1985-2005).

We finally restrict our resulting sample data to 1996-2005, after having calculated the lagged variables on 3 years and 5 years averages. The reason for concentrating on this subset is twofold; first according to the growth of nanotechnology research outputs, scientists had only recently started being involved in this emerging area before 1996 and the data is rather scarce prior to that period, hence this timeframe seems too early for nanotechnology. Second, there has been a considerable change for the better in the quality of Scopus after 1996.

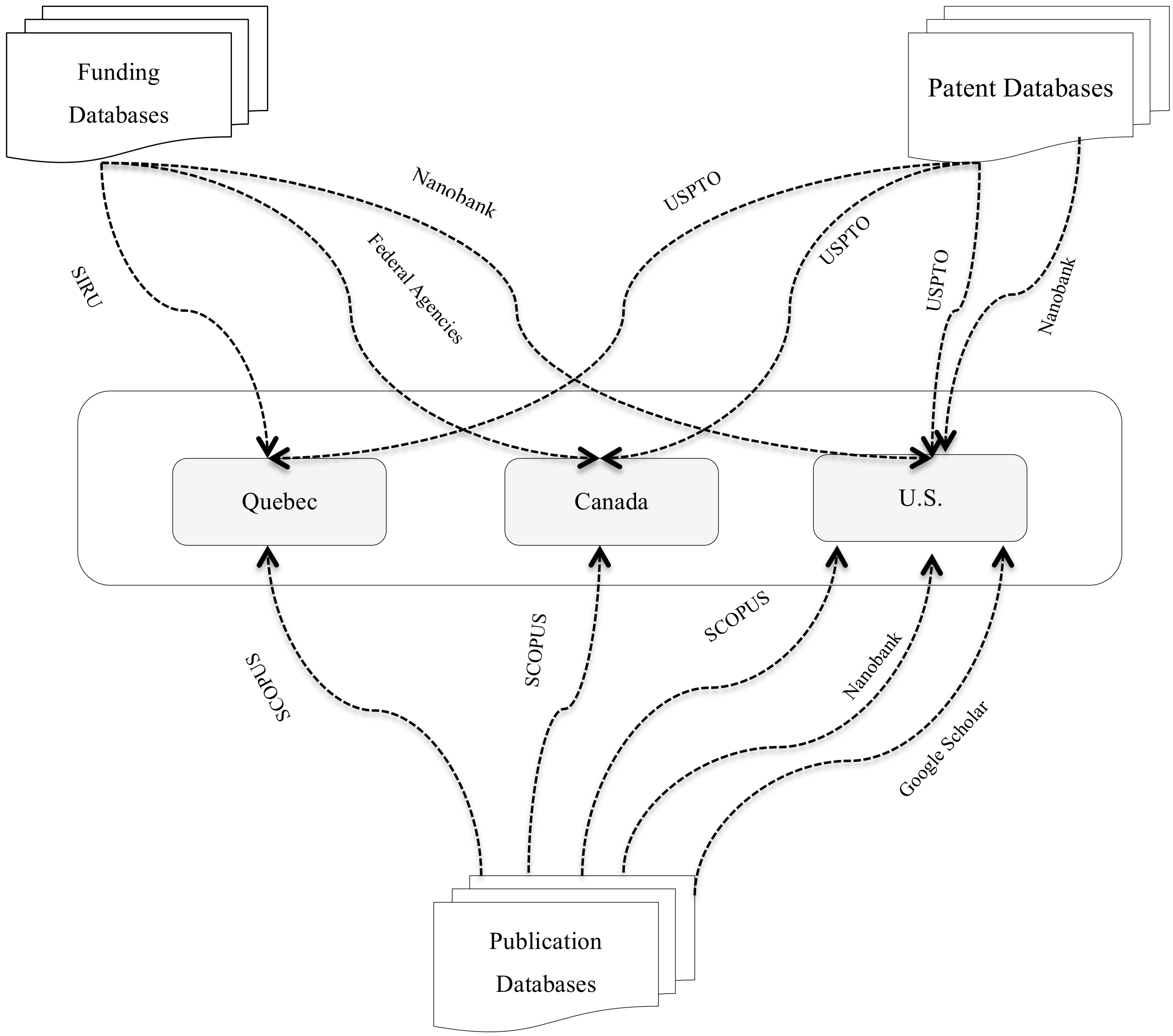

Figure 2.1: Various databases used for the analysis

2.4 Methodology

In this research, we use bibliometric methods and social network analysis to create the indicators that enter econometric models. Despite some limitations, bibliometrics are useful to quantify some characteristics of data analysis.

2.4.1 Publications

It is increasingly important to measure the scientific output of researchers and provide accurate research assessments for government and universities to efficiently allocate funding to researchers. High performance researchers are generally determined by their scientific production and the number of citations their papers receive (Alonso et al. 2010; Kosmulski, 2011). Bibliometric indicators are commonly used to evaluate research performance and provide a quick impression of the quality of research. Citation analyses generate relatively short-term quantifiable measures based on an assumption of a linear relationship between scientific quality and citation counts.

Publication and citation counting are appropriate techniques as they are indicators of productivity and can be used to evaluate scientific activity (Narin, 1976). Bibliometrics yield an acceptable assessment of scientific activities and continue to evolve in response to policies (Hicks et al., 2004).

There has been an increased interest in the importance of research quality as against mere quantity; therefore, citations by other scientists are generally accepted as an indicator of a paper's impact in the scientific community.

Additionally, these citations measure the connectivity between authors, scientific fields and research departments (Durieux and Gevenois, 2010).

According to Bornmann and Leydesdorff (2013), research quality is a complex attribute in which there is no specific formula to quantify the quality of a paper. However, citation-based indicators are widely acknowledged as quality metrics and are used to understand trends in context and assess the influence of research (Leydesdorff, 2009).

In relation to our analysis, we defined a variable that counts the number of papers that are published every year by an individual scientist. We used three spans of citation counts, that the articles of a scientist received within three, five and seven years after the publication year to measure paper quality. We found more consistent results using five-year citations for our time period (1996-2005). Additionally, the average number of past articles of researchers over three years as an instrument variable is included in our models to explain the fact that funding is generally given to academic researchers with a high publication rate (Van Raan, 2004).

2.4.2 Patents

Patents are reliable proxy indicators of innovative effort and are therefore an important element of the analysis of innovations. Patent data are readily available via patent offices and can be used to study knowledge flows in innovation systems (Acs et al., 2002). According to Mansfield (1986), patent protection is at the heart of national policies on technological change since it has prominent effects on the innovation rate. However, patent counts and patent citations are also commonly accessible and viable measures that can capture the innovative performance of inventors. Further, given the use of these measures, many studies suggest them as reasonable measures of innovative activity (Cantwell and Hodson, 1991; Griliches, 1998; Patel and Pavitt, 1995).

Although Arundel and Kabla (1998) and Mansfield (1986) raise some critical concerns on the general use of patents as a measure of innovative performance (for example, not all patentable inventions were patented), they suggest using this indicator in many high technology fields.

Daim et al. (2006) point out that patents are vastly different in their importance, which patent counts cannot capture. Subsequently, patent citations present a measure of patent quality based on a presumption that the impact of a patent is correlated with the number of times it is cited in other patents as their relevant prior art (Hagedoorn and Cloodt, 2003).

Trajtenberg (1990) highlights the importance of using citations as indicators of the invention's value to overcome the limitations of a simple patent count. Patent citations also create the opportunity to trace relationships between inventors and inventions and can be used to study the importance of a patent (Hall et al., 2001). According to Trajtenberg (1990), these citations are correlated with the value of inventions and are potentially useful for technology spillovers. The key idea behind the patent citation analysis is that a highly cited patent is more likely to contain important technological advances, and is thus an indicator of technological quality (Karki 1997).

Lanjouw and Schankerman (1999) indicate that patent claims are a measure of patent quality since they influence the decision to renew a patent.

Claims in the patent specification denote the property rights protected by a patent and define novel features of the invention in the patent application (Lanjouw and Schankerman, 2004). Further, patent claim is an important quality-related index that indicates the broadest greater potential profitability of an invention. The number of claims illustrates that a broader area of technological space is contained in an invention and points to the fact that a patent is technologically significant (Tong and Frame, 1994). According to Lanjouw and Schankerman (1999), forward citations and the number of claims are the most informative indicators of quality that are positively related to patent quality.

To establish our analysis, we take into account the number and quality of patents. We specify one dependent variable, the number of patents, to account for the production of patents and two other variables, the number of citations received over five years and the number of claims, to proxy for patent quality in our models. Similarly to the citation counts for publications, three different windows of time were considered in order to count the number of citations: 3-year, 5-year 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 time windows. We also used the Number of patents of an academic-inventor over past three years as an independent variable in our models to examine that how past experience in patenting activity is associated with new patents. We also add the square of this variable to investigate the non-linear effect.

This aspect of methodology is implanted in Chapter 5 and 6 where we use these two indicators to measure the impact of funding on patent quality.

2.4.3 Network Analysis

Social network analysis enables the study of social systems behavior on different levels including individual actors, groups and subgroups (Wasserman and Faust, 1994). These networks consist of a finite set of nodes and edges that connect pairs of nodes (Freeman, 1979). According to Streeter and Gillespie (1993), network analysis is an appropriate methodology for complex interactions between actors within direct and indirect relationships. In a scientific or technological network, scientists and inventors share their knowledge within the co-authorship or co-invention relationships to accelerate the knowledge diffusion. In turn, these relationships greatly foster technological development.

Some scholars (see Newman, 2001; Balconi et al., 2004) applied social network techniques to study scientists and inventors in these networks as individual actors. In this study, we construct the collaborative networks between scientists and academic inventors to study a variety of network properties. Two scientists/academic inventors are considered connected if they have co-authored/ co-invented one or more papers/patents together. However, according to Newman (2001), these networks are in some ways truly social networks as most pairs of scientists who have published/patented together are acquainted with other one.

In order to investigate a scientist's position in scientific networks, we characterize the networks of co-authors and co-inventors using the software Pajek. We construct time evolving sub-networks corresponding to three-year and five-year windows using the co-authorship and co-invention links in order to track and measure the evolution of collaboration over time. We then only include the network characteristics of three-year intervals and analyze the impact of these indicators on the publication quality of researchers as these three-year intervals generate the most significant results.

Thus, to study the collaborative networks from bibliographic data, we concentrate on three characteristics related to the network position of researchers:

2.4.3.1 Degree centrality

Degree centrality of a researcher corresponds to the number of other researchers connected directly to that researcher; it can indicate local centrality in a network and a researcher's popularity. The normalized measure of researcher degree centrality R_k is given in Eq. (2-1) where n is the number of researchers in the network and $d(R_i,R_k)$ is a function that equals 1 if researcher R_i is connected to R_k, and 0 otherwise (Freeman, 1979; Chung and Hossain, 2009).

$$C_D(R_k) = \frac{\sum_{i=1}^{n} d(R_i, R_k)}{n-1} \tag{2-1}$$

betweenness centrality, which is generally employed to evaluate the importance of a researcher as an intermediary connector within a network (Benedictis and Tajoli 2008; Izquierdo and Hanneman 2006); and cliquishness or clustering coefficient, which refers to the likelihood that two researchers have tendency to cluster together (Barabasi 2002; Singh 2007).

2.4.3.2 Betweenness centrality

This measure proposed by Freeman (1979) is an indication of the number of times a researcher connects two other researchers in a network. The number of shortest paths (geodesics) between two researchers is considered in calculating this measure. Eq. (2-2) 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).

$$C_B(R_k) = \sum_{i}^{n} \sum_{j}^{n} \frac{g_{ij}(R_k)}{g_{ij}} \qquad where\ i \neq j \neq k \qquad (2\text{-}2)$$

2.4.3.3 Cliquishness

The clustering coefficient or cliquishness is commonly used to measure the tendency of researchers to cluster together. This indicator, introduced by Watts and Strogatz (1998), and is always a number between 0 and 1. Given three researchers (*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. (2-3) shows the clustering coefficient for a particular researcher (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).

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

In this research, these network indicators are calculated in two co-publication and co-invention networks and we chose 3-year intervals with a two-year lag to determine the importance of a researcher as a node in the networks. We created three-year co-authorship/co-invention sub-networks[3] for all the three-year moving intervals using the social network analysis software Pajek, which is considered to be very suitable for the analysis of large networks (Batagelj and Mrvar 1998). We define two sets of variables to account for each of these network measures, degree centrality, betweenness centrality and cliquishness to explain the connections in co-authorship networks; and the same metrics to account for co-invention ties in our models.

2.4.4 Econometric models

To measure the impact of funding on publications and patents, our econometric approach mainly analyzes the relationship between funding and the number of publications/patents, and between funding and the forward citations of these publications/patents. We also use the number of claims as another measure of patent quality. Since this study addresses the impact that funding granted for nanotechnology academic research has on scientific output, we calculate the average amount of public funding received over three years lagged by one-year to account for the time lapse between receiving government grants and generating scientific/technological output. We also add the square of this variable to investigate the non-linear effect of public funding. SIRU contains both government and industry funding that was awarded to all university scientists in Quebec for the period of 20 years (1985-2005)[4] that enabled us to analyze the assess the influence of private funding on publication quality in Quebec. We then calculate the average amounts of private contracts over the past three years lagged by one year.

It should be noted that our funding variable causes potential endogeneity due to simultaneity and omitted variable bias. Governments implement various mechanisms to allocate funding to universities based on research performance (Geuna et al. 2003; Liefner 2003). A notable concern

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[3] We also constructed five-year sub-networks, but three-year sub-networks gave us more consistent results.

[4] The data are available for this period and not for subsequent years.

in our study is that researchers with a higher performance receive more funding from governments, in addition to which we may have some omitted variables that affect the opportunity to receive grants. To specifically address this concern and control for potential endogeneity, we use two techniques: Two Stage Least Squares (2SLS) and Two Stage Residual Inclusion (2SRI) (Biro 2009; Terza et al. 2008; Stephan et al. 2007) and express the first and second stage of our estimations to account for endogeneity in the average grant amount received by scientists/ awarded to scientists. We therefore estimate a variant of the model using a set of instruments for the estimation of funding, our 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 for the nanotechnology experience of academic researchers. The quadratic form of this variable helps account for potential non-linearities. The other instrument variable that we included in our models was the average number of papers published by researchers in the past three years.

We also add the type of chair for our study within Canada that these researchers occupied at some point in their career using an ordinal indicator that takes the value 0 for no chair, 1 if they occupy an industrial chair and also receive funding from NSERC or CIHR, and 2 for being a Canada Research Chair. We also added an ordered measure to our set of instruments for the type of funding (Award), which equals 1 if a researcher receives funding through an award and 0 otherwise. The granting of academic research can further act as a signal of scientist productivity and these scientists may attract additional funding in subsequent years. The literature generally finds that scientists with prestigious awards and public funding contribute to more scientific and technological outputs (Sauer, 1988; Payne and Siow, 2003; Adams et al., 2005; Jacob and Lefgren, 2007; Blume-Kogut et al., 2009).

The residuals of the first-stage equation are then added to the regressors of the second stage equation prior to its estimation. We considered our models estimated both with and without controlling for potential endogeneity and our analysis has considered various sets of variables in a hierarchical progression including non-linear effects.

We employ time series analysis to develop dynamic econometrics. Our method consists of performing hierarchical regressions with the number of publications, the number of paper citations, the number of patents, the number of patent citations and the number of claims as dependent variables. We also test the moderating effect between our variables by introducing interactive variables. This helps us to examine whether one variable has an intrinsic relation with other variables, and it also moderates the influence of them on the dependent variables.

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 one-year lag for funding and a two-year lag for the network determinants before publication/application of research output. The description of variables present in each paper is shown in Table 2.1

Table 2.1: Description of variables

Variable Description	Type	Paper 2	Paper 3	Paper 4	Paper 5
Dependent variables					
Number of papers of a scientist *i* in a given year *t*	D	$nbPaper_{it}$			$NumPaper_{it}$
Number of patents of an academic inventor *i* in a given year *t*	D			NP_{it}	$NumPatent_{it}$
Number of citations received by the paper(s) of a scientist *i* over the following five years.	D	$nbCitation5_{it}$	$nbArtCit5_{it}$		
Number of citations received by the patent(s) of an academic-inventor *i* over the following five years.	D			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.	D			$C(NCi_{it})$	
Number of claims contained in the patent(s) of an academic-inventor *i* applied for in year *t*.	D			NCl_{it}	
Independent variables					
Average yearly amount of government funding received by a scientist/ an academic-inventor i over the past three years (*t*-3 to *t*-1)	En/In[5]	$\ln(GovGrant3_{it-1})$	$\ln(AvgGrant3_{it-1})$	$\ln(F_{it-1})$	$GrantAmount_{it-1}$
Average yearly amount of private funding received by a scientist/ an academic-inventor i over the past three years (*t*-3 to *t*-1)	Ex		$\ln(AvgContract3_{it-1})$		
Number of applied patents of a scientist/ an academic-inventor *i* over past three years (*t*-3 to *t*-1)	Ex	$nbPast3Pat_{it-1}$	$nbPatent3_{it-1}$	NPP_{it-1}	
Betweenness centrality of an academic-inventor *i* in the three-year **co-invention** sub-network lagged two years.				$\ln(10^4 \times PBC_{it-2})$	$\ln(10^4 \times BetCentPatent3_{it-2})$
Clustering coefficient of an academic-inventor *i* in the three-year **co-invention** sub-network lagged two years.	Ex			$\ln(10^3 \times PCC_{it-2})$	$\ln(10^3 \times CliquishnessPatent3_{it-2})$
Degree centrality of an academic-inventor *i* in the three-year **co-invention** sub-network lagged two years.	Ex				$\ln(10^4 \times DegCentPatent3_{it-2})$

[5] This variable is considered as instrument variable in paper 5

Table 2.1: Description of variables (continued)

Variable Description	Type	Paper 2	Paper 3	Paper 4	Paper 5
Betweenness centrality of an academic-inventor *i* in the three-year **co-publication** sub-network lagged two years.	Ex	$\ln(10^4 \times BetweenCent_{it-2})$	$\ln(10^4 \times BtwCent3_{it-2})$	$\ln(10^4 \times ABC_{it-2})$	$\ln(10^4 \times BetCentPaper3_{it-2})$
Clustering coefficient of an academic-inventor *i* in the three-year **co-publication** sub-network lagged two years.	Ex/En[6]	$\ln(10^3 \times Cliquishness_{it-2})$	$\ln(10^3 \times Cliqness3_{it-2})$	$\ln(10^3 \times ACC_{it-2})$	$\ln(10^3 \times CliquishnessPaper3_{it-2})$
Degree centrality of an academic-inventor *i* in the three-year **co-publication** sub-network lagged two years.	Ex				$\ln(10^4 \times DegCentPaper3_{it-2})$
Dummy variables					
Dummy variables for different years (*t* = 1985, …, 2005)	Dummy	D_t	D_t	D_t	D_t
Dummy variable for Canada, which takes the value 1 for Canadian scientists/academic inventors and the value 0 for scientists/academic inventors that are affiliated to the US	Dummy	dCanada		dCA	
Dummy variable for Quebec, which takes the value 1 for scientists/academic inventors in Quebec and the value 0 for scientists/academic inventors that are affiliated to the other provinces in Canada	Dummy				dQC
Instrumental variables					
Career age of a scientist since the first publication or the first grant or the first patent in the field of nanotechnology.	In	$CareerAge_t$	Age_t	Age_t	$NanoAge_{it}$
Ordinal indicator that takes the value 0 if a researcher has no chair, the value 1 if he holds an industrial chair, the value 2 if being a chair of one of two Canadian federal granting councils, and the value 3 for a scientist who is a Canadian Research chair at some point in his career	In		$Chair_t$		

[6] This variable is considered endogenous in paper 5.

Table 2.1: Description of variables (continued)

Variable Description	Type	Paper 2	Paper 3	Paper 4	Paper 5
The type of chair that these researchers occupied at some point in their career using an ordinal indicator that takes the value 0 for no chair, 1 if they occupy an industrial chair and also receive funding from NSERC or CIHR, and 2 for being a chair of the Canada Research Chair.	In				$CanadaChair_{it}$
An ordered measure to our set of instruments for the type of funding, which equals 1 if a researcher receives funding through an award and 0 otherwise.	In				$Award_{it}$
Number of past articles published by an academic inventor *i* over three years.	In	$nbAvgPaper3_{t-1}$	$nbArticle3_{t-1}$	NA_{it}	$NumPaper3_{it}$

Notes: D: Dependent Variable, En: Endogenous Variable, Ex: Exogenous variable, In: Instrumental Variable

There are various models for count data that have been used in economics. The Poisson model is the most frequently employed method in such modeling (Hausman et al. 1984; King 1989; Riphahn et al. 2003). Because of the restriction on the distribution in the Poisson model regarding over-dispersion, some researchers find that the Negative Binomial Model (NB) is more appropriate (Greene 2008; Hilbe 2011). Many scholars have employed one of these two methods to analyze count data (Wang et al. 1998; Fleming and Sorenson 2001; Maurseth and Verspagen 2002; Mowery et al. 2002; Payne and Siow 2003; Tsionas 2010; Petruzzelli 2011). In case of having excessive zeros in our count data, we consider zero-inflated Poisson vs. Poisson and zero-inflated negative binomial vs. negative binomial model and use Voung test as suggested by Vuong (1989). Zero-inflated models allow for complication of analyzing datasets with an excessive number of outcome zeros (Greene 1994; Long 1997; Vuong 1989).

We implement the zero-inflated poisson model, zero-inflated negative binomial model, negative binomial model and ordered probit model to validate our hypotheses.

2.4.5 Contributions

The results of this research have provided the following original contributions:

Main Papers

1. Tahmooresnejad, L., Beaudry, C. (2014). Impact of Funding and Collaborations on Scientific and Technological Performance in Universities, A Review of Literature, European Management Journal, Submitted in November 2014.

2. Tahmooresnejad, L., Beaudry, C., & Schiffauerova, A. (2014). The role of public funding in nanotechnology scientific production: Where Canada stands in comparison to the United States. Scientometrics, 1-35.

3. Tahmooresnejad, L., Beaudry, C. (2014). Impact of Public and Private Funding on Nanotechnology Research Quality, International Journal of technology management, submitted in June 2014.

4. Tahmooresnejad, L., Beaudry, C. (2014). Collaboration or Money: Lessons from a Study of Nanotechnology Patenting in Canada and the United States, Journal of Engineering and Technology Management, Submitted in October 2014.

5. Tahmooresnejad, L., Beaudry, C. (2014). Collaborative networks, productivity, and academic research: evidence and implications for the field of nanotechnology, Social Networks, Submitted in November 2014.

Secondary papers:

- Tahmooresnejad, L., Beaudry, C., (2013). Impact du financement privé et public sur le développement de la nanotechnologie : étude de la productivité de la recherche au Québec, Compendium d'indicateurs de l'activité scientifique et technologique au Québec, édition 2013.

  PS: Published in Compendium 2013

- Tahmooresnejad, L., Beaudry, C., (2013). Does government funding increase patenting in the nanotechnology field? A comparison of Quebec and the rest of Canada, Patent Statistics For Decision Makers, Rio de Janeiro, Brazil, Novomber 2013.

- Tahmooresnejad, L., Beaudry, C., (2014). Does government funding have the same impact on academic publications and patents? A comparison of Quebec with other provinces, ISPIM conference, Montreal, Canada, October 2014.

  PS: Received The ALEX GOFMAN BEST STUDENT PAPER AWARD
  Accepted in the special issue of International Journal of Innovation Management

CHAPTER 3 ARTICLE 2 : THE ROLE OF PUBLIC FUNDING IN NANOTECHNOLOGY SCIENTIFIC PRODUCTION: WHERE CANADA STANDS IN COMPARISON TO THE UNITED STATES

Leila Tahmooresnejad, Catherine Beaudry, Andrea Schiffauerova

3.1 Abstract

This paper presents cross-country comparisons between Canada and the United States in terms of the impact of public grants and scientific collaborations on subsequent nanotechnology-related publications. In this study we present the varying involvement of academic researchers and government funding to capture the influence of funded research in order to help government agencies evaluate their efficiency in financing nanotechnology research. We analyze the measures of quantity and quality of research output using time related econometric models and compare the results between nanotechnology scientists in Canada and the United States. The results reveal that both research grants and the position of researchers in co-publication networks have a positive influence on scientific output. Our findings demonstrate that research funding yields a significantly positive linear impact in Canada and a positive non-linear impact in the United States on the number of papers and in terms of the number of citations we observe a positive impact only in the US. Our research shows that the position of scientists in past scientific networks plays an important role in the quantity and quality of papers published by nanotechnology scientists.

Keywords : Nanotechnology, Research funding, Scientific papers, Collaboration, Network analysis

3.2 Introduction

Nanotechnology is an emerging technology that is considered one of the primary forces to drive future economic development. For this reason, worldwide investment in this emerging technology has increased substantially in the past two decades and governments have considerably subsidized nanotechnology-related R&D in recent years. Fitzgibbons and McNiven (2006) indicate that in Canada the main funding source for nanotechnology R&D is the Canadian government which provides the funding through different organizations: the Natural Sciences and Engineering Research Council (NSERC), Canadian Institutes for Health Research (CIHR), National Research Council (NRC), Canada Foundation for Innovation (CFI), etc. In addition to the federal funding, various activities are concentrated in specific provinces in Canada to develop nanotechnology. The British Columbia Nanotechnology Alliance, Nanotechnology Network of Ontario, NanoQuebec and NanoAlberta are the main provincial frameworks that help develop nanotechnology along with the federal programs (Dufour 2005; Allan et al. 2008; Pelley and Saner 2009). According to Roco (2005), the United States invested approximately $1 billion US in government funding dedicated to nanotechnology R&D in 2005, 65% of which was specifically allocated to academic R&D and education. The US government nanotechnology funding has been raised mainly by the National Nanotechnology Initiative (NNI), which was launched in 2000 and consists of numerous federal agencies. Fifteen NNI agencies are responsible for the funding of nanotechnology research and development. The NNI has invested $18 billion in total since 2001, and $1.8 billion has been provided for 2013 alone. The National Institutes of Health (NIH) and the National Science Foundation (NSF) are two agencies that occupy the second largest investment rank in 2011 between the agency members of the NNI after the Department of Energy (DOE) (NNI 2013; Jacob and Lefgren 2011; Sargent 2010).

Given the magnitude of government investment in nanotechnology research in recent years, it is of great importance to measure the efficiency and productivity of research financing. The efficient allocation of government resources requires a better understanding of how funding influences scientists' productivity and their scientific output. Such financing evaluations can help governments develop policies that will foster the development of this emerging technology.

Nanotechnology is an emerging technology that will have enormous impact on future products and processes. This technology has potential to affect economic development and gives new tools for governments to take advantage of the recent leaps in technology and science. Growing understanding of the role of public funding research in nanotechnology development will help governments to launch strategies that meet their high expectations associated with this new concept. Considering the potential new world market of nanotechnology related products, countries develop research in the field of nanotechnology to ensure that they are going to take advantage of the opportunities that are available in this area. In this study, we therefore focus on government grants rather than other funding sources. This leads to a strong necessity to study the impact of public funding, with a special focus on the public funding sources in the field of nanotechnology. We hence compare the impact of investments in Canada with that of the US, which is a leader in setting up numerous targeted nanotechnology programs and research grants in the hope of fostering future economic development. It is of great importance to discover whether the research funding strategies have been productive in this field.

To explore the impact of public funding on scientific papers, to reflect how nanotechnology research grants influence researchers' productivity, we utilize econometric models to measure this impact on the quantity and quality of nanotechnology-related papers. The evidence of past studies (Huang et al. 2005; Payne and Siow 2003) reveals the positive impact of government funding on research output. Because scientists increasingly work in larger teams, in addition to research financing, we wish to discuss the role that scientific networks play in the scientific production. This paper thus explores the effects that collaboration networks have on research productivity by measuring the position of these researchers within scientific co-publication networks. According to the work by Ni et al. (2011) and Breschi et al. (2006), researchers who have more connections with other scientists in networks publish more papers and tend to collaborate more with other researchers, enhancing research output.

There are some important differences between the US and the Canadian science, technology and innovation system. Although Canadian universities play key roles in basic research and produce a reasonable number of research papers, their contribution to domestic industrial research is less than that of US institutions. The majority of university research funding is provided through government grants and industry accounts for a small part in Canada whereas private funding is considerable in the US (Niosi 2000).

Our main contribution consists in further understanding how government research funding and scientific networks influence research publications in the field of nanotechnology. The remainder of the paper is organized as follows. In Sect. 2, the theoretical background focuses on university research funding and social network analysis, from which hypotheses are drawn concerning public grants and collaborations. In Sect. 3, we discuss variables, econometric models and the methodology employed. Section 4 discusses regression results and graphs, and finally Sect. 5 concludes.

3.3 Conceptual framework

Nanotechnology is a relatively young discipline characterized by different subfields. It generated almost a quarter trillion dollars worth of products worldwide in 2009 and $91 billion of these products found their market in the US. This emerging technology draws substantial amounts of public and private investment and its relative success encourages governments to increase their funding in nanotechnology research (Canton 1999; Freeman and Shukla 2008; Roco and Bainbridge 2005; Roco 2011).

US financial investment in nanotechnology research has been substantial in the last decade. The US government plays a central role in nanotechnology research programs and is among the 10 leading countries in nanotechnology. The US ranked first in terms of nanotechnology public funding in 2006 (Roco et al. 2011; Sargent 2008). Youtie et al. (2008) reviewed the rapid growth of nanotechnology publications in different countries between 1990 and 2006 and showed that the US has been one of the leading countries in nanotechnology research and that it has ranked first in terms of the quality of publications.

Furthermore, the major US federal support of nanotechnology academic research is provided by the interagency program of the NNI which is mostly motivated by an interest in economic outcomes (Mowery 2011). The public funding of nanotechnology academic research fosters the emergence of collaboration among universities, industry and government and highlights a Triple-Helix of relationships between these organizations (Etzkowitz 2008; Leydesdorff and Meyer 2006; Schultz 2011). Niosi (2000) shows that universities in the US are frequently encouraged to collaborate more with industries and this collaboration streams industry funding toward university research.

In Canada, the majority of university research funding is provided through public funding, while private firms account for only a small part of research funding (Fitzgibbons and McNiven 2006; Mcfetridge 1993; Niosi 2000). The Natural Sciences and Engineering Research Council (NSERC) focuses on university and industry collaborations through Industrial Chairs and Collaborative R&D programs. The Canadian Institutes for Health Research (CIHR), the Canada Foundation for Innovation (CFI) and National Research Council (NRC) are other federal agencies that provide funding for R&D (Gordon 2002).

Addressing how universities play a significant role in knowledge-based nanotechnology research, Hullmann (2006) and Mcfetridge (1993) indeed suggest that the number of academic publications is an appropriate indicator to understand the growth of this new technology. Furthermore, the number of citations papers receive is a quality index that can properly measure the impact of researchers.

Many scholars (Hudson 2007; Lawani 1986; Moed 2005; Schoonbaert and Roelants 1996) study the number of citations to measure the quality of papers and argue that high quality papers receive significantly more citations. Despite some problems that arise in using the number of citations as a quality index for papers, it is widely used and still considered to be an appropriate indicator. For example critics such as Adler et al. (2009) highlight that citation analysis does provide worthwhile information and should be part of the evaluation process.

Following the massive investment in nanotechnology, the interest in the influence funded research has on scientific output has also increased in recent years. Huang et al. (2005) highlight that it is imperative to understand the impact of public funding on nanotechnology research output and nanotechnology development. Some scholars examine the impact of funding on scientific output and their results indicate that government R&D funding in universities increases the number of publications (Adams and Griliches 1998; Blume-Kohout et al. 2009; Fitzgibbons and McNiven 2006; Mcfetridge 1993). Payne and Siow (2003) demonstrate that a one million dollar increase in government funding in a research university yields ten additional papers. In another study in the US, Jacob and Lefgren (2007) investigate the influence of the National Institutes of Health (NIH) grants on researchers and research productivity. According to their study, NIH postdoctoral fellowships increase the rate of publications by nearly twenty percent in the following 5 years as well as the citations received by these papers. Obtaining research funding affects the productivity of researchers in other ways, for instance, Adams et al. (2005) recognized that according to a study in the top 110 US universities, public funding significantly affects the size of scientific teams. Scientists with prestigious awards and a large stock of federal funding are encouraged to collaborate in larger teams. This collaboration increases research quality and consequently these scientists are more cited (Sauer 1988; Adams et al. 2005). Arora et al. (1998) raised the point of a positive influence on publication quality and mentioned that it acts as a signal for the government to allocate additional funding to higher-quality researchers.

Although the number of citations can be used as a proxy to measure the scientific quality of papers, we must recognize and address the disparity in citation rates of papers published in English compared to those in French, a concern evident for Canada. Poomkottayil et al. (2011)

found that English papers are seven times more cited based on the Google Scholar database compared to non-English papers (German or French papers in their study). The theoretical study of Van Leeuwen et al. (2001) showed that the impact factors of non-English language journals are considerably lower than English-language journals. Due to increased interest in the bibliometric evaluation of papers in recent years, it is important to recognize that the language of publication affects such analyses.

Empirical evidence of Matthew effect can be shown at various aggregation levels: countries, research institutions and individual researchers. The Matthew effect holds that the most influential scientists gain more influence (Merton 1968; Larivie`re and Gingras 2010). Some studies used the number of citations as Matthew indicator and showed that specific papers, researchers or even universities are more frequently cited compared to others (Bonitz et al. 1997; Katz 1999; Tol 2009). According to Laudel (2006), scientists that have already received funding are more likely to receive more funding, which is evidence of Matthew effect in research funding. This effect can occur at the individual or department level, hence indicating that those that obtain the most funds become even more successful in subsequent grant applications.

Since the US is a leading country in nanotechnology research and research funding, in light of the impact of government research financing on nanotechnology-related scientific output and the difference between the influence of research funding in Canada and the US, we aim to probe the following hypotheses in this paper separately for Canada and the US.

Hypothesis 1 Increased public funding to nanotechnology scientists contributes to (a) more nanotechnology-related publications and (b) higher-quality nanotechnology-related publications.

Scientists generally work in research communities and tend to publish the results in research groups. Glänzel and Schubert (2005) highlighted co-publication networks as a tangible measure of scientific collaborations. Since the collaboration of researchers is seen to be of great importance in fostering output productivity research, funding is commonly allocated to research teams, particularly when the amount of financing is rather large.

Theoretical studies show a positive correlation between the collaboration of researchers and their respective scientific output. For example Newman (2001) and Balconi et al. (2004) constructed a scientist network using co-authorship information to study the interconnected nature of scientists in these networks. Ni et al. (2011) and Breschi et al. (2006) stated that scientists with central positions in the network produce more papers compared to other scientists that are less central. Velema (2012) argues that collaborative ties in co-authorship networks lead to receiving more citations. The diffusion of knowledge is thus more efficient among researchers who actively collaborate and the numerous collaborations help researchers to increase their productivity. The question we address in this paper is how evolving scientific networks influence the emergence of new publications and enhance the quality of these publications in Canada, as well as the difference in this impact between Canada and the US. In order to measure whether collaborations in Canada have a similar impact as in the US on nanotechnology scientific output, we therefore consider the following hypotheses separately for Canada and the US:

Hypothesis 2 A better network position[7] of nanotechnology scientists within co-publication networks has a positive effect on (a) the number of publications and on (b) the quality of publications.

In Canada the proportion of government-funded R&D is high compared to industrial R&D (Niosi 2000). We therefore propose in our third Hypothesis to test whether this government funding leads to scientific production of higher quality and quantity in Canada in comparison to the impact of public funding in the US:

Hypothesis 3 Increased public funding to nanotechnology scientists in Canada contributes to (a) more nanotechnology-related publications and (b) higher-quality nanotechnology-related publications in Canada compared to increased public funding to nanotechnology scientists in the US.

3.4 Data and methodology

3.4.1 Data and variables

The rapid growth of nanotechnology implies that governments have to develop a complete database of all desired information about nanotechnology development and commercial utilization (Holtz 2007). This study requires the evaluation of scientific output during the periods

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[7] We consider higher betweenness centrality and higher cliquishness in terms of better network position.

in which public grants were received by researchers. Our data was extracted from different databases of articles and patents to which at least one Canadian-affiliated and one American-affiliated scientist contributed: We extracted publication and authorship data from Elsevier's Scopus using specific keyword searches, described below, for nanotechnology-related publications, while the United States Patent and Trademark Office (USPTO) provided the related patenting information for these researchers. We chose Elsevier's Scopus since it provides accurate and more comprehensive information regarding author affiliations, which greatly facilitates the disambiguation of author's names, especially for data dating as far back as 1985. Scopus directly links authors and their affiliations while this feature is relatively recent in other databases. We examined other databases (JCR, Science Direct, Web of Science, Microsoft Academic Search, Scirus, Google Scholar, etc.) and realized that Scopus covers a wide diversity of fields and additional information, which was deemed more appropriate to our needs regarding an emerging multidisciplinary field that may not at first get published in the ''best'' journals that are currently listed in the Web of Science for instance.

The Canadian Federal granting agencies database provided information on government research financing from the National Sciences and Engineering Research Council of Canada (NSERC) and the Canadian Institutes of Health Research (CIHR). For US researchers we used Nanobank which is a dataset of scientific journal articles, patents and government grants (NIH and NSF grants) in nanotechnology (Nanobank 2013; NSF 2013; Zucker et al. 2011). For the purpose of this research and in order to have precise data on nanotechnology related publications in the US, we combined the keywords from various keyword search strategies of several scholars (Alencar et al. 2007; Fitzgibbons and McNiven 2006; Mogoutov and Kahane 2007; Noyons et al. 2003; Porter et al. 2008; Zucker and Darby 2005; Zitt and Bassecoulard 2006) while removing the redundant keywords after consulting with nanotechnology experts. We believe that the final set of keywords is quite comprehensive and is able to effectively identify articles directly related to nanotechnology.

In order to complement and clean the large data, we extracted data using a combination of Scopus and Google Scholar since the latter enabled us to search the full text of publications for nanotechnology-related keywords. We used the ''Publish or Perish'' software to filter the results in Google Scholar and then matched each identified article with the data from Scopus. This methodology allowed us to combine an in-depth full-text search of Google Scholar with well structured data from Scopus.

We then merged our data from different sources using a unique ID for each individual scientist. A considerable amount of work was required to perform the disambiguation of scientists' names in merging different publishing, patenting and funding databases. We performed a check of individuals' name to avoid ambiguity and bias in our data. We then created a panel dataset in which we compiled yearly information for each individual scientist over the period 1985–2005. Selecting for the regressions the years 1996 onwards yields 33,655 individual US scientists and 3,684 Canadian scientists in our final panel data[8].

In relation to our hypotheses, let us first define the variables measuring the quantity and quality of papers (H1a and H1b). The variable nbPaper counts the number of papers that are published every year by an individual scientist. It is used to measure the impact of government funding on the quantity of scientific output. We used three spans of citation counts, nbCitation, that the articles of a scientist received within three, 5 and 7 years after the publication year to measure paper quality. We found more consistent results using 5-year citations (*nbCitation5*) for our time period (1996–2005).

This study addresses the impact that funding granted for nanotechnology academic research has on scientific output. We thus calculate the average amount of public funding received over 3 years (*GovGrant3*) lagged by 1-year to account for the time lapse between receiving government grants and generating scientific output. We also add the square of GovGrant3, to investigate the non-linear effect of public funding. This will allow the validation of hypothesis 1.

To examine our second hypothesis we explore how a researcher's position in his/her coauthorship network influences his/her scientific output by computing two measures related to their network position: betweenness centrality (*BetweenCent*) and cliquishness or clustering coefficient (*Cliquishness*). Betweenness centrality is generally employed to evaluate the importance of a researcher as an intermediary in a network and refers to the proportion of all geodesic distances[9] between two scientists that include the specific scientist. This measure indicates which researcher potentially controls the flow of knowledge between pairs of scientists

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[8] Even though the regressions are estimated on a sample starting in 1996, we extracted data from 1985 onwards to build the 'career age' variable described below.

[9] Geodesic distance is a shortest path between any particular pair of researchers in a scientific network.

(Benedictis and Tajoli 2008; Izquierdo and Hanneman 2006).

Cliquishness is computed using the egocentric density[10] that refers to the likelihood that two scientists who are both connected to a specific third scientist are also connected to each other (Barabasi et al. 2002; Singh 2007). These two variables will allow the validation of hypothesis 2 (H2a and H2b).

The evolution of collaborations between scientists over years was analyzed using 3-year co-publication sub-networks. An important consideration relates to the time period of collaboration networks. Fleming et al. (2007) used 3-year windows to analyze the effect of past network structure on collaborative creativity. Nerkar and Paruchuri (2005) also opt for 3-year windows to study the R&D activities in inventor networks. We therefore created 3-year co-authorship sub-networks[11] for all the 3-year moving intervals using the social network analysis software Pajek, which is considered to be very suitable for the analysis of large networks (Batagelj and Mrvar 1998).

In addition to the variables of interest, another issue that we take into account is nonpublication innovative output of researchers that may restrict their scientific output. Debates have arisen around the question of whether the involvement of academics in patenting can produce negative impacts on their publication record. Despite the concerns about the substitution effects of university patents on publications, Geuna and Nesta (2006) argue that university papers and patents are not really substitutes, and a growing literature (e.g. Azoulay et al. 2006; Louis et al. 1989; Carayol and Matt 2004) is in fact proposing that patents and publications are complements. Moreover, Van Looy et al. (2004, 2006) show that university researchers who are involved in patenting activities publish more articles in applied fields and Azoulay et al. (2009), Czarnitzki et al. (2007) and Wong and Singh (2010) reveal that the patenting activity of academic researchers positively influences publication output in universities. In this regard, we study the influence of academic researchers' nanotechnology-related patents from the past 3 years to examine whether there is a correlation between these patents and their future publications (*nbPast3Pat*). We also add the square of nbPast3Pat to investigate the non-linear effect of researchers' past patents on

[10] Egocentric density is the density among a researcher's direct connections and indicates the fraction of possible links present in the network (Koput 2010).

[11] We also constructed 5-year sub-networks, but 3-year sub-networks gave us more consistent results.

scientific output.

Governments implement various mechanisms to allocate funding to universities based on research performance (Geuna and Martin 2003; Liefner 2003). A notable concern in our study is that researchers with a higher performance receive more funding from governments: this causes potential endogeneity due to simultaneity and omitted variable bias. To deal with this potential endogeneity, we employ instrumental variables techniques in our econometrics models to correct for endogeneity and add a number of control variables in addition to the variables of interest.

We first identify the career age (*CareerAge*) of nanotechnology scientists as the time elapsed since their first publication in nanotechnology. This variable shows how long a scientist has been active in this field and is a proxy for experience of a scientist in this field over time. Some scholars such as Cole (1979), Costas et al. (2010) and Stephan and Levin (1993) highlight the influence of career age on the performance of scientists to account for the fact that older scientists are more productive and more likely to receive grants. To consider the fact that the past articles are used to evaluate the proposals that lead to the granting of public funding, we use the average number of papers published by researchers in the past 3 years with a 1-year lag (*nbAvgPapers3*).

3.4.2 Model specification

There are various models for count data that have been used in economics and industrial organizations. The Poisson model is the most frequently employed method in such modeling (Hausman et al. 1984; King 1989; Riphahn et al. 2003). Because of the restriction on the distribution in the Poisson model regarding over-dispersion, some researchers find that the Negative Binomial Model (NB) is more appropriate (Greene 2008; Hilbe 2011). Many scholars have employed one of these two methods to analyze count data (Wang et al. 1998; Fleming and Sorenson 2001; Maurseth and Verspagen 2002; Mowery et al. 2002; Payne and Siow 2003; Tsionas 2010; Petruzzelli 2011). In the Poisson model, it is assumed that the conditional variance equals the mean. The dependent variable y_{it} in Eq. (3-1) follows a Poisson distribution where the mean is function of the coefficients β and of the covariates x_{it} as shown in Eq. (3-2), (*i* indexes individual researchers and *t* indexes years).

$$\Pr(y_{it} | x_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{y_{it}}}{y_{it}!} \qquad (3\text{-}1)$$

$$E(y_{it}|x_{it}) = \lambda_{it} = e^{x_{it}\beta} \tag{3-2}$$

The Poisson model imposes equi-dispersion as shown by Equation (4-3):

$$E(y_{it}|x_{it}) = Var[y_{it}|x_{it}] = \lambda_{it} \tag{3-3}$$

If the variance of y_{it} is larger than the mean ($E(y_{it}|x_{it}) = Var[y_{it}|x_{it}]$), we have over-dispersion in the data, which implies that the Negative Binomial Regression is a proper alternative for this method. $Exp(\varepsilon_{it})$ is assumed to follow a gamma distribution where the variance equals α and the mean equals 1 (Hausman et al. 1984; King 1989; Greene 2008), which yields equations (3-4) and (3-5).

$$\lambda_{it} = Exp(\beta x_{it} + \varepsilon_{it}) \tag{3-4}$$

$$Var[y_{it}|x_{it}] = E(y_{it}|x_{it})\left(1 + \alpha\left[E(y_{it}|x_{it}\right]\right) \tag{3-5}$$

We thus use both the Poisson and Negative Binomial models in our regressions to find the most consistent and significant results in measuring the impact of government grants and of network position on the quantity of scientific publications (represented by $nbPaper_{it}$ of academic researcher i in year t) and on the publication quality (represented by $nbCitation5_{it}$). In case of having excessive zeros in our count data, we consider zero-inflated Poisson versus Poisson and zero-inflated negative binomial versus negative binomial model and use the test suggested by Vuong (1989). Zero-inflated models allow for complication of analyzing datasets with an excessive number of outcome zeros (Greene 1994; Long 1997; Vuong 1989). For the given data, the Vuong test proved that zero-inflated models are superior to standard Poisson and negative binomial models.

We express the model to be estimated in Eq. (3-6), which shows our two dependent variables explained by the same function. We examined a variety of lag structures during the course of our study and presented the models which yield the most consistent results.

Logically, however, one would think that the team is formed first, then they apply for funding and do the work to finally publish. Learning from collaborators and integrating into knowledge networks needs time to lead to further jointly developed publications. So we would expect that the network variables to be lagged by at least 2 years and the funding variables to be lagged by at least 1 year.

$$\begin{bmatrix} nbPaper_{it} \\ nbCitation5_{it} \end{bmatrix} = f\begin{pmatrix} (GovGrant3_{it-1}),\left[(GovGrant3_{it-1})\right]^2 \\ nbPast3Pat_{it},[nbPast3Pat_{it}]^2, BetweenCent3_{it-2}, Cliquishness3_{it-2}, \\ \left[Cliquishness3_{it-2})\right]^2, nbPast3Pat_{it} \times BetweenCent3_{it-2}, \\ BetweenCent3_{it-2} \times Cliquishness3_{it-2}, d_t) \end{pmatrix}$$

(3-6)

We also test the moderating effect between our variables by introducing interactive variables. This helps us to examine whether betweenness centrality has an intrinsic relation with patenting and cliquishness, and it also moderates the influence of these two measures on the dependent variables. To account for the fact that funding may affect both scientific output and the number of patents to which a researcher may have contributed, we treat the amount of grants received as endogenous. Given the potential endogeneity, we test three instruments for this variable to correct this problem. One of the alternatives that is suggested in econometric studies to estimate the parameters in this model on a set of instrumental variables is the Two Stage Least Squares (2SLS) method (Biro 2009; Terza et al. 2008; Stephan et al. 2007).

We thus express the first and second stage of our estimations in Eq. (3-7) to account for the endogeneity bias on the average amount of grants received over 3 years by scientists in nanotechnology. The first stage regression estimates the endogenous variable on a set of instruments and the predicted value is then computed and added to the second stage regressions. The resulting first stage and second stage regressions are given by:

$$\begin{pmatrix} GovGrant3_{it-l} = f(CareerAge_{it-1}, CareerAge^2_{it-1}, nbAvgPaper3_{it-l}, Variables2^{nd}\,Stage, d_t) \\ \\ 2SLS: \\ \begin{bmatrix} nbPaper_{it} \\ nbCitation5_{it} \end{bmatrix} = f\begin{pmatrix} (predicted1st(GovGrant3_{it-1}),\left[predicted1st(GovGrant3_{it-1})\right]^2 \\ nbPast3Pat_{it},[nbPast3Pat_{it}]^2, BetweenCent3_{it-2}, Cliquishness3_{it-2}, \\ \left[Cliquishness3_{it-2})\right]^2, BetweenCent3_{it-2} \times Cliquishness3_{it-2}, \\ BetweenCent3_{it-2} \times Cliquishness3_{it-2}, d_t) \end{pmatrix} \end{pmatrix}$$

(3-7)

3.5 Regression results

Our study evaluates the impact of research funding and collaborations on scientific productions by measuring the quantity and quality of publications. The results showed in this section present the most reliable results. As mentioned previously we examined a variety of lag structures (1, 2 and 3 years) to investigate the most appropriate time period for each variable. As expected, the most significant results were obtained with a 1-year lag for government grants and a 2-year lag for the network. Two groups of results are presented in which the first group does not account for potential endogeneity of public funding and the second group represents the results of the second stage for 2SLS regressions. We find that the *zero-inflated Poisson* model (clustering method) yields significant and consistent results and hence present only this model in the paper[12] as justified by Hall and Ziedonis (2001). We start from a simple model and hierarchically add the quadratic term of variables to the model. The second stage of four models, shown in Tables 3.1, 3.2 for the number of papers and Tables 3.3, 3.4 for the number of citations, enable us to study the factors that influence scientific production in Canada and the US (for the first stage of regressions see Appendix A.1, and Poisson and xtpoisson regressions are presented in Appendix A.4). Before turning to the second stage regressions, let us briefly address the first stage results. Among the instruments used to correct for endogeneity in the first stage of our model, *CareerAge* is strongly significant to explain the endogenous variable *GovGrant3* in both countries.

[12] We estimated more than 15 models as we considered and neglected potential endogeneity using panel data via xtnbreg and xtpoisson. We also performed non-paneled regressions using the clustering method of nbreg and Poisson to account for repeated measures of the same individual scientist. Note that we tried zero inflated negative binomial model as well, but it does not work on our data for the number of papers and the results for the number of citations are similar to zero-inflated Poisson model.

Table 3.1:Impact of public funding on nanotech papers in Canada - Second stage of regression results of zero-inflated Poisson

Canada	**zip – model (1)**		**zip – model (2)**		**zip – model (3)**		**zip – model (4)**	
$nbPaper_{it}$	**W/O Endog**	**2SLS**	**W/O Endog**	**2SLS**	**W/O Endog**	**2SLS**	**W/O Endog**	**2SLS**
ln($GovGrant3_{it-1}$)	-0.0056		-0.0055		-0.0088		0.0873 *	
	(0.0086)		(0.0087)		(0.0085)		(0.0480)	
$nbPast3Pat_{it-1}$	0.1045 ***	0.0962 ***	0.1506 ***	0.1293 **	0.1120 **	0.1103 **	0.1194 **	0.1101 **
	(0.0149)	(0.0149)	(0.0527)	(0.0520)	(0.0551)	(0.0546)	(0.0552)	(0.0545)
ln($10^4 \times BetweenCent_{it-2}$)	0.3492 ***	0.3330 ***	0.3480 ***	0.3340 ***	0.1782 ***	0.1795 ***	0.1847 ***	0.1792 ***
	(0.0515)	(0.0487)	(0.0508)	(0.0487)	(0.0509)	(0.0510)	(0.0503)	(0.0509)
ln($10^3 \times Cliquishness_{it-2}$)	0.0495 ***	0.0429 ***	0.0476 ***	0.0416 ***	0.7381 ***	0.7147 ***	0.7233 ***	0.7147 ***
	(0.0127)	(0.0133)	(0.0131)	(0.0137)	(0.0932)	(0.1014)	(0.0918)	(0.1010)
[$nbPast3Pat_{it}$]^2			-0.0033	-0.0015	-0.0016	-0.0014	-0.0022	-0.0012
			(0.0030)	(0.0029)	(0.0034)	(0.0033)	(0.0034)	(0.0034)
[ln($10^3 \times Cliquishness_{it-2}$)]^2					-0.1047 ***	-0.1015 ***	-0.1026 ***	-0.1017 ***
					(0.0143)	(0.0154)	(0.0141)	(0.0153)
[ln($GovGrant3_{it-1}$)]^2							-0.0095 **	
							(0.0046)	
Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prediction($GovGrant3_{it-1}$)-2SLS		0.0890 **		0.0801 **		0.0126		0.0688
		(0.0375)		(0.0363)		(0.0319)		(0.0884)
[Prediction($GovGrant3_{it-1}$)-2SLS]^2								-0.0051
								(0.0086)
Constant	0.7147 ***	0.2103	0.7211 ***	0.2656	0.6965 ***	0.5845 ***	0.6842 ***	0.4375 *
	(0.0812)	(0.2164)	(0.0802)	(0.2082)	(0.0826)	(0.1822)	(0.0830)	(0.2504)
Inflate								
ln($GovGrant3_{it-1}$)	-0.0124 *		-0.0120		-0.0101		0.1244 **	
	(0.0073)		(0.0073)		(0.0075)		(0.0598)	
$nbPast3Pat_{it-1}$	-0.0977 ***	-0.0940 ***	-0.1999 *	-0.1889 *	-0.1721	-0.1617	-0.1638	-0.1673
	(0.0350)	(0.0352)	(0.1073)	(0.1093)	(0.1181)	(0.1200)	(0.1193)	(0.1215)
ln($10^4 \times BetweenCent_{it-2}$)	-0.6803 ***	-0.6729 ***	-0.6763 ***	-0.6691 ***	-0.1940 **	-0.1995 **	-0.1853 **	-0.1943 **
	(0.0667)	(0.0669)	(0.0668)	(0.0670)	(0.0779)	(0.0778)	(0.0790)	(0.0777)
ln($10^3 \times Cliquishness_{it-2}$)	-0.0989 ***	-0.0981 ***	-0.0984 ***	-0.0975 ***	-1.6485 ***	-1.6148 ***	-1.6730 ***	-1.6418 ***
	(0.0127)	(0.0127)	(0.0128)	(0.0128)	(0.1779)	(0.1782)	(0.1831)	(0.1773)
[$nbPast3Pat_{it}$]^2			0.0126	0.0118	0.0121	0.0113	0.0114	0.0117
			(0.0144)	(0.0148)	(0.0172)	(0.0176)	(0.0174)	(0.0178)
[ln($10^3 \times Cliquishness_{it-2}$)]^2					0.2286 ***	0.2239 ***	0.2322 ***	0.2282 ***
					(0.0264)	(0.0265)	(0.0272)	(0.0263)
[ln($GovGrant3_{it-1}$)]^2							-0.0132 **	
							(0.0059)	
Prediction($GovGrant3_{it-1}$)-2SLS		-0.0391 **		-0.0401 **		-0.0390 **		-0.1041
		(0.0176)		(0.0175)		(0.0174)		(0.0671)
[Prediction($GovGrant3_{it-1}$)-2SLS]^2								0.0080
								(0.0072)
Constant	1.5421 ***	1.6764 ***	1.5439 ***	1.6864 ***	1.5334 ***	1.6848 ***	1.5165 ***	1.7610 ***
	(0.0635)	(0.1105)	(0.0637)	(0.1097)	(0.0643)	(0.1053)	(0.0652)	(0.1454)
Nb observations	8180	8180	8180	8180	8180	8180	8180	8180
Nb Groups	3684	3684	3684	3684	3684	3684	3684	3684
Loglikelihood	-6801.2	-6783.95	-6796.89	-6782.06	-6652.18	-6651.25	-6644.2	-6649.16
χ^2	200.40 ***	178.09 ***	185.02 ***	165.81 ***	238.11 ***	206.49 ***	246.22 ***	205.61 ***

Note : Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1)

Table 3.2:Impact of public funding on nanotech papers in the US - Second stage of regression results of zero-inflated Poisson

The US $nbPaper_{it}$	**zip – model (1)**		**zip – model (2)**		**zip – model (3)**		**zip – model (4)**	
	W/O Endog	**2SLS**	**W/O Endog**	**2SLS**	**W/O Endog**	**2SLS**	**W/O Endog**	**2SLS**
ln($GovGrant3_{it-1}$)	0.0264***		0.0264***		0.0264***		-0.0530*	
	(0.0037)		(0.0037)		(0.0037)		(0.0303)	
$nbPast3Pat_{it-1}$	0.0035	-0.0006	0.0050	-0.0157	0.0054	-0.0156	0.0058	-0.0062
	(0.0089)	(0.0075)	(0.0130)	(0.0110)	(0.0130)	(0.0110)	(0.0131)	(0.0094)
ln($10^4 \times BetweenCent_{it-2}$)	0.1646***	0.1377**	0.1646***	0.1347 **	0.1633***	0.1296**	0.1609***	0.1272 **
	(0.0595)	(0.0573)	(0.0596)	(0.0573)	(0.0593)	(0.0570)	(0.0596)	(0.0564)
ln($10^3 \times Cliquishness_{it-2}$)	0.0865***	0.0921***	0.0865***	0.0912 ***	0.2135***	0.2781***	0.2111***	0.3243 ***
	(0.0059)	(0.0059)	(0.0060)	(0.0059)	(0.0674)	(0.0686)	(0.0670)	(0.0672)
[$nbPast3Pat_{it}$]^2			-0.0001	0.0008 **	-0.0001	0.0008**	-0.0001	-0.0001
			(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)
[ln($10^3 \times Cliquishness_{it-2}$)]^2					-0.0187*	-0.0276***	-0.0184*	-0.0320 ***
					(0.0098)	(0.0099)	(0.0097)	(0.0097)
[ln($GovGrant3_{it-1}$)]^2							0.0067**	
							(0.0026)	
Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prediction($GovGrant3_{it-1}$)-2SLS		0.2246***		0.2267 ***		0.2272***		-0.1958 ***
		(0.0238)		(0.0239)		(0.0238)		(0.0379)
[Prediction($GovGrant3_{it-1}$)-2SLS]^2								0.0400 ***
								(0.0037)
Constant	0.5491***	-0.5575***	0.5482***	-0.5560 ***	0.5500***	-0.5590***	0.5617***	0.4177 ***
	(0.0798)	(0.1586)	(0.0798)	(0.1583)	(0.0796)	(0.1579)	(0.0789)	(0.1205)
Inflate								
ln($GovGrant3_{it-1}$)	-0.0143***		-0.0147 ***		-0.0148***		-0.0078	
	(0.0030)		(0.0030)		(0.0030)		(0.0233)	
$nbPast3Pat_{it-1}$	0.0518***	0.0532***	0.0763***	0.0890 ***	0.0760***	0.0885***	0.0758***	0.0951 ***
	(0.0050)	(0.0049)	(0.0079)	(0.0086)	(0.0080)	(0.0086)	(0.0080)	(0.0074)
ln($10^4 \times BetweenCent_{it-2}$)	-0.5410***	-0.5253***	-0.5390***	-0.5228 ***	-0.5070***	-0.4922***	-0.5097***	-0.4875 ***
	(0.1175)	(0.1212)	(0.1177)	(0.1218)	(0.1160)	(0.1201)	(0.1168)	(0.1195)
ln($10^3 \times Cliquishness_{it-2}$)	-0.3030***	-0.2873***	-0.3025***	-0.2863 ***	-0.8107***	-0.7937***	-0.8122***	-0.7790 ***
	(0.0056)	(0.0058)	(0.0056)	(0.0058)	(0.0796)	(0.0825)	(0.0797)	(0.0820)
[$nbPast3Pat_{it}$]^2			-0.0015***	-0.0022 ***	-0.0015***	-0.0022***	-0.0015***	-0.0029 ***
			(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)
[ln($10^3 \times Cliquishness_{it-2}$)]^2					0.0751***	0.0750***	0.0753***	0.0739 ***
					(0.0117)	(0.0121)	(0.0117)	(0.0121)
[ln($GovGrant3_{it-1}$)]^2							-0.0007	
							(0.0020)	
Prediction($GovGrant3_{it-1}$)-2SLS		-0.1094***		-0.1090 ***		-0.1078***		-0.3372 ***
		(0.0126)		(0.0127)		(0.0128)		(0.0362)
[Prediction($GovGrant3_{it-1}$)-2SLS]^2								0.0205 ***
								(0.0036)
Constant	2.2126***	2.5099***	2.1952***	2.4759 ***	2.1993***	2.4735***	2.2021***	3.0163 ***
	(0.0292)	(0.0816)	(0.0295)	(0.0817)	(0.0297)	(0.0821)	(0.0294)	(0.0853)
Nb observations	56511	56511	56511	56511	56511	56511	56511	56511
Nb Groups	33655	33655	33655	33655	33655	33655	33655	33655
Loglikelihood	-31075.8	-30079.1	-31064.7	-30052.5	-31029.5	-30016.6	-31003.1	-29717.7
χ^2	454.95***	502.94***	460.95***	508.74 ***	460.52***	518.98	468.44***	804.35 ***

Note : Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1)

Table 3.3:Impact of public funding on nanotech papers' quality in Canada - Second stage of regression results of zero-inflated Poisson

Canada	**zip – model (1)**		**zip – model (2)**		**zip – model (3)**		**zip – model (4)**	
nbCitation5$_{it}$	**W/O Endog**	**2SLS**	**W/O Endog**	**2SLS**	**W/O Endog**	**2SLS**	**W/O Endog**	**2SLS**
ln(*GovGrant3$_{it-1}$*)	0.0038		0.0038		0.0018		0.0617	
	(0.0103)		(0.0103)		(0.0101)		(0.0552)	
nbPast3Pat$_{it-1}$	0.1228***	0.1206***	0.1082	0.1032	0.0861	0.0906	0.0861	0.0906
	(0.0154)	(0.0152)	(0.0690)	(0.0673)	(0.0692)	(0.0689)	(0.0692)	(0.0689)
ln(10^4×*BetweenCent$_{it-2}$*)	0.2796***	0.2750***	0.2796***	0.2750 ***	0.2796***	0.2750***	0.2796***	0.2750 ***
	(0.0839)	(0.0816)	(0.0839)	(0.0816)	(0.0839)	(0.0816)	(0.0839)	(0.0816)
ln(10^3×*Cliquishness$_{it-2}$*)	0.0182	0.0164	0.0188	0.0175	0.4710***	0.4913***	0.4627***	0.4923 ***
	(0.0175)	(0.0180)	(0.0182)	(0.0187)	(0.1213)	(0.1313)	(0.1201)	(0.1308)
[*nbPast3Pat$_{it}$*]^2			0.0009	0.0014	0.0020	0.0016	0.0017	0.0018
			(0.0035)	(0.0033)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
[ln(10^3×*Cliquishness$_{it-2}$*)]^2					-0.0685***	-0.0713***	-0.0673***	-0.0717 ***
					(0.0186)	(0.0200)	(0.0184)	(0.0199)
[ln(*GovGrant3$_{it-1}$*)]^2							-0.0059	
							(0.0051)	
Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prediction(*GovGrant3$_{it-1}$*)-2SLS		0.0328		0.0252		-0.0199		0.0465
		(0.0455)		(0.0444)		(0.0407)		(0.1046)
[Prediction(*GovGrant3$_{it-1}$*)-2SLS]^2								-0.0062
								(0.0098)
Constant	3.7830***	3.6283***	3.7806***	3.6669 ***	3.7689***	3.8822***	3.7587***	3.7174 ***
	(0.1051)	(0.2568)	(0.1038)	(0.2481)	(0.1043)	(0.2252)	(0.1051)	(0.3011)
Inflate								
ln(*GovGrant3$_{it-1}$*)	-0.0138**		-0.0135 **		-0.0100		0.0619	
	(0.0063)		(0.0063)		(0.0065)		(0.0467)	
nbPast3Pat$_{it-1}$	-0.1075***	-0.0995***	-0.2024*	-0.1796	-0.1626	-0.1451	-0.1601	-0.1502
	(0.0345)	(0.0351)	(0.1067)	(0.1093)	(0.1168)	(0.1191)	(0.1180)	(0.1205)
ln(10^4×*BetweenCent$_{it-2}$*)	-0.7170***	-0.7060***	-0.7140***	-0.7035 ***	-0.2161***	-0.2268***	-0.2142***	-0.2227 ***
	(0.0629)	(0.0628)	(0.0629)	(0.0628)	(0.0732)	(0.0733)	(0.0736)	(0.0732)
ln(10^3×*Cliquishness$_{it-2}$*)	-0.1177***	-0.1140***	-0.1166***	-0.1130 ***	-1.8045***	-1.7371***	-1.8130***	-1.7615 ***
	(0.0111)	(0.0111)	(0.0111)	(0.0111)	(0.1659)	(0.1675)	(0.1681)	(0.1673)
[*nbPast3Pat$_{it}$*]^2			0.0112	0.0094	0.0099	0.0085	0.0097	0.0089
			(0.0143)	(0.0148)	(0.0171)	(0.0176)	(0.0174)	(0.0179)
[ln(10^3×*Cliquishness$_{it-2}$*)]^2					0.2504***	0.2409***	0.2517***	0.2449 ***
					(0.0246)	(0.0248)	(0.0249)	(0.0248)
[ln(*GovGrant3$_{it-1}$*)]^2							-0.0071	
							(0.0046)	
Prediction(*GovGrant3$_{it-1}$*)-2SLS		-0.0751***		-0.0744 ***		-0.0604***		-0.1343 ***
		(0.0146)		(0.0145)		(0.0146)		(0.0504)
[Prediction(*GovGrant3$_{it-1}$*)-2SLS]^2								0.0086
								(0.0056)
Constant	2.0567***	2.3675***	2.0592***	2.3673 ***	2.0567***	2.3099***	2.0482***	2.4142 ***
	(0.0508)	(0.0858)	(0.0508)	(0.0857)	(0.0511)	(0.0847)	(0.0509)	(0.1115)
Nb observations	8180	8180	8180	8180	8180	8180	8180	8180
Nb Groups	3684	3684	3684	3684	3684	3684	3684	3684
Loglikelihood	-49944.9	-49906	-49939.8	-49916.4	-49297.3	-49278.5	-49242.8	-49262.8
χ^2	215.54***	218.76***	363.10***	367.07 ***	304.72***	304.95***	301.16***	298.35 ***

Note : Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1)

Table 3.4:Impact of public funding on nanotech papers' quality in the US - Second stage of regression results of zero-inflated Poisson

The US	**zip – model (1)**		**zip – model (2)**		**zip – model (3)**		**zip – model (4)**	
nbCitation5it	**W/O Endog**	**2SLS**	**W/O Endog**	**2SLS**	**W/O Endog**		**W/O Endog**	**2SLS**
ln($GovGrant3_{it-1}$)	0.0229***		0.0229***		0.0228***		-0.1577	
	(0.0087)		(0.0087)		(0.0086)		(0.0511)	
$nbPast3Pat_{it-1}$	0.0134	0.0076	0.0083	-0.0112	0.0081	-0.0115	0.0076	-0.0045
	(0.0213)	(0.0184)	(0.0327)	(0.0279)	(0.0326)	(0.0278)	(0.0312)	(0.0258)
ln($10^4 \times BetweenCent_{it-2}$)	0.3232***	0.3027***	0.3222***	0.3000 ***	0.3187***	0.2936**	0.3082	0.2977
	(0.1205)	(0.1153)	(0.1200)	(0.1147)	(0.1216)	(0.1157)	(0.1219)	(0.1161)
ln($10^3 \times Cliquishness_{it-2}$)	0.0367***	0.0452***	0.0365***	0.0444 ***	0.1384	0.2082	0.1437	0.2522
	(0.0132)	(0.0140)	(0.0134)	(0.0142)	(0.1411)	(0.1445)	(0.1381)	(0.1434)
[$nbPast3Pat_{it}$]^2			0.0002	0.0010 *	0.0002	0.0010	0.0002	0.0003
			(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0007)
[ln($10^3 \times Cliquishness_{it-2}$)]^2					-0.0150	-0.0242	-0.0161	-0.0289
					(0.0203)	(0.0206)	(0.0199)	(0.0205)
[ln($GovGrant3_{it-1}$)]^2							0.0150	
							(0.0044)	
Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prediction($GovGrant3_{it-1}$)-2SLS		0.1882***		0.1894 ***		0.1900***		-0.1312
		(0.0519)		(0.0522)		(0.0522)		(0.0798)
[Prediction($GovGrant3_{it-1}$)-2SLS]^2								0.0303
								(0.0086)
Constant	3.7692***	2.8438***	3.7726***	2.8526 ***	3.7750***	2.8494***	3.7944	3.6014
	(0.1763)	(0.3497)	(0.1785)	(0.3525)	(0.1780)	(0.3529)	(0.1753)	(0.2613)
Inflate								
ln($GovGrant3_{it-1}$)	-0.0285***		-0.0289 ***		-0.0291 ***		0.0111	
	(0.0043)		(0.0043)		(0.0043)		(0.0317)	
$nbPast3Pat_{it-1}$	0.0640***	0.0663***	0.0938***	0.1119 ***	0.0932***	0.1113***	0.0927	0.1154
	(0.0079)	(0.0077)	(0.0097)	(0.0096)	(0.0097)	(0.0096)	(0.0097)	(0.0105)
ln($10^4 \times BetweenCent_{it-2}$)	-0.3637***	-0.3704***	-0.3619***	-0.3661 ***	-0.3407***	-0.3423	-0.3420	-0.3410
	(0.0990)	(0.0976)	(0.0991)	(0.0976)	(0.0988)	(0.0980)	(0.0987)	(0.0980)
ln($10^3 \times Cliquishness_{it-2}$)	-0.3013***	-0.2920***	-0.3005***	-0.2907 ***	-0.8074***	-0.8314***	-0.8082	-0.8226
	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0932)	(0.0941)	(0.0932)	(0.0946)
[$nbPast3Pat_{it}$]^2			-0.0019***	-0.0028 ***	-0.0019***	-0.0028	-0.0019	-0.0032
			(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
[ln($10^3 \times Cliquishness_{it-2}$)]^2					0.0748***	0.0798	0.0749***	0.0790
					(0.0137)	(0.0138)	(0.0137)	(0.0139)
[ln($GovGrant3_{it-1}$)]^2							-0.0034	
							(0.0027)	
Prediction($GovGrant3_{it-1}$)-2SLS		-0.1892***		-0.1919 ***		-0.1910***		-0.2667
		(0.0123)		(0.0123)		(0.0124)		(0.0565)
[Prediction($GovGrant3_{it-1}$)-2SLS]^2								0.0080
								(0.0059)
Constant	3.8502***	4.5818***	3.8316***	4.5583 ***	3.8425***	4.5632***	3.8391	4.6994
	(0.0420)	(0.0706)	(0.0419)	(0.0700)	(0.0423)	(0.0701)	(0.0421)	(0.1201)
Nb observations	56511	56511	56511	56511	56511	56511	56511	56511
Nb Groups	33655	33655	33655	33655	33655	33655	33655	33655
Loglikelihood	-111860	-107574	-111839	-107474	-111779	-107356	-110476	-105360
χ^2	41.57 ***	40.24***	43.82***	43.22 ***	43.88***	43.33***	55.68***	73.14 ***

Note : Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1)

Surprisingly we cannot find a significant effect of *nbAvgPaper3* on future grants in Canada. However, Arora and Gambardella (1998) found that the past performance indirectly affects the probability of receiving grants in future. This may be due to the fact that nanotechnology is a young discipline in Canada and that researchers only recently started publishing in this field. In contrast this variable is strongly significant in the US. The effect of nanotechnology being a young discipline also becomes apparent when we examine the non-linear impact of *CareerAge*. We observe a negative coefficient for the square of age on the scientific production. This result is consistent with the findings of Costas et al. (2010) who highlight the fact that as scientists grow older, they are likely to be more reluctant to be involved in new fields. However, we need to be careful in proposing this interpretation, as there have been many mixed findings on this issue. Rappa and Debackere (1993) highlight that the relationship between age and the ability in science is influenced by numerous factors such as substantive and methodological perceptions, specialized interests and affiliations with certain schools of thoughts, and not only the age of scientists. Accordingly, Wray (2003; 2004) examined the contribution of young scientists in new scientific specialties and found that it is middle-aged scientists that are responsible for significant discoveries. There is an extended and inconclusive literature on age in science, which we will not review here.

In the second stage regressions, we find that the number of publications rises as public funding increases. Our findings in Canada and the US show an increasing linear trend for the amount of publications. The results show that more simple models may be better able to represent the influence of government funding in Canada as we captured endogeneity in the first two models, but the additional parameters may not be useful. In the US when we increase the complexity of model by adding the quadratic term of government funding in model (4), we observe a right-hand of a U-shaped curve which also shows the increasing trend of the number of articles (Fig. 3.1a).

In regard to the influence of public funding on the number of citations (*nbCitation5*), the average amount of government funding seems to have no impact for Canada to enhance the quality of publications, but exhibiting a J-shaped relationship beyond a point for the US. This observation highlights that beyond the minimum value of the J-shaped curve, the number of citations increases (Fig. 3.1b)[13]. These results generally are in accordance with the findings of Blume Kohout et al. (2009), Fox and Milbourne (1999) and Payne and Siow (2003), who imply that there is a positive correlation between funding and academic outputs. Accordingly, the positive

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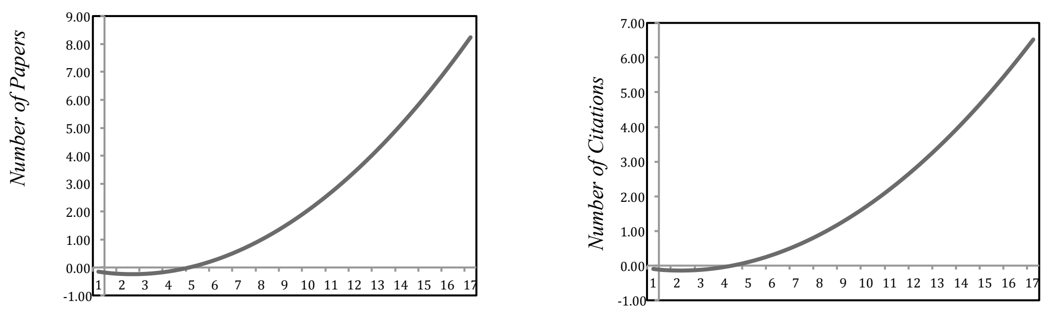
[13] We do not believe that this relationship between funding and scientific production (and of its quality) is infinite. We examined a cubic term in the regressions but it turned out non significant. Considering the wisdom of the granting councils and of the peer review process, however, we very much doubt that an embarrassment of riches in academia is likely to appear.

effect of funding suggests that a Matthew effect (Merton 1968) that is at play here, hence suggesting that greater productivity and greater influence imply greater funding and thus that greater funding implies greater productivity and greater influence.

The relationship between funding and scientific output always matters to answer policy questions and funding allocation decisions. Although prior studies in various fields or specific universities have examined this relationship (see Arora et al. 1998; Jacob and Lefgren 2011; Lewison and Dawson 1998; Zucker et al. 2007), our study presents a detailed comparison of nanotechnology between Canada and the US.



(a) ln(GovGrant3) - The US

(b) ln(GovGrant3) - The US

Figure 3.1: The effect of average amount of government grants, ln(GovGrant3), on (a) the number of papers in the US, (b) the number of citations in the US

Regarding scientific collaborations, we find that betweenness centrality has a remarkably positive and significant effect on the number of papers in both Canada and the US. Turning to the influence of this central position of researchers on the number of citations received by papers, we find a positive impact on the number of citations in both the US and Canada. It shows that a higher intermediary position of researchers in co-publication networks increase the number of scientific papers and research quality in the field of nanotechnology.

Continuing on network measures, we find that past individual cliquishness of scientists contributes to a positive impact on the publications in Canada and the US.

When we add the quadratic term of cliquishness, we lose the significant results for the models accounting for endogeneity (2SLS models) in Canada. But in the US plotting the resulting quadratic curves shows a positive effect on the number of publications up to the maximum value of an inverted U-shaped curve (see Figure A.1 in the Appendix A). This suggests that the number of papers starts decreasing with higher cliquishness.

Although researchers tend to collaborate with other scientists to generate more publications, a greater integration eventually hampers their activities beyond their collaborative circle in this multidisciplinary field: therefore, researchers should avoid acting solely in higher cliquishness groups and explore beyond their restricted networks.

Similarly, the impact of the past individual cliquishness follows an inverted U-shaped curve on the number of citations in Canada when we account for the nonlinear impact indicating that scientific production quality starts decreasing beyond the maximum value of the cliquishness, but in the US we only capture the linear impact on the number of citations (see Figure A.1 in the Appendix A). A better network position generally enhances research productivity and research quality of scientists in both studied countries.

We also examined whether there is a relationship between invention disclosures of academic researchers and their scientific output. The results show that the average number of patents to which a researcher has contributed over the past 3 years has a positive influence on his/her scientific production in Canada. These industrial interests increase the number of publications and the results of our first econometric model (model 1) show a reinforcing effect on the research quality of academic scientists in Canada. This can also reflect a self-selection effect rather than superior performance (see Moed 2007; Wildhagen 2009; Wagner 2010). The observed reinforcing effect may therefore derive from the fact that academic scientists with higher prior performance regarding scientific production move to patenting activities. Similarly, Cummings and Kiesler (2008) show the self-selection bias in successful collaborations in which collaborators that have had experience of working closely in the past develop strong ties with those collaborators in the future again and this plausibly result in higher performance.

In the US, no significant results are found for the correlation between the number of patents in the past 3 years and the quantity and quality of scientific production in the field of nanotechnology. However, our results in Canada are similar to those of Azoulay et al. (2009), Czarnitzki et al. (2007) and Van Looy et al. (2006), who suggest a reinforcing effect of patenting on scientific outputs and highlight the fact that academic inventors create output of significantly higher quantity and quality. We posit that the same effect is at play in Canada in the field of nanotechnology and as a consequence, that the involvement in entrepreneurial activities within universities is not negatively associated with publication: on the contrary, these patenting activities may increase the quantity and quality of publications.

We defined a dummy variable taking the value 1 for Canadian scientists and the value of 0 for scientists that are affiliated to the US, to examine the difference between Canada and the US. We then re-estimated our regressions on the pooled sample. We run regressions for all four models but only present the first model in this paper[14]. The findings show that in the US, government funding has a stronger impact on both the quantity and the quality of scientific production compared to Canada. But regarding the network characteristics, the intermediary position of scientists measured by betweenness centrality comes to be more important in nanotechnology research outputs in Canada and cliquishness has higher impact on the quantity of research in the US. The results are shown in Table 3-5.

Our results reveal that scientists who receive government funding contribute to a more prolific scientific production in both countries and of a higher quality in the US. Marginal effects are commonly used to examine how much a dependent variable is expected to increase or decrease by one unit change of other variables (Cameron and Trivedi 2009; Wooldridge 2002). We calculated Marginal Effects at the Means (MEMs)[15] for the number of papers and the number of citations in both Canada and the US (presented in Table 3-6). The marginal effect of government grants on the number of papers in Canada and the US shows that additional funding leads to approximately 4 times more citations in the US than in Canada but only to a slight increase in impact on the number of papers in the US. We also find that for the marginal effect of the network characteristics, betweenness centrality corresponds to more papers and higher quality papers in Canada compared to the US while cliquishness has quite the same impact on the quantity of papers in both countries and higher impact on research quality in Canada. We can however conclude that while government funding is more important in the US, collaboration between researchers is more likely to enhance quantity and quality of research outputs in Canada.

[14] The full results are available from the authors in an unpublished appendix.

[15] In this model, marginal effects are computed to measure a change in one of explanatory variables when the values of other explanatory variables are set at their means.

Table 3.5:The comparison of the impact of public funding on nanotech papers' quantity and quality in Canada and the US - Second Stage of regression results

Variables	**nbPaper$_{it}$** W/O Endog Model (1)	**nbPaper$_{it}$** 2SLS Model (1)	**nbCitation5$_{it}$** W/O Endog Model (1)	**nbCitation5$_{it}$** 2SLS Model (1)
ln(*GovGrant3$_{it-1}$*)	0.0265***		0.0225***	
	(0.0037)		(0.0087)	
nbPast3Pat$_{it-1}$	0.0034	-0.0011	0.0128	0.0082
	(0.0089)	(0.0078)	(0.0215)	(0.0194)
ln(10^4×*BetweenCent$_{it-2}$*)	0.1671***	0.1333**	0.3245***	0.3007**
	(0.0577)	(0.0548)	(0.1218)	(0.1176)
ln(10^3×*Cliquishness$_{it-2}$*)	0.0916***	0.0956***	0.0359***	0.0411***
	(0.0061)	(0.0059)	(0.0132)	(0.0137)
dCanada	0.2937***	1.2064***	-0.2335*	0.4073**
	(0.0716)	(0.1036)	(0.1257)	(0.1890)
dCanada × *ln(GovGrant3$_{it-1}$)*	-0.0255***	-0.2295***	-0.0071	-0.1445***
	(0.0085)	(0.0190)	(0.0125)	(0.0367)
dCanada × *nbPast3Pat$_{it-1}$*	0.1003***	0.1051***	0.1116***	0.1174***
	(0.0159)	(0.0152)	(0.0268)	(0.0242)
dCanada × ln(10^4×*BetweenCent$_{it-2}$*)	0.2005***	0.2337***	-0.0483	-0.0275
	(0.0765)	(0.0631)	(0.1456)	(0.1364)
dCanada × ln(10^3×*Cliquishness$_{it-2}$*)	-0.0759***	-0.0757***	-0.0190	-0.0207
	(0.0145)	(0.0134)	(0.0223)	(0.0218)
Years (1996-2005)	Yes	Yes	Yes	Yes
Prediction(*GovGrant3$_{it-1}$*)-2SLS		0.2424***		0.1715***
		(0.0203)		(0.0399)
Constant	0.5276***	-0.6292***	3.7725***	2.9861***
	(0.0823)	(0.1354)	(0.1762)	(0.2799)
Inflate				
ln(*GovGrant3$_{it-1}$*)	-0.0144***		-0.0291***	
	(0.0028)		(0.0034)	
nbPast3Pat$_{it-1}$	0.0557***	0.0546***	0.1021***	0.0988***
	(0.0049)	(0.0049)	(0.0083)	(0.0081)
ln(10^4×*BetweenCent$_{it-2}$*)	-0.5422***	-0.5253***	-0.7851***	-0.7689***
	(0.0550)	(0.0564)	(0.0517)	(0.0501)
ln(10^3×*Cliquishness$_{it-2}$*)	-0.2712***	-0.2583***	-0.2471***	-0.2414***
	(0.0054)	(0.0055)	(0.0061)	(0.0061)
Prediction(*GovGrant3$_{it-1}$*)-2SLS		-0.0566***		-0.1097***
		(0.0075)		(0.0081)
Constant	2.0990***	2.1576***	3.3520***	3.7285***
	(0.0269)	(0.0536)	(0.0320)	(0.0494)
Nb observations	64691	64691	64691	64691
Nb Groups	37339	37339	37339	37339
Loglikelihood	-38077.5	-37107.6	-163417	-158949
χ^2	639.20***	921.81***	114.74***	125.62***

Note : Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1)

Table 3.6: Estimated Marginal Effects in Canada and the US

Variables	**Canada** Delta method (dy/dx) **nbPaper$_{it}$** Model (1)	**Canada** Delta method (dy/dx) **nbCitation5$_{it}$** Model (1)	**The US** Delta method (dy/dx) **nbPaper$_{it}$** Model (1)	**The US** Delta method (dy/dx) **nbCitation5$_{it}$** Model (1)
ln(*GovGrant3$_{it-1}$*)	0.0443 ***	0.0856	0.0507 ***	0.3361 ***
	(0.0124)	(0.0634)	(0.0025)	(0.0377)
nbPast3Pat$_{it-1}$	0.0629 ***	1.1827 ***	-0.0075 ***	-0.0515 ***
	(0.0125)	(0.2040)	(0.0010)	(0.0195)
ln(10^4×*BetweenCent$_{it-2}$*)	0.3179 ***	4.9079 ***	0.0948 ***	0.5987 ***
	(0.0275)	(0.6094)	(0.0159)	(0.1243)
ln(10^3×*Cliquishness$_{it-2}$*)	0.0442 ***	0.6525 ***	0.0545 ***	0.2978 ***
	(0.0049)	(0.1124)	(0.0014)	(0.0232)

Note : Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1)

3.6 Conclusions

As we mentioned in the introduction, in recent years, governments have launched research financing programs increasingly targeted towards nanotechnology development within universities to incite the growth of this emerging technology. It is thus of great importance to further understand whether government funding can indeed enhance the success of this development and can be powerful to lead research in the academic realm. Debates have arisen on the question of whether public funding enhances the scientific outputs in emerging high technologies and to that effect we have examined publications of the very promising field of nanotechnology as a typical example of science-based technology. Nanotechnology is still in the early stages of its lifecycle and as such, the role of public funding is of paramount importance for its development. We take into account the nanotechnology-related scientific output in Canada and compare the efficiency and productivity of government funding in this high technology with the US as a leading country in nanotechnology research development.

At the beginning of this article, we set out to examine three hypotheses, one related to the public funding of research and another one to the collaboration related to research. In the third hypothesis, we compare the funding effect in Canada and the US. Let us address each of these hypotheses in turn. Regarding the influence of public funding on scientific production, the impact on the number of papers is overwhelmingly significant and positive in the United States, where both the number and the quality of publications increases as funding amount rises. However, for the publication quality, this positive relationship is only observed in the US. The results for Canada do not show that government funding has an impact on the publication quality. These results are supporting both *Hypothesis 1a* and *Hypothesis 1b* for the US and only *Hypothesis 1a* for Canada. Our results, hence, are in general accordance with the work of various scholars (Adams et al. 2005; Adams and Griliches 1998; Arora et al. 1998; Blume-Kohout et al. 2009; Jacob and Lefgren 2007; Payne and Siow 2003; Sauer 1988), on the crucial importance of funding for the production of scientific output. Although, in general our results are in line with previous studies, to our knowledge, this is the first time that a study focuses on the impact of funding on nanotechnology in both Canada and the US and the comparison between these two countries in addition to considering the importance of scientific networks at the same time.

We include the industrial interests of academic researchers to further understand whether patents representing potential commercialization are associated with the production of academic publications. Our study on nanotechnology-related patents shows that patenting activities in universities are associated with more scientific papers only in Canada and not in the US and even in Canada this positive effect is more consistent in terms of the productivity of researchers rather than in terms of the quality of their publications.

However, the relationship between these two types of research outputs could be described as complementary and reinforcing rather than substitutive. Although we expected to observe a shift in research output of academic inventors toward more applicable and commercial research, we found that researchers who contribute to more and higher quality patents in previous years are more likely to generate publications of higher quantity in Canada. Nanotechnology, however, is a young field and has considerable potential in a wide range of disciplines: It is an emerging technology which is close to its science base, but it is getting increasingly closer to technology applications in a variety of domains and subdomains. As such, we could find a direct connection of academic inventors with their publications, generally similar to the work of some scholars in other fields (Azoulay et al. 2009; Breschi et al. 2007; Czarnitzki et al. 2007; Wong and Sing 2010), implying that academic scientists who produce patents also exhibit a higher research performance. We however support their findings in the field of emerging nanotechnology in Canada.

In the field of nanotechnology, we observe an increasing tendency of researchers to form research teams whose expertise span over a wide range of domains. Funding agencies thus commonly allocate financial resources to teams of scientists rather than individual researchers. In our second hypothesis we therefore focus on the way in which these collaborative teams are structured and shed some light on the impact of the network architecture on the scientific production of the teams. We examine the research performance of scientists using previous collaborations in the past 3 years to find the impact on scientists' subsequent productivity.

In this empirical study, we discover that the position of individual researchers in scientific networks does influence their knowledge production. We find a remarkably positive and significant impact of the intermediary position of scientists on their number of publications and article quality in both Canada and the US. With respect to the past individual cliquishness of researchers in their co-authorship networks, we find that the cliquishness value yields a positive impact on scientific output in Canada. As such, we observe this positive impact only when we add a quadratic term of cliquishness to the model in which it shows a positive impact until a threshold is reached.

Beyond this specific point further along the curve, a higher clustering coefficient decreases the efficiency of articles published implying that researchers working in more clustered collaborative environments become less productive and efficient. This may be explained by the possible inclination of authors in cliquish environments to cite scientists with whom they are linked in their network.

Regarding this collaboration measurement in the US, our results tend to support the notion that clustered environments enhance scientific productivity and confirm the efficiency of these collaborative networks in knowledge diffusion. We find that clustered networks increasingly augment scientific productivity and efficiency of a scientist. We thus accept *Hypothesis 2a* and *Hypothesis 2b* for which our results are generally in line with Balconi et al. (2004), Breschi et al. (2006), Newman (2001), Ni et al. (2011), Persson et al. (2004) and Velema (2012) who highlight the positive influence of collaborations on research productivity.

In regards to the comparison of Canada and the US, when we compare the marginal effects in both countries and regression results of pooled sample, we find that government grants yield a greater effect on the nanotechnology publication in the US, while better network characteristics lead to more and higher quality publications in Canada compared to the US. Thus we reject both *Hypothesis 3a* and *Hypothesis 3b* in terms of the higher influence of government grants in Canada rather than in the US.

There are a number of limitations to this research. One concern is the mobility of researchers across the US and Canada: Since the main purpose of this research is the comparison of the research productivity for the researchers affiliated to Canadian and American institutions, the mobility of these researchers and the resulting changes in the institutional affiliations clearly affect the results of this study. This issue, however, could not be considered in this study. The other limitation lies in the accurate identification of nanotechnology papers. In spite of our attempt to extract and analyze papers most closely related to nanotechnology, we may lose some papers due to our narrow definition of what constitutes a nanotechnology article. The other limitation is merging different databases that may have caused some deterioration or loss of the data. Another issue that concerns this study is using different data sources for Canada and the US, which can cause inconsistency in our comparison of the two countries. Despite these caveats, we are confident that our results are a step in the right direction and identify avenues for future research on research funding and on the importance and influence of research networks.

3.7 Acknowledgments

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CHAPTER 4 ARTICLE 3: IMPACT OF PUBLIC AND PRIVATE FUNDING ON NANOTECHNOLOGY RESEARCH QUALITY

Leila Tahmooresnejad, Catherine Beaudry

4.1 Abstract

Government agencies have a long history in funding academic research and are one of the primary forces fostering new technologies in the last decades. Nanotechnology seems to have a huge potential to bring benefits for economic growth and has shown its ability to attract interest from the private sector as well. This paper analyzes the effects of public and private funding on subsequent scientific outputs of academic research in this emerging technology. We investigate whether public grants increase research quality and whether private funding is complementary in enhancing the quality of scientific publications. Using a panel data set from 1985 to 2005 in Quebec, we estimate time-related models that study the factors that influence citations 5 years after publication. The results show that the influence of public grants on the number of citations as a proxy of paper quality follows almost a positive linear curve implying a positive impact proportional to the amount of public funding received. In contrast, industry funding exhibits a non-linear negative effect. The estimates suggest that private research funding from industry is a detrimental to publication impact.

Keywords: Research funding, private funding, scientific papers, citations, nanotechnology

4.2 Introduction

In the past decades, the government has heavily funded nanotechnology research as larger amount of public grants have been awarded for academic research in this emerging technology. Various scholars (Canton, 2001, 2007; Knol, 2004; Lorenzoni *et al.*, 2009; Schummer and Baird, 2006; Vokhidov and Dobrovol'skii, 2010) have studied the anticipated economic value of nanotechnology and have forecasted that nanotechnology applications undoubtedly stimulate economic growth. This led to a fast increase in nanotechnology funding and subsequent research growth to meet this challenge. On an international level, the number of nanotechnology publications has increased tremendously over recent years (Hullmann, 2006; Roco, 2011; Ye et al. 2012; Youtie, 2008).

Although, federal funding is responsible for a considerable portion of university funding, this new technology attracts private funding despite the fact that nanotechnology is still inherently closer to basic research (Knol, 2004; Lorenzoni *et al.*, 2009; Payne and Siow, 2003; Schummer and Baird, 2006). In general, although basic research is significant for development of new technologies (Rubini, 2010), but it is less likely to attract private funding and requires sufficient government funding, as forecasting or even measuring its economic value is difficult. Dasgupta and David (1994) rightfully show that the outcomes of basic research are highly uncertain and economic payoffs are not properly observed in the short term. In this regard, private companies mostly follow short-term objectives rather than blue-sky research. Yet, according to Gulbrandsen and Smeby (2005), private funding might have a role in defining research topics since researchers with more industry funding collaborate more with other scientists and their research is described as more applied. Identifying the distinctive impact of public and private funding in this research will thus contribute to our understanding of the efficiency of funding allocation. This is particularly important in light of the recent investments in nanotechnology research.

Previous studies mostly focus on government funding in academic research and generally show that federal funding has a small positive impact on publication quality (Jacob and Lefgren, 2011; Payne and Siow, 2003). It is not yet clear from the literature, which still lacks enough studies on this issue, especially regarding scientific quality, that research funding from private sources has an impact on scientific productivity and quality, whether positive or negative. The lack of studies is mainly due to confidentiality issues regarding this type of company-related data. Confidentiality issues often preclude scholars from having access to such private investments. As a consequence, most prior studies suffer from a lack of information on private funding, particularly at the level of the individual researcher. Our access to privileged information regarding private contracts for Quebec academic researchers gives us the opportunity to remedy to this lack of evidence.

Quebec has been one of the most active Canadian provinces in terms of nanotechnology investment, science, research and development since 2001, and has initiated considerable financial support. The creation of NanoQuébec in 2001 exemplifies this public support

(NanoQuebec, 2010). Our paper hence complements the studies that find a positive impact of public funds on scientific productivity by focusing on the other important source of funding, i.e. that invested by industry in a high technology field which has been growing over the last few decades. We therefore aim to measure the influence of funding on academic research and to compare the impact of two funding sources, i.e. public and private. Following the work of Beaudry and Allaoui (2012) on nanotechnology publications, in this study, we focus on the quality of scientists' publications as a measure of a scientist's impact rather than on scientific productivity.

Understanding the impact of different sources of funding is critical and can result in the efficient allocation of each or in a combination of these investments, which then generates higher quality research outputs. This paper offers important contributions to the literature to further understand the impact of public and private research funding on the quality of publications in an emerging field. For instance, our results show that although public funding has considerable impact on the quality of publications generated by nanotechnology Quebec scientists, private funding has a strong negative impact, even when controlling by the patenting activities of these academics.

The remainder of the paper is organized as follows. Section 2 presents the conceptual framework, based on the literature, that inspires our research hypotheses. We then describe the data, the variables and the methodology employed in Section 3. Finally, regression results are analysed in Section 4 and concluding remarks are presented in Section 5.

4.3 Conceptual framework

In recent years, many countries have increased their investment in nanotechnology research in universities in order to incite future innovations (Bhattacharya, 2007; Canton, 2001; Davies, 2007; Hullmann, 2006; Knol, 2004; NSF, 2001). The findings of Seear *et al*. (2008) illustrate that the main sources of global nanotechnology research funding is composed of government and corporate investment. According to Roco (2011), the worldwide investment in nanotechnology R&D from both the public and private sectors was $15 billion in 2008, resulting from a 35% average annual growth between 2000 and 2008. Providing the complex infrastructure and instruments to develop nanotechnology research requires access to sufficiently large amounts of investment in order to foster the knowledge development in this multidisciplinary field.

The relationship between funding and research performance is demanding by policy makers since evidences of performance and benefits of funded research are required as sources of funding are scarce and needs to be effectively employed (Kuhlmann, 2003; Shapira and Furukawa, 2003).

Mostly prior studies examine the frequency of publications as a performance indicator and only a few focus on research quality; the publication rate of research outputs is a more common issue to investigate. For example, Adams and Griliches (1998) find that at the aggregate level (group of universities), the relationship between scientific output (measured by both the number of publications and citations) and research funding exhibits a constant returns of production process, while at the individual university level, the relationship is more akin with diminishing returns. In addition, the authors also make a distinction between federal research funding and non-federal funding, which could be construed as closer to private funding. They find the elasticities of non-federal funding to be systematically lower than federal funding, hence implying a more important impact of public research funds. In another study, Boyack and Börner (2003) suggest that there is little correlation between government funding and citation rates of research publications in the behavioural and social sciences field. According to a study by Payne and Siow (2003) on 74 research universities, government funding has a positive influence on the research outputs of universities, although the effect on the number of citations is small and imprecise. In the same vein, Jacob and Lefgren (2011) also suggest a relatively modest effect of National Institutes of Health (NIH) grants on the number of citations obtained by publications resulting from NIH grants. While Similarly Shapira and Wang (2010) found a mixed impact on the citation, Lewison and Dawson (1998) found that the number of funding sources matters in publishing articles in journals of higher impact factor.

Receiving public grants has a lever effect on the capacity to raise further research funds. The findings of Jacob and Lefgren (2011) show that in the US, receiving NIH funding influences the capacity to raise funding from other sources such as that from the National Science Foundation (NSF) and from private sources, i.e. from industry. A study of US universities reveals that receiving federal funding from NSF and NIH can be a sign of recipient quality and increases the chance of receiving non-federal funding (Blume-Kohout et al., 2009). These non-federal organizations assume that federal funding reflects higher quality, which prompts them to allocate additional funding. Researchers unsuccessful in obtaining public funding must however find other sources in the private sector. Hence there seem to be a substitute/complement ambiguity related to public and private funding.

Previous studies have used different quantitative and qualitative methods to measure how funding influences academic research. Wallin (2005) indicates that bibliometric indicators need precise knowledge and should be used correctly to obtain appropriate results. Although some studies raise a general concern in using citations - such as the number of citations may be due to the growth or development of a specific field; or, researchers may discover a flaw in a paper and try to correct it in a new publication (Kostoff, 1998; MacRoberts and MacRoberts, 1996; Wallin, 2005) - citation analyses are frequently used to identify valuable research and to assist grant awarding bodies in the efficient allocation of investment (Agasisti et al., 2012; Laudel, 2005; Rigby, 2011).

Other works emphasize the importance of collaboration and social networks on the impact of funding on research quality. Adams *et al*. (2005), for example, state that public funding affects the size of scientific teams, which in return leads to more citations. Scientists with prestigious awards and a large stock of federal funding indeed collaborate in larger teams and this collaboration generally provides better opportunities for their work to be more cited.

In light of the evidence presented in the literature, we propose the following hypothesis regarding the impact of public grants on the quality of nanotechnology-related publications:

Hypothesis 1: *Nanotechnology scientists who receive greater amounts of public funding contribute to higher-quality publications.*

The current debate exposes very different views regarding the issue that the integration of university research with industry can also influence research outputs. Some studies state that increased links with industry have a positive impact on research outputs (Abramo *et al*., 2009; Baba *et al*., 2009; Banal-Estanbol *et al*., 2011; Guan & Wang, 2010; Landry *et al*., 1996; Siegel *et al*., 2003), others argue that it has a negative impact (Argyres and Liebskind, 1998; Owen-Smith and Powell, 2001; Siegel *et al*., 2003; Ambos *et al*., 2008) on scientific outputs. For example, Lexchin (2005) shows that industry funding hampers scientific progress and it may result in stopping research in mid-flow. Banal-Estanol *et al*. (2010) suggest that an average level of industry collaboration yields higher quality research outputs, although the number of publications diminishes with higher levels of private funding and industry involvement. Blumenthal *et al.* (1996) and Gulbrandsen and Smeby (2002) suggest that industry funding positively contributes to academic productivity. Bruno and Orsenigo (2003) highlight the importance of university productivity in attracting industrial funds, as scientifically productive universities are more likely to receive high levels of funding. These previous studies however aimed at discovering the impact of collaboration between university and industry rather than directly analyze the effects of funding from industry.

Despite the mixed evidence presented above, we propose in our second hypothesis that private funds resulting in industry links with academic research have a positive impact on the quality of nanotechnology-related publications.

Hypothesis 2: *Nanotechnology scientists who receive greater amounts of private funding contribute to higher-quality publications.*

4.4 Methodology

4.4.1 Data and Variables

The data used in this paper come from a unique dataset of Quebec scientists that relies on a combination of several sources: Elsevier's Scopus provides information on publications and authors; Public and private funding information is available via the Système d'Information sur la Recherche Universitaire (SIRU) of the Quebec Ministry of Education, Leisure and Sports; The United States Patent and Trademark Office (USPTO), the federal agency for granting US patents and registering trademarks, provides information on inventors and patents[16] (name, affiliation, city, application date, grant date, assignees, etc.). We prefer to use the US database because Canadian inventors largely tend to register their patents in the USPTO (Beaudry and Schiffauerova, 2011). Among the most frequently used scientific databases (Science Direct, Scopus, Web of Science, Microsoft Academic Search, Scirus, Google Scholar, etc.), we decided

[16] Patents are used as control variables and will be described further in this section.

to choose Scopus because this database covers a wide diversity of fields and journals, and more importantly, it generally matches individuals with their affiliations which greatly facilitates the disambiguation of similarly named scientists. Given the multidisciplinary nature of nanotechnology a wide range of disciplines is crucial for the purpose of this study.

SIRU contains both government and industry funding that was awarded to all university scientists in Quebec for the period of 20 years (1985-2005)[17]. The data comes directly from the university accounts for each project and provides exact data on a yearly basis[18].

We used the nanotechnology keyword queries of Porter *et al*. (2008) to extract the relevant nanotechnology papers and patents, from which we extracted the names of individuals that we then matched to the other databases to build the final dataset. Matching was not trivial our approach involved matching data using scientists' names. This process is likely to result in possible errors in uniquely identifying scientists having similar names (synonymy) or assigning different IDs to the same scientist whose name is written differently in various databases (homonymy). To circumvent these common problems, we utilize a variety of other information about scientists to define a unique ID for each academic researcher and thus to minimize the incidence of wrong matches. The main information was provided by the affiliation of scientists in both Scopus and SIRU in addition to the address of academic inventors in the USPTO database. A large amount of manual work and careful examination was however necessary to clean the data and assign a unique ID number.

To validate the hypotheses mentioned in the previous section, we need to integrate these publications, patents and funding databases into one dataset using the unique ID for each scientist. We then condensed these databases to obtain data on a yearly basis (panel data) which contains the number of publication and patents, the number of citations, and the amount of grants and contracts per scientist, per year for the 1985-2005 period. We finally restrict our resulting sample data to 1996-2005, after having calculated the lagged variables on 3 years and 5 years averages. The reason for concentrating on this subset is twofold; first according to the growth of

[17] The data are available for this period and not for subsequent years.

[18] Any funds that do not transit via the university system is not available but given the size of the grants awarded and the necessity for expensive infrastructure, we estimate the hidden funds (grants and contracts) to be minimal.

nanotechnology research outputs, scientists had only recently started being involved in this emerging area before 1996 and the data is rather scarce prior to that period, hence this timeframe seems too early for nanotechnology. Second, there has been a considerable change for the better in the quality of Scopus and SIRU after 1996.

Following the literature that states that higher-quality research receives more citations (Kostoff, 1998; Lin et al. 2007; MacRoberts and MacRoberts, 1996; Wallin, 2005; Weingart, 2005), we use the number of citations as a proxy for paper quality. There is a positive correlation between the importance of a paper and the degree to which a paper is cited in later research publications. Kostoff (1998) indeed states that citations provide links to the historical context of specific contributions to papers and highlight a wide interest in those contributions. We define *nbArtCit5* as the number of citations received within 5 years[19] of publication by the articles published. During the course of this research, we tried different dependent variables. The average number of citations per paper did not provide robust results, nor did the h-index calculated on a yearly basis (it is important to note here that we use panel data for our analyses). In fact, the h-index[20] is somewhat inappropriate because it evaluates the impact of an individual over the course of a career while we are interested here in whether better funding enhances paper quality on a yearly basis.

We assess the influence of funding on publication quality based on average amounts of public grants (*AvgGrant3*) and private contracts (*AvgContract3*) over the past three years. Yearly measures proved too volatile to provide robust results and longer periods (five years for instance) reduced the sample size because of unreliable data prior to 1996 and were very rarely significant. In addition to these two variables of interest, our models include a number of controls which are described in the following paragraphs.

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[19] We have calculated citations after 3, 5 and 7 years but present the 5-year citations in this paper as they provided the most consistently significant results in the regressions.

[20] The h-index is an indicator based on the set of the most cited papers. This index aims to measure both the productivity and citation impact. A researcher has index h if h of the papers received at least h citations each and the other papers have not received more than h citations each (Hirsch, 2005).

Industry contracting often fosters patenting activities and may contribute to increasing university patents because firms are generally associated with applied knowledge and focus on short-term objectives. Patenting can however be result of both government and industry funding. To our knowledge, few studies in literature concentrate on the effect of academic patenting on research quality, although more debates exist on publishing-patenting trade offs. Azoulay *et al*. (2009), for instance, find a positive effect on the rate of publications, but a weak effect on publication quality. A study by Breschi *et al.* (2008) based on a sample of 592 Italian academic inventors show that academic inventors publish more and better quality papers compared to their non-patenting colleagues. We therefore seek to examine the reinforcing or limiting effect of patenting activity on nanotechnology publication quality. We therefore include the number of patents to which researchers have contributed in the past three years (*nbPatent3*) in the models to examine the influence of innovative activities on the research quality.

In the theoretical framework, we alluded to the fact that research is rarely performed alone but rather within collaborative teams. Many scholars have studied the impact of collaboration on research productivity (Breschi and Lissoni, 2005; Eblen et al., 2012; Lee and Bozeman, 2005; Sala et al., 2011; Wang and Guan, 2010). Research generally finds that increasing levels of collaboration within scientific networks have a positive impact on scientific productivity (Frenken *et al.*, 2005; Glänzel and Schubert, 2005; Rigby and Edler, 2005). Balconi *et al.* (2004) specifically suggest that working in collaboration with other scientists helps academic scientists gaining a higher citation rate. Within networks, co-authorship enhances research performance (Baba *et al*., 2009; Balconi *et al*., 2004; Breschi and Lissoni, 2005; Breschi *et al*., 2006; Ni *et al*. 2011; Singh, 2007; Wang and Guan, 2010; Youtie et al., 2013).

Social network analysis provides sophisticated tools to measure the importance of various individuals with the co-publication network. The resulting network characteristics can thus be used as controls regarding collaborative work. Better-positioned researchers in the co-publication network are more likely to attract citations due to their enhanced reputation. In order to investigate a scientist's position in scientific networks, we characterize the networks of co-authors using the software Pajek[21]. We construct time evolving sub-networks corresponding to

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[21] Pajek is an appropriate program to analyze large networks and it is easy to use and free for noncommercial use.

three-year and five-year windows using the co-authorship links in order to track and measure the evolution of collaboration over time. In this paper, we only include the network characteristics of three-year intervals and analyze the impact of these indicators on the publication quality of researchers as these three-year intervals generate the most significant results.

More precisely, we calculate two network indicators: betweenness centrality (*BtwCent3*) and individual cliquishness (*Cliqness3*) of researchers in three-year moving intervals within co-authorship networks. Betweenness centrality measures the importance of a node (researcher) as an intermediary in the network. For one specific researcher, this attribute is measured by the sum of the shortest paths between two researchers that include this researcher over the total number of possible shortest paths between these two researchers (Brandes, 2001; West, 2001). Individual cliquishness refers to the clustering coefficient of a researcher in the network, defining the probability of a connection between two researchers if both are connected to a mutual collaborator (Barabasi, 2002). The clustering coefficient, used as a measure of cliquishness, is high for the researchers who co-author articles in a highly interconnected subfield and is low for an individual researcher who collaborates widely with other researchers that tend not to publish together (Pike, 2010).

Finally, we add year dummy variables to account for residual time related effects. Table B.1 in Appendix B presents the variables and their definitions. Tables B.2 and B.3 show the standard descriptive statistics.

4.4.2 Model Specification

Our model relies upon the assumption that the quality of scientific productions published by academic researchers depends on the average amount of research funding that a researcher receives from government and industry sources. Due to the fact that the dependent variable is count data, two techniques are recommended: the Poisson and negative binomial regressions specific to panel data. In the case of over-dispersion, the negative binomial regression is more appropriate and enables the model to have better flexibility in modeling. The negative binomial model removes the equidispersion restriction of the Poisson via the introduction of latent heterogeneity in the conditional mean of the Poisson model (Greene, 2008).

While the negative binomial model takes the over-dispersion into account, it cannot adequately deal with an excessive number of zero observations in the data. High number of zero counts in such data is common and frequently affects estimations and standard errors. To verify the presence of an excess number of zeros in our panel data, the Vuong statistic is suggested to test whether the number of observed zeros exceeds the number of expected zeros under the negative binomial distribution assumption (Vuong, 1989; Green, 1994). The results of the Vuong test indeed show that the zero-inflation problem exists in our data and we have to use zero-inflated negative binomial (ZINB) regressions instead of negative binomial regressions to accommodate for excess zeros.

If research grants were randomly allocated to researchers in the absence of endogeneity, equation (4-1) would be a sufficient model to be estimated. It shows the relationship between our explanatory variables and the dependent variable, *nbArtCit5*$_{it}$, the number of forward citations received by the papers of scientist i in year t, within 5 years of publication[22].

$$nbArtCit5_{it} = f\left(\begin{array}{l} AvgGrant3_{it-1}, \left[AvgGrant3_{it-1}\right]^2, \\ AvgContract3_{it-1}, \left[AvgContract3_{it-1}\right]^2, \\ nbPatent3_{it-1}, \left[nbPatent3_{it-1}\right]^2, \\ BtwCent3_{it-2}, Cliqness3_{it-2}, \left[Cliqness3_{it-2}\right]^2, \\ \left[BtwCent3_{it-2} \times nbPatent3_{it-1}\right], \\ \left[BtwCent3_{it-2} \times Cliqness3_{it-2}\right], d_t \end{array}\right) \tag{4-1}$$

An important consideration regards the fact that researchers with higher-quality outputs receive more funding, which in turn contributes to generating more publications that then receive more citations and contribute to facilitate raising further research funding. Blume-Kohout *et al*. (2009) demonstrate that federal funding is allocated to higher-quality researchers and that it also affects the non-federal funding raised. Private companies use the attribution of government funding as a sign of researchers' quality to identify higher quality scientist with whom collaborate. Our funding variable (*AvgGrant3*) is therefore endogenous due to its potential correlation with other explanatory variables. A second cause for concern regarding endogeneity arises in our study via

[22] We tested 3-year, 5-year and 7-year citations and found the consistently significant results using 5-year citations.

the omitted variable measuring the intrinsic quality of scientists. Funding is assigned to higher quality and highly cited researchers, who are more likely to receive more citations for their later publications. Hence, we need to identify a number of instrumental variables to correct for potential endogeneity bias. Furthermore, funding is generally allocated to teams rather than to single researchers. The two factors, collaboration and funding, are thus intrinsically linked.

In order to address the bias caused in regressions when faced with endogeneity, Wooldridge (2002) suggests the use of instrumental variables. Biro (2009) and Stephan et al. (2007) propose specific Two-Stage-Residual-Inclusion (2SRI) regressions as suitable modeling approach for IV estimations in this case. The main idea of this method is to estimate the endogenous variable *(AvgGrant3)* using ordinary least squares (OLS) regressions on a set of instruments and on the exogenous variables, which is the first stage regression. The second stage regression then uses the residual of the first stage regression as an explanatory variable in the model. More specifically, the first and second stage regressions to be estimated in our model are expressed as follows:

$$\begin{aligned}\ln\left(AvgGrant3_{it-1}\right) = {} & \alpha_1 + \lambda_{A1}Age_{it-1} + \lambda_{A2}Age^2_{it-1} + \lambda_{Ch}Chair_i + \lambda_a nbArticle3_{it-1} \\ & + Variables2^{nd}\,Stage + \left(\nu_{1i} + \varepsilon_{1it}\right)\end{aligned}$$

$$\begin{aligned}nbArtCit5_{it} = {} & \alpha_2 + \beta_{G1}\ln\left(AvgGrant3_{it-1}\right) + \beta_{G2}\left[\left(AvgGrant3_{it-1}\right)\right]^2 + \left(\nu_{1i} + \varepsilon_{1it}\right) \\ & + \beta_{c1}\ln(AvgContract3_{it-1}) + \beta_{c2}[\ln(AvgContract3_{it-1})]^2 \\ & \gamma_b(\ln(10^4 \times BtwCent3_{it-2})) + \gamma_{c1}(\ln(10^3 \times Cliqness3_{it-2})) \\ & + \gamma_{c2}\left[\ln(10^3 \times Cliqness3_{it-2})\right]^2 + \beta_{P1}nbPatent3_{it-1} + \beta_{P2}nbPatent3^2_{it-1} \\ & + \gamma_{bp}[\ln(10^4 \times BtwCent3_{it-2}) \times nbPatent3_{it-1}] \\ & + \gamma_{bc}[\ln(10^4 \times BtwCent3_{it-2}) \times \ln(10^3 \times Cliqness3_{it-2})] \\ & + \sum_{t=1985}^{2005}\delta_t d_t + \nu_{2i} + \varepsilon_{2it}\end{aligned} \tag{4-2}$$

As instrumental variables, we include the time elapsed since researchers began their nanotechnology-related activities, and use a scientist's first publication as a proxy for their career age in nanotechnology (*Age*); this variable accounts for the fact that younger scientists probably receive less research funds because of their lack of a track record. Furthermore, we add the type of research chair (*Chair*) held by scientists to proxy the quality of a scientist. This variable is defined as an ordinal indicator that takes the value 0 if a researcher never had a Chair in the period considered, the value 1 if he holds an industrial chair, the value 2 for being a chair of one of two Canadian federal granting councils, and the value 3 for a scientist / academic inventor who is a Canadian Research chair[23, 24]. Finally, to take researchers' past publications into account for the capacity to raise funds from a publication track record, we include the average number of papers published over the past three years (*nbArticle3*) lagged one year.

Using STATA, we perform the regression analyses with the *zinb* procedure by hierarchically adding the quadratic term of specific variables to examine possible nonlinearities, and interactive variables to analyze moderating effects of other variables. Although our data is built as a panel, there is no procedure in Stata to run zero-inflation models using panel data. In addition, to account for the non independence of repeated observations for the same academic researcher over several years we must thus revert to using the clustering option of the zinb procedure.

4.5 Regression Results

Our analyses considered numerous factors and lag structures for variables to achieve the most consistently significant results. The chosen lag structures of our independent variables are a one-year lag for research funding and two-year lag for the network characteristics. Table 4.1 presents the basic estimates for the effect of public and private funding on the number of 5-year citations. These are the results of the zero-inflated negative binomial model that do not account for potential endogeneity. In Table 4.2 we empirically shed light on the issue of endogeneity with a rich set of control variables.

As expected, the 2SRI regression suggests that public funding is endogenous. The instruments used to capture the potential endogeneity of the amount of grants are generally significant. We find that having a higher number of articles in previous years (*nbArticle3*) and being older and more experienced (*Age*) to have a significant effect in the first stage of regression (see Table B.4 in Appendix B). Surprisingly, the importance of occupying a chair at some point in one's career (*Chair*) does not influence fund raising.

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[23] The Canada Research Chair program is at the center of a national strategy to enhance research excellence in various fields such as engineering, the natural sciences, health sciences, humanities and social sciences. Chair holders aim to improve the knowledge and train students to be highly skilled researchers (http://www.chairs-chaires.gc.ca/).

[24] We tested both a yearly measure of the chair variable and a fixed 'career' measure, and chose the latter as a better measure of the inherent quality of a researcher.

Table 4.1 : Regression results of zero-inflated negative binomial model without accounting for possible endogeneity

nbArtCit5$_t$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
$\ln(AvgGrant3_{t-1})$	-0.0076	-0.0073	-0.0072	-0.0168	-0.2095***	-0.2230***	-0.2050***
	(0.0227)	(0.0225)	(0.0226)	(0.0221)	(0.0627)	(0.0629)	(0.0623)
$[\ln(AvgGrant_{t-1})]^2$					0.0144***	0.0161***	0.0142***
					(0.0040)	(0.0040)	(0.0040)
$\ln(AvgContract3_{t-1})$	0.0087	0.0301	0.0327	0.0232	0.0342	0.0294	0.0288
	(0.0120)	(0.0581)	(0.0576)	(0.0590)	(0.0557)	(0.0555)	(0.0564)
$[\ln(AvgContract_{t-1})]^2$		-0.0020	-0.0024	-0.0012	-0.0033	-0.0030	-0.0029
		(0.0051)	(0.0051)	(0.0052)	(0.0050)	(0.0050)	(0.0051)
$nbPatent3_{t-1}$	0.0444	0.0475	0.1028*	0.0906*	0.0855*	0.0416	0.1150*
	(0.0482)	(0.0492)	(0.0536)	(0.0546)	(0.0503)	(0.0515)	(0.0637)
$[nbPatent3t_{t-1}]^2$			-0.0026**	-0.0023*	-0.0022*		-0.0029*
			(0.0013)	(0.0014)	(0.0013)		(0.0016)
$\ln(10^4 \times BtwCent3_{t-2})$	0.3394***	0.3393***	0.3350***	0.0927	0.1073	2.0232***	-0.1083**
	(0.0582)	(0.0583)	(0.0586)	(0.0715)	(0.0701)	(0.5701)	(0.0444)
$\ln(10^3 \times Cliqness3_{t-2})$	0.0095	0.0095	0.0089	0.8397***	0.7679***	0.0088	0.6544***
	(0.0192)	(0.0191)	(0.0191)	(0.1809)	(0.1752)	(0.0183)	(0.1778)
$[\ln(10^3 \times Cliqness3_{t-2})]^2$				-0.1257***	-0.1157***		-0.0978***
				(0.0264)	(0.0257)		(0.0262)
$\ln(10^4 \times BtwCent3_{t-2})$						-0.0176	0.0489
$\times\ NbPatent3_{t-1}$						(0.0356)	(0.0617)
$[\ln(10^4 \times BtwCent3_{t-2})$							-0.0174
$\times\ NbPatent3_{t-1}]^2$							(0.0111)
$\ln(10^4 \times BtwCent3_{t-2})$						-0.3076***	0.3561***
$\times \ln(10^3 \times Cliqness3_{t-2})$						(0.1019)	(0.0911)
$[\ln(10^4 \times BtwCent3_{t-2})$							-0.0561***
$\times \ln(10^3 \times Cliqness3_{t-2})]^2$							(0.0152)
Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.5961***	3.5821***	3.5823***	3.6116***	3.9417***	3.9357***	3.9110***
	(0.3760)	(0.3602)	(0.3614)	(0.3633)	(0.3835)	(0.3806)	(0.3850)
Inflate							
$\ln(AvgGrant3_{t-1})$	-0.0439***	-0.0446***	-0.0444***	-0.0364***	0.0704*	0.0775**	0.0719*
	(0.0132)	(0.0133)	(0.0133)	(0.0130)	(0.0384)	(0.0393)	(0.0384)
$[\ln(AvgGrant_{t-1})]^2$					-0.0080***	-0.0089***	-0.0080***
					(0.0028)	(0.0029)	(0.0028)
$\ln(AvgContract3_{t-1})$	-0.0041	-0.0521	-0.0546	-0.0543	-0.0719*	-0.0721*	-0.0732*
	(0.0079)	(0.0423)	(0.0423)	(0.0418)	(0.0422)	(0.0428)	(0.0423)
$[\ln(AvgContract_{t-1})]^2$		0.0045	0.0048	0.0047	0.0066*	0.0069*	0.0069*
		(0.0039)	(0.0039)	(0.0038)	(0.0039)	(0.0039)	(0.0039)
$nbPatent3_{t-1}$	-0.0906*	-0.0967*	-0.1562**	-0.1354*	-0.1225	-0.0774*	-0.1080
	(0.0516)	(0.0496)	(0.0740)	(0.0748)	(0.0751)	(0.0448)	(0.0773)
$[nbPatent3t_{t-1}]^2$			0.0031	0.0025	0.0022		0.0016
			(0.0029)	(0.0028)	(0.0028)		(0.0026)
$\ln(10^4 \times BtwCent3_{t-2})$	-0.8084***	-0.8082***	-0.8029***	-0.2536***	-0.2565***	-5.2657***	-16.3332
	(0.0873)	(0.0874)	(0.0870)	(0.0899)	(0.0898)	(1.4665)	(18.6714)
$\ln(10^3 \times Cliqness3_{t-2})$	-0.1395***	-0.1391***	-0.1381***	-1.8442***	-1.8236***	-0.1407***	-1.7782***
	(0.0127)	(0.0127)	(0.0128)	(0.1929)	(0.1919)	(0.0128)	(0.1940)
$[\ln(10^3 \times Cliqness3_{t-2})]^2$				0.2527***	0.2501***		0.2430***
				(0.0283)	(0.0281)		(0.0285)
$\ln(10^4 \times BtwCent3_{t-2})$						-0.2668*	-0.0741
$\times\ NbPatent3_{t-1}$						(0.1563)	(0.1945)
$[\ln(10^4 \times BtwCent3_{t-2})$							-0.0508
$\times\ NbPatent3_{t-1}]^2$							(0.0651)
$\ln(10^4 \times BtwCent3_{t-2})$						0.7782***	5.1317
$\times \ln(10^3 \times Cliqness3_{t-2})$						(0.2495)	(6.3146)
$[\ln(10^4 \times BtwCent3_{t-2})$							-0.4051
$\times \ln(10^3 \times Cliqness3_{t-2})]^2$							(0.5333)
Constant	2.4631***	2.4769***	2.4788***	2.4266***	2.2524***	2.2524***	2.2349***
	(0.1480)	(0.1492)	(0.1490)	(0.1449)	(0.1402)	(0.1396)	(0.1384)
$\ln(alpha)$	0.6048***	0.6042***	0.6009***	0.5423***	0.5117***	0.5511***	0.5054***
	(0.0739)	(0.0734)	(0.0738)	(0.0722)	(0.0705)	(0.0719)	(0.0712)
Nb observations	8319	8319	8319	8319	8319	8319	8319
Nb groups	1382	1382	1382	1382	1382	1382	1382
Loglikelihood	-9200.15	-9198.98	-9196.45	-9113.92	-9096.26	-9156.21	-9083.25
χ^2	93.32***	94.34***	99.87***	119.80***	139.89***	131.25***	207.48***
Vuong test	14.77***	14.79***	14.84***	15.45***	15.48***	15.13***	15.73***

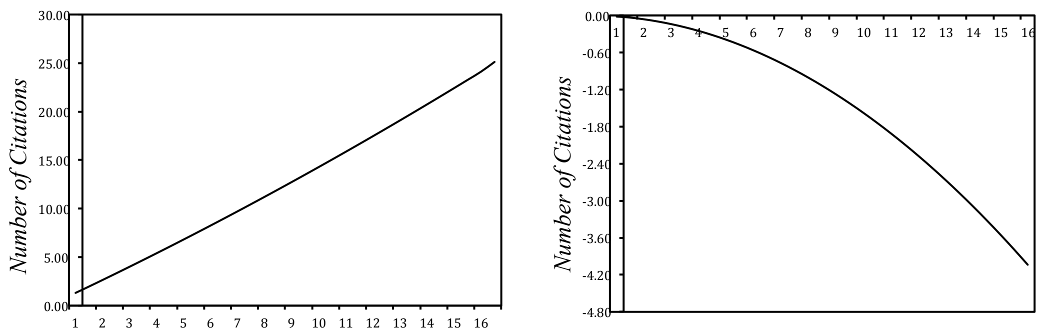
Note: ***, **, * show significance at the 1%, 5% and 10% levels and standard errors are presented in parentheses

Table 4.2 : Second stage regression results of zero-inflated negative binomial model accounting for possible endogeneity (2SRI)

nbArtCit5$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(*AvgGrant3$_{t-1}$*)	1.4658***	1.4485***	1.4391***	1.7921***	1.5293***	0.9964***	1.3445***
	(0.1815)	(0.1810)	(0.1821)	(0.2722)	(0.2662)	(0.1760)	(0.2603)
[ln(*AvgGrant$_{t-1}$*)]^2					0.0129***	0.0132***	0.0127***
					(0.0039)	(0.0039)	(0.0039)
ln(*AvgContract3$_{t-1}$*)	-0.2263***	-0.0739	-0.0715	-0.0936	-0.0755	-0.0505	-0.0749
	(0.0299)	(0.0597)	(0.0594)	(0.0596)	(0.0573)	(0.0571)	(0.0578)
[ln(*AvgContract$_{t-1}$*)]^2		-0.0139***	-0.0141***	-0.0175***	-0.0188***	-0.0129***	-0.0159***
		(0.0052)	(0.0051)	(0.0057)	(0.0054)	(0.0050)	(0.0054)
nbPatent3$_{t-1}$	-0.0545	-0.0334	-0.0072	-0.0188	-0.0208	-0.0656*	-0.1056
	(0.0361)	(0.0348)	(0.0535)	(0.0552)	(0.0481)	(0.0377)	(0.0734)
[*nbPatent3t$_{t-1}$*]^2			-0.0009	-0.0009	-0.0008		0.0012
			(0.0013)	(0.0013)	(0.0012)		(0.0017)
ln(10^4×*BtwCent3$_{t-2}$*)	-0.0488	-0.0455	-0.0455	0.1448***	0.1522***	0.9095*	0.1551***
	(0.0592)	(0.0591)	(0.0595)	(0.0558)	(0.0563)	(0.4975)	(0.0593)
ln(10^3×*Cliqness3$_{t-2}$*)	-0.0645***	-0.0650***	-0.0647***	-0.9200***	-0.8926***	-0.0534***	-0.9019***
	(0.0188)	(0.0187)	(0.0187)	(0.3159)	(0.3032)	(0.0184)	(0.3097)
[ln(10^3×*Cliqness3$_{t-2}$*)]^2				0.1238***	0.1198***		0.1233***
				(0.0453)	(0.0435)		(0.0445)
ln(10^4×*BtwCent3$_{t-2}$*)						0.1795***	-0.0066
× *NbPatent3$_{t-1}$*						(0.0393)	(0.0508)
[ln(10^4×*BtwCent3$_{t-2}$*)							0.0328***
× *NbPatent3$_{t-1}$]^2*							(0.0118)
ln(10^4×*BtwCent3$_{t-2}$*)						-0.1752**	0.3129***
× ln(10^3×*Cliqness3$_{t-2}$*)						(0.0877)	(0.0842)
[ln(10^4×*BtwCent3$_{t-2}$*)							-0.0553***
× ln(10^3×*Cliqness3$_{t-2}$*)]^2							(0.0146)
Res(*AvgGrant3$_{t-1}$*)[a]	-1.4825***	-1.4652***	-1.4557***	-1.8103***	-1.7213***	-1.1897***	-1.5320***
	(0.1868)	(0.1864)	(0.1877)	(0.2779)	(0.2593)	(0.1627)	(0.2537)
Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-10.7829***	-10.6265***	-10.5344***	-13.9724***	-12.8192***	-7.6513***	-10.9924***
	(1.7938)	(1.7958)	(1.8046)	(2.6759)	(2.5240)	(1.6032)	(2.4624)
Inflate							
ln(*AvgGrant3$_{t-1}$*)	-0.7665***	-0.7705***	-0.7669***	-0.5966***	-0.4893***	-0.6500***	-0.4824***
	(0.0853)	(0.0854)	(0.0855)	(0.0828)	(0.0955)	(0.0998)	(0.0964)
[ln(*AvgGrant$_{t-1}$*)]^2					-0.0071**	-0.0076***	-0.0072***
					(0.0028)	(0.0029)	(0.0028)
ln(*AvgContract3$_{t-1}$*)	0.1169***	-0.0053	-0.0072	-0.0183	-0.0343	-0.0181	-0.0334
	(0.0157)	(0.0423)	(0.0424)	(0.0422)	(0.0426)	(0.0431)	(0.0428)
[ln(*AvgContract$_{t-1}$*)]^2		0.0114***	0.0116***	0.0101***	0.0116***	0.0127***	0.0115***
		(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)
nbPatent3$_{t-1}$	-0.0420	-0.0580	-0.0949	-0.0985	-0.0882	-0.0225	-0.0376
	(0.0398)	(0.0386)	(0.0676)	(0.0710)	(0.0714)	(0.0384)	(0.0733)
[*nbPatent3t$_{t-1}$*]^2			0.0019	0.0018	0.0016		0.0002
			(0.0025)	(0.0025)	(0.0026)		(0.0025)
ln(10^4×*BtwCent3$_{t-2}$*)	-0.7169***	-0.7170***	-0.7142***	-0.3426***	-0.3430***	-4.3428***	-16.9988
	(0.0868)	(0.0872)	(0.0872)	(0.0920)	(0.0917)	(1.1985)	(18.5618)
ln(10^3×*Cliqness3$_{t-2}$*)	-0.1081***	-0.1069***	-0.1064***	-1.3228***	-1.3135***	-0.1095***	-1.2472***
	(0.0133)	(0.0133)	(0.0133)	(0.2110)	(0.2090)	(0.0132)	(0.2135)
[ln(10^3×*Cliqness3$_{t-2}$*)]^2				0.1795***	0.1784***		0.1680***
				(0.0308)	(0.0305)		(0.0312)
ln(10^4×*BtwCent3$_{t-2}$*)						-0.1349	-0.0462
× *NbPatent3$_{t-1}$*						(0.1512)	(0.1934)
[ln(10^4×*BtwCent3$_{t-2}$*)							-0.0605
× *NbPatent3$_{t-1}$]^2*							(0.0629)
ln(10^4×*BtwCent3$_{t-2}$*)						0.6348***	5.3090
× ln(10^3×*Cliqness3$_{t-2}$*)						(0.2024)	(6.2656)
[ln(10^4×*BtwCent3$_{t-2}$*)							-0.4181
× ln(10^3×*Cliqness3$_{t-2}$*)]^2							(0.5280)
Res(*AvgGrant3$_{t-1}$*)[a]	0.7417***	0.7452***	0.7416***	0.5748***	0.5623***	0.7284***	0.5579***
	(0.0869)	(0.0869)	(0.0870)	(0.0845)	(0.0842)	(0.0878)	(0.0854)
Constant	9.5093***	9.5661***	9.5326***	7.8786***	7.6020***	9.2166***	7.5391***
	(0.8440)	(0.8458)	(0.8466)	(0.8151)	(0.8210)	(0.8633)	(0.8308)
ln(*alpha*)	0.5209***	0.5207***	0.5190***	0.5037***	0.4755***	0.4832***	0.4782***
	(0.0724)	(0.0723)	(0.0726)	(0.0733)	(0.0721)	(0.0712)	(0.0723)
Nb observations	8319	8319	8319	8319	8319	8319	8319
Nb groups	1382	1382	1382	1382	1382	1382	1382
Loglikelihood	-9093.59	-9092.03	-9090.85	-9052.53	-9037.73	-9064.63	-9030.36
χ^2	176.4721***	181.9911***	187.3738***	228.1735***	295.4559***	255.6566***	343.2301***
Vuong test	15.09***	15.13***	15.15***	15.62***	15.68***	15.44***	15.82***

Note: [a] Residual from the first-stage equation. ***, **, * show significance at the 1%, 5% and 10% levels.

Table 4.2 provides evidence of the importance of government grants on academic publications considering the potential endogeneity. The estimates of the IV models described above demonstrate that obtaining public funding (*AvgGrant3*$_{t-1}$) eventually increases the quality of publications and this strong positive effect is consistent and robust for all 7 models that we present. In contrast, we see that receiving private funding (*AvgContract3*$_{t-1}$) from industry yields a negative impact as the citation rate of publications declines with higher amounts of funding. In Figure 4.1, we plot the non-linear impacts corresponding to government grants (see Figure 4.1a) and industry contracts (see Figure 4.1b) on the number of citations.



(a) ln(*AvgGrant3*$_{t-1}$) **(b) ln(*AvgContract3*$_{t-1}$)**

Figure 4.1: Quadratic effect of (a) average amount of grants, ln(AvgGrant3), (b) average amount of contracts, ln(AvgContract3), on the number of citations

Three possible effects are at play here. First, researchers with industry funding are probably associated with applied research that may result in patent applications. Banal-Estanbol *et al.* (2011) explain that collaborative research projects with industry typically are generally more applied in nature. Second, collaboration with industry may limit scientists in publishing their research outputs if the firm wants to patent the research results. Confidential content and ownership of intellectual property of the research prevent scientists to freely publish the results as they usually do in academic research. Owen-Smith and Powell (2001) mention that the commercial interest of industry undermines and controls university research and hence bring a degree of secrecy to knowledge. While academic researchers tend to quickly publish their new knowledge, companies might hide their findings to benefit from the research outcomes and maintain their competitive advantage, otherwise they patent (Argyres and Liebskind, 1998; Ambos *et al*., 2008). This may affect the quality of publications which are the results of private funded research. Third, companies are generally more concerned by their industrial problems and short-term research projects may possibly not attract the interest of researchers for them to use and cite the resulting publications. The second of these points can be directly addressed on our regressions by the inclusion of the number of patents as our explanatory variable.

An involvement in patenting activities (measured by $nbPatent3_{t-1}$) in previous years appears to have no significant effect on a scientist's publication quality, and this is true whether we include only the linear effect or its non-linear form (models 3, 4, 5 and 7). Only when we moderate the patenting activities by the intermediary position of a scientist ($BtwCent3_{t-2} \times nbPatent3_{t-1}$) in models 6 and 7, we get a significant result: For patenting to have a positive influence in the quality of publications, one has to be fairly central in the co-publication network. In addition, when we include a non-linear effect of this interactive variable, we observe a positive impact of the quadratic term, implying an exponential rather than a linear moderating effect.

Whether moderating other variables or not, we generally find that a better intermediary position ($BtwCent3_{t-2}$) has a significantly and consistently positive impact in last 4 models (4, 5, 6 and 7). Researchers at the center of the collaboration network seem to benefit from their position to gain a higher number of citations. Research is a team activity and the collaboration patterns reflected in researchers' teams not only influence scientific output and control the amount of government funding received by team players, but also increasingly contribute to scientific output quality. While these findings generally support the assumption that research collaborations are positively associated with research production, similarly to the findings of a number of scholars (Frenken *et al.*, 2005; Lee and Bozeman, 2005; Rigby and Edler, 2005), these results are new contributions in terms of nanotechnology research quality.

4.6 Concluding Remarks

The efficacy impact of private and public funding for research purposes is an issue of much debate. Previous studies generally concentrate on government funding and the literature extensively suffers from a lack of data on the impact of private research financing in universities. Moreover the magnitude of this investment in new high technologies deserves as much consideration to understand the impact of funding sources on the quality of scientific production. In this paper, we set out to examine the efficiency of two different funding sources on research quality in a recently emerging and rapidly growing field. To that effect we suggested two hypotheses on nanotechnology research quality: one on public funding and the other on private funding. We find that government research funding increases the number of citations received up to five years after publication. The consistently significant results confirm that there is a positive impact of public funding on research quality hence supporting our first hypothesis.

Since high quality scholars are more likely to attract funding, we consider public funding as an endogenous variable and our instruments for the quality of scholars and their scientific production properly address this potential endogeneity. Nanotechnology research and development is highly multidisciplinary, drawing from different fields, and needs extensive research teams from various departments. Scientists of greater importance undoubtedly occupy more central positions in the collaboration network. Our results show that scientists who occupy better intermediary positions produce more highly cited research. Hence, we could say that the combination of both government funding and a more central position is influencing research quality.

In contrast, contracts with industrial firms have a negative non-linear effect on nanotechnology research quality. While raising government funding is considered a sign of a higher quality researcher, receiving research funding from the private sector is more likely to restrict the publication quality. Industry benefits greatly from nanotechnology research, but unfortunately limits knowledge flows and generally delays publications of, or does not completely divulge, the results due to commercial issues. This problem highlights a concern about collaboration between two different scientific worlds of academic research and commercial innovation, i.e. the desire of private companies to protect their scientific outputs from being freely accessible. As a consequence, since the amount of private research financing yields a negative effect on the number of citations, we reject our second hypothesis.

Results from scientific research may lay the foundation for advancements of technologies, which may then be protected by patents in a variety of patent offices. Our examination of the influence of the number of patents to which an academic scientist has contributed in previous years shows no hindrance from patenting activities on the quality of publications being produced by academics. Previous literature generally considers either private funding or patents, but rarely both measures are considered together in scientific productivity or impact studies. While the former can be considered a research input and the latter a research output, our study addresses the possible influence that private endeavours may have on scientific impact from both points of view. One must also stress that collaboration with the private sector does not necessarily result in patents; academics often perform consulting activities that benefit firms without there being a patent at the end of the contract. Similarly, all patents are not necessary the result of private research investments, but of government supported scientific research. Our models consider these two possibilities by accounting for both private funding and patenting activities.

Our empirical results suggest that government grants represent an important gateway to nanotechnology research development and nanotechnology knowledge diffusion. Publicly funded research contributes to the worldwide knowledge network and stimulates economic growth. Furthermore, this investigation shows that the relationship between public and private funding is not one of reinforcement with regards to publication quality. While government research financing contributes to increasing the quality of knowledge being produced, and sharing it as open science for the benefit of society, industry streams investment toward nanotechnology research to the benefit of applied research, new products and potential markets, and to the detriment of publication quality. The private sector is interested in short-term research; long-term and highly risky research, with a potential for greater impact, should accordingly be supported by government. This is not to say that academics should not seek private funding. One must recognize that in the filed of nanotechnology, private funding is complementary, but serves other purposes than high quality publications.

There are a number of limitations to this study. The first limitation is the mobility of researchers: given that we focus on Quebec and as researchers move out of the province, we lose track of their funding. The second limitation is that the field of nanotechnology is an emerging and very narrow field and we may not be able to generalize to other fields. The third limitation is our data, which was extracted from Scopus, which does not cover all journals; we may be missing a number of citations of papers. Despite these limitations, we are nevertheless confident that our results provide an interesting contribution to the public versus private support or university research.

CHAPTER 5 ARTICLE 4: COLLABORATION OR FUNDING: LESSONS FROM A STUDY OF NANOTECHNOLOGY PATENTING IN CANADA AND THE UNITED STATES

Leila Tahmooresnejad, Catherine Beaudry

5.1 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. Our results suggest that technological output has the potential to offer governments useful guidance concerning the effectiveness of academic grants in the United States, and collaboration 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

5.2 Introduction

The rapid increase in academic patenting raises issues regarding the development of new technologies but more importantly concerning the factors that affect these technological outputs. Recent development in relationship between university and industry, especially the growth of 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).

Academic research, however, has been a significant source for research, particularly in emerging knowledge-based technologies (Aghion *et al.,* 2008). 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).

Because of the large amount of investment in nanotechnology, the question of whether this substantial investment in nanotechnology research enhances technological innovations in universities or only generates scientific output gains is a key issue here. This paper aims to find to what extend government research funding influences academic patenting in the field of nanotechnology in Canada and the US.

Paul *et al.* (2003) indicate that government investment plays an important role in the development of emerging technologies which are risky and need long-term research. 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 like 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 totals almost $21 billion increasing from $464 million since 2001 including 2015 federal budget (NNI, 2014). Roco (2005) declares that accordingly many countries have since surged investment in nanotechnology in recent years.

Similarly, Canada has launched various government-funding programs to support nanotechnology development. Federal research funding is 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. In Canada, the nanotechnology field receives a considerable amount of public funding, with provincial and private sector investments being less than federal investments. These investments earmarked for nanotechnology help 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).

In order to advance knowledge in this field, we examine academic research collaborations linking scientists to one another in an open science environment with two types of networks: co-authors and co-inventors. 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. There has been much attention paid to university patenting in recent years and its role in university-industry collaborations is of great interest (Geuna and Lionel, 2006; Lissoni, 2009; Murray, 2004). Our paper focuses on this collaborative behavior of researchers and compares its effect with that of funding on technological output. While this study concentrates on an important field, 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 1975-2000. Similarly, Wong *et al*. (2007) ranked Canada in the 6^{th} position amongst the top 10 inventor countries for nanotechnology patents between 1976-2004. In addition, they also found that Canada had the largest improvement in average citations received per patent between 2000-2004. In assessing nanotechnology patents, Chen and Roco (2009) demonstrate 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 the prior study. 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 collaborations between academic researchers, we examine the crucial role of networks in driving technological progress. Third, we supplement our analyses with a comparison between the US and Canada. 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 Section 3, and Section 4 presents the results. Finally, we conclude with a concise discussion in Section 5.

5.3 Conceptual framework

Academic research has been regarded as a key source of new knowledge that contributes to technological changes. Since the field of nanotechnology is increasingly knowledge-based in nature, universities appear to have an enhanced role in innovations and economic development (Etzkowitz *et al*., 2000). 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; Musico *et al*., 2013). Basic and applied science are highly interconnected in this emerging technology; Narin *et al,* (1997) highlight that rapidly growing linkages exist between scientific publications and patents. Wong *et al*. (2007) found that universities play an increasing role in patenting in Canada and the US. In this regard, governments establish and aggressively support academic research to accelerate this progress via grants to cover research costs and infrastructure expenses, which are rather high in these new technologies.

Given the influence of this emerging technology on future scientific and economic development, it is vital to distinguish the pivotal role of government funding in order to stimulate nanotechnology. Due to the growth of funding trends in nanotechnology (Bhattacharya, 2007; Crawley, 2007; Davies, 2007; Hullmann, 2006; Roco, 2005; Roco, 2010; Sargent 2008; Seear *et al.,* 2008), it is not surprising that investors seek to determine whether such funding increases the return to academic research output. According to Arora *et al*. (1998), public grants affect current researcher output and consequently influence their future 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 nanotechnology in the US demonstrates 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 ownership rights to academic patents derived from publicly funded research (Argyres and Liebskind, 1998; Mowery and Sampt, 2005; Siegel *et al*., 2003; Zucker and Darby, 2005). According to their study of university patenting between 1965-1992, 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) raise 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 hold the ownership of the patents that resulted from publicly funded research (Mowery and Sampt, 2005). However, prior studies that examined the impact of government grants in universities, more specifically focused on the scientific output of academic researchers rather their technological interests. A few studies (see Huang, *et al*., 2005; Huang, *et al*., 2006) also consider nanotechnology funding.

A patent is an open source 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, 2005; 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 better 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, 2005; 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.*, 2007; Wallin, 2005). Forward citations are the most common indicator to measure patent quality and are suggested by many scholars (Baron and Delcamp, 2010; Breschi and Lissoni, 2005; Harhoff *et* *al*., 1999; Hall *et al*., 2000; Lanjouw and Schankerman, 1999; Maurseth 2005; Serrano, 2010; Weingart, 2005).

We also include the number of claims as a proxy of patent quality. 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 wide 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).

We examine how academic inventors are affected by government funding to measure whether this dedicated nanotechnology R&D funding increases the technological productivity and quality in universities. This assessment is essential for decision-making and R&D planning. In the emerging technology fields, however, there is a great need to understand how nanotechnology development has evolved through and been influenced by government funding over this quite 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 patents and (b) higher quality patents than other academic inventors.*

Despite research funding, numerous studies have investigated factors other than funding that have impacted academic innovation activities. Some 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; Newman, 2001; Wasserman and Faust, 1994).

Ma and Lee (2008), and Ruegg (2007) further study technological collaborations and highlight the role of these collaborative relationships on technological development. Such analysis presumes that when inventors apply for a patent together, they will keep in touch afterwards for a period of time to exchange and share their knowledge. In this regard, patents can be exploited to map the social relationships between these researchers 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 on research productivity, innovations and knowledge flows (Powell, *et al.*, 1999; Ahuja, 2000; Breschi and Lissoni, 2005; Breschi and Lissoni, 2009; Lecocq and Van Looy, 2009).

Co-invention networks are more fragmented than co-publication networks, 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) find 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.*

We also compare the influence of research financing on the technological performance of academic inventors in Canada and the US. Although Canadian nanotechnology funding represents only a small fraction of the US investment, it is nevertheless crucial to compare the influence of public funding and of its contribution to the development of public policies. To benefit from the nanotechnology advantages, it is important to identify the key issues of policy initiatives undertaken by other nanotechnology pioneering countries. Surveying worldwide nanotechnology investment shows that the US has dominated the research efforts and emerged as an important player in the global nanotechnology research. The US is amongst the top investors in nanotechnology and the support from its government has been increasing in order to advance capabilities in contributing to economic growth. According to the substantial amount of funding in nanotechnology development in the US comparing to Canada, we suggest the following hypothesis.

Hypothesis 4: *Academic inventors in the US who receive government funding contribute to (a) more patents and (b) higher quality patents compared to Canadian academic inventors.*

5.4 Data and methodology

5.4.1 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. 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) suggest that Canadian nanotechnology inventors file their patent applications in the US as well as, or in lieu of, in Canada. Similarly, a study of country patent analysis by Li *et al*. (2007b) demonstrates 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 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) and utilized the intersection of the search strategies and then removed the redundant keywords after consulting with nanotechnology experts. Using a similar keyword query, we then add nanotechnology-related scientific publications from Elsevier's Scopus.

Patents were employed to build collaborative co-invention networks and articles were used to construct the co-publication networks in three-, five- and seven-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.

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). We then precisely cleaned the data and merged databases 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 to have minimised ambiguities by proceeding this way for Canada. We used a unique ID for each individual researcher to merge the data to avoid ambiguity of researchers' names in merging various databases.

5.4.2 Dependent variables

To establish the base model, we take into account the number and quality of patents and the complex relationship between funding and collaborative determinants. We specify one dependent variable, the number of patents (NP_{it}), to account for the production of patents and two other variables, the number of citations received over five years (NCi_{it}) and the number of claims (NCl_{it}), to proxy for patent quality in the base model (in Eq. 5-6). Additionally, 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. Despite the existence of other indicators such as patent renewal, triadic patents, backward citations, etc. that have been used in the literature (Maurseth, 2005; Lanjouw and Schankerman, 2001; Pakes and Schankerman, 1984), 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). Similarly to the networks, three different windows of time were considered in order to count the number of citations: 3-year, 5-year 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 time windows.

For each academic inventor the dependent variables are the following:

$$NCi_{it} = \sum_{p=1}^{n} \sum_{j}^{j+4} nCit_{pitj} \qquad (5\text{-}1)$$

$$C\left(NCi_{it}\right) = \begin{cases} 0 & if\ NCi_{it} = 0 \\ 1 & if\ 1 \le NCi_{it} \le 5 \\ 2 & if\ NCi_{it} > 5 \end{cases} \qquad (5\text{-}2)$$

$$NCl_{it} = \sum_{p=1}^{n} nClaim_{pit} \qquad (5\text{-}3)$$

Where $nCit_{pitj}$ and $nClaim_{pit}$ are the number of forward citations after and up to j years and the number of claims of patents p for inventor i in year t.

5.4.3 Independent variables

The average yearly amount of government funding received by an academic-inventor i over the past three years (F) enables us to validate our first hypothesis. For the collaboration variables, we make use of the tools developed by 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[25]) between two other academic researchers. 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 as (Leydesdorff, 2007):

$$BC(k) = \sum_{i} \sum_{j} \frac{g_{ik}(k)}{g_{ij}}, \forall i \neq j \neq k \qquad (5\text{-}4)$$

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

where g_{ij} indicates the number of geodesic paths between i and j and g_{ikj} is defined as the number of these paths that include researcher k. For 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. According to Schilling and Phelps (2007), 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. The clustering coefficient is calculated by Eq. 5-5:

$$CC_i = \frac{2E_i}{k_i(k_i - 1)} \tag{5-5}$$

where k_i is the number of neighbours of i and E_i denotes the number of direct links that connects 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-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.

5.4.4 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 one-year lag for funding and a two-year lag for the network determinants before publication/application of research output. Our model can therefore be expressed as:

$$\begin{Bmatrix} NP_{it} \\ C\left(NCi_{it}\right) \\ NCl_{it} \end{Bmatrix} = f\begin{pmatrix} \ln\left(F_{it-1}\right), NPP_{it-1}, PBB_{it-2}, \\ PCC_{it-2}, ABC_{it-2}, ACC_{it-2}, D_t \end{pmatrix} \tag{5-6}$$

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 as we 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 (described above). 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).

The inclusion of funding and innovative performance 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. To specifically address this concern and control for potential endogeneity, we employ the Two-Stage-Residual-Inclusion used by Biro (2009). We therefore estimate a variant of the model using a set of instruments for the estimation of funding (Eq. 5-7), our 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-linearities. The number of past articles of researchers over three years (NA) is included to explain the fact that funding is generally given to academic researchers with a high publication rate (Van Raan, 2004).

$$\ln\left(F_{it-1}\right) = g\begin{pmatrix} Age_{it-1}, NA_{it-2}, \\ NPP_{it-1}, PBC_{it-2}, PCC_{it-2}, \\ ABC_{it-2}, ACC_{it-2}, D_t \end{pmatrix} \tag{5-7}$$

The residuals of this first-stage equation are then added to the regressors of the second stage equation given by Eq. (5-6) prior to its estimation. Because of a small number of years of observations per academic-inventor (our panel is very unbalanced), our estimations provide clustered robust standard errors rather than what would be obtained from panel regressions.

5.5 Empirical Results

The estimation results for models mentioned in the previous section are shown in Tables 5.1, 5.2 and 5.3 and include the results of Ordered probit regressions (Table 5.2), Negative Binomial regressions (Table 5.1 and Table 5.3 of Eq. 5-6 (second stage) and OLS regression of Eq. 5-6 (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. 5-7) are presented in Appendix C. Our analysis has 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 5.1 show no impact of funding (F) on technological productivity in Canada: even when we re-estimated the results to correct for potential endogeneity, the results are not significant. In the US, in contrast, there is a positive impact of lagged federal funding (one-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) and to adding an interactive variable (Models 2 and 5). In terms of control variables, all instrument variables are strongly significant and appropriate for the US, and in Canada only the number of articles over the past three years (NA_{it}) does not seem to be a consistently good instrument. While, we successfully account for endogeneity in the US, the results cannot capture the endogeneity in Canada.

Table 5.1 : Impact of funding and collaborations on nanotechnology patents in Canada and the United States

NP_{it}	Canada						US					
	(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)**
$ln(F_{it-1})$	-0.0948	-0.1215	-0.0824	-0.1225	-0.0943	-0.2167	0.0218	0.2236 ***	0.0173	0.2216 ***	0.0110	0.1608 ***
	(0.1299)	(0.1911)	(0.1280)	(0.1907)	(0.1291)	(0.1984)	(0.0287)	(0.0391)	(0.0285)	(0.0388)	(0.0259)	(0.0372)
$[ln(F_{it-1})]^2$	0.0100	0.0100	0.0085	0.0086	0.0097	0.0099	-0.0010	-0.0027	-0.0006	-0.0024	-0.0002	-0.0016
	(0.0130)	(0.0129)	(0.0128)	(0.0128)	(0.0129)	(0.0128)	(0.0025)	(0.0026)	(0.0025)	(0.0026)	(0.0022)	(0.0023)
NPP_{it-1}	0.3108 ***	0.3100 ***	0.3624 ***	0.3634 ***	0.4127 ***	0.4229 ***	0.1691 ***	0.1540 ***	0.1735 ***	0.1588 ***	0.3097 ***	0.2871 ***
	(0.0308)	(0.0310)	(0.0283)	(0.0290)	(0.0545)	(0.0560)	(0.0072)	(0.0074)	(0.0074)	(0.0076)	(0.0299)	(0.0287)
$[NPP_{it-1}]^2$					-0.0096 ***	-0.0112 ***					-0.0086 ***	-0.0077 ***
					(0.0035)	(0.0041)					(0.0021)	(0.0020)
$ln(10^4 \times PBC_{it-2})$	0.4189 **	0.4289 **	0.6574 ***	0.6850 ***	0.2310	0.2552	0.1223	0.1202	0.4884 ***	0.5455 ***	0.0983	0.1341
	(0.1666)	(0.1736)	(0.1665)	(0.1856)	(0.1848)	(0.1854)	(0.0935)	(0.1081)	(0.1325)	(0.1362)	(0.0956)	(0.1119)
$ln(10^4 \times ABC_{it-2})$	0.0286	0.0330	0.0155	0.0219	-0.0592	-0.0871	0.0321	-0.0514	0.0820	-0.0138	0.0845	-0.0087
	(0.0767)	(0.0811)	(0.0756)	(0.0797)	(0.0984)	(0.1013)	(0.1688)	(0.1980)	(0.1641)	(0.1876)	(0.1690)	(0.1943)
$ln(10^3 \times PCC_{it-2})$	-0.0303	-0.0292	-0.0386 *	-0.0373	0.4024 *	0.4481 *	0.0056	0.0066	0.0036	0.0044	-0.0641	-0.1570 *
	(0.0231)	(0.0233)	(0.0231)	(0.0232)	(0.2249)	(0.2348)	(0.0073)	(0.0072)	(0.0074)	(0.0073)	(0.0882)	(0.0909)
$[ln(10^3 \times PCC_{it-2})]^2$					-0.0660 **	-0.0722 **					0.0081	0.0221
					(0.0330)	(0.0344)					(0.0131)	(0.0135)
$ln(10^3 \times ACC_{it-2})$	0.0559 **	0.0562 **	0.0567 **	0.0571 **	0.4125 *	0.5839 **	-0.0227 **	-0.0492 ***	-0.0216 **	-0.0487 ***	0.0552	0.0957
	(0.0232)	(0.0230)	(0.0232)	(0.0230)	(0.2207)	(0.2800)	(0.0093)	(0.0097)	(0.0092)	(0.0096)	(0.1270)	(0.1315)
$[ln(10^3 \times ACC_{it-2})]^2$					-0.0547	-0.0802 *					-0.0101	-0.0191
					(0.0334)	(0.0423)					(0.0189)	(0.0196)
$ln(10^4 \times PBC_{it-2}) \times NPP_{it-1}$			-0.2099 ***	-0.2205 ***					-0.0444 ***	-0.0536 ***		
			(0.0448)	(0.0571)					(0.0104)	(0.0132)		
$Residual(ln(F_{it-1}))$		0.0271		0.0405		0.1219		-0.1877 ***		-0.1892 ***		-0.1377 ***
		(0.1237)		(0.1238)		(0.1332)		(0.0270)		(0.0250)		(0.0270)
Constant	-2.7798 ***	-2.6133 ***	-2.7460 ***	-2.4979 ***	-2.7503 ***	-2.0046 **	-1.1075 ***	-1.8673 ***	-1.1135 ***	-1.8787 ***	-1.2488 ***	-1.7978 ***
	(0.2668)	(0.8424)	(0.2581)	(0.8322)	(0.2568)	(0.8821)	(0.0680)	(0.1368)	(0.0678)	(0.1292)	(0.0818)	(0.1336)
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln(alpha)	0.0384	0.0428	-0.1376	-0.1319	0.0088	0.0250	-0.3165 ***	-0.3795 ***	-0.3274 ***	-0.3982 ***	-0.6455 ***	-0.6679 ***
	(0.2385)	(0.2432)	(0.2828)	(0.2851)	(0.2451)	(0.2440)	(0.0871)	(0.0861)	(0.0874)	(0.0867)	(0.1175)	(0.1136)
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	-655.463	-655.432	-650.532	-650.464	-650.7	-650.2	-6828	-6786.6	-6820	-6777.4	-6689	-6666
Wald X^2	168.54 ***	166.48 ***	287.86 ***	285.68 ***	206.86 ***	200.11 ***	256126 ***	214370 ***	212632 ***	214841 ***	227187 ***	211769 ***

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

Table 5.2 : Impact of government funding and collaborations on the citations received by nanotechnology patents in Canada and the United States

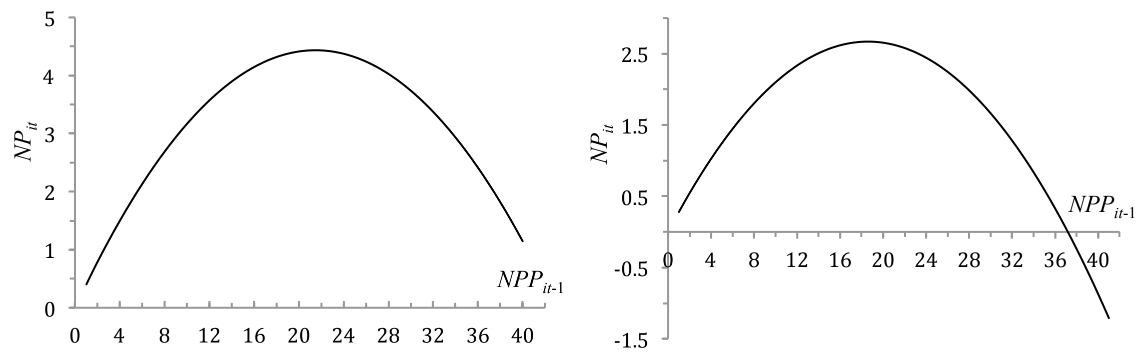
$C(NCi_{it})$	Canada				US			
	(1)		(2)		(3)		(4)	
	1-1 (NO End.)	**1-2 (2SRI)**	**2-1 (NO End.)**	**2-2 (2SRI)**	**3-1 (NO End.)**	**3-2 (2SRI)**	**4-1 (NO End.)**	**4-2 (2SRI)**
$ln(F_{it-1})$	-0.0142	0.1047	-0.0058	0.1019	-0.0569	-0.2364	-0.0656	-0.2556
	(0.1194)	(0.1805)	(0.1203)	(0.1821)	(0.1722)	(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
Nb Groups	155	155	155	155	1966	1966	1966	1966
Wald X^2	62.80 ***	65.43 ***	77.79 ***	82.00 ***	2060.77 ***	1950.95 ***	1950.54 ***	1827.52 ***
Pseudo R^2	0.2700	0.2723	0.2745	0.2738	0.3003	0.3119	0.3140	0.3087

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

Table 5.3 : Impact of government funding and collaborations on the number of claims of nanotech patents in Canada and the United States

NCL_{it}	Canada						US					
	(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)**
$ln(F_{it-1})$	-0.1471	-0.4137 **	-0.1502	-0.4153 **	-0.1775	-0.5744 **	0.2397 ***	0.4352 ***	0.2346 ***	0.4275 ***	0.2379 ***	0.4161 ***
	(0.1634)	(0.2095)	(0.1630)	(0.2093)	(0.1709)	(0.2324)	(0.0576)	(0.0705)	(0.0576)	(0.0705)	(0.0591)	(0.0713)
$[ln(F_{it-1})]^2$	0.0153	0.0146	0.0154	0.0148	0.0174	0.0169	-0.0188 ***	-0.0193 ***	-0.0184 ***	-0.0189 ***	-0.0188 ***	-0.0196 ***
	(0.0163)	(0.0163)	(0.0162)	(0.0163)	(0.0171)	(0.0174)	(0.0049)	(0.0050)	(0.0049)	(0.0050)	(0.0050)	(0.0051)
NPP_{it-1}	0.3629 ***	0.3651 ***	0.3996 ***	0.4124 ***	0.4482 ***	0.5051 ***	0.2393 ***	0.2115 ***	0.2468 ***	0.2192 ***	0.3066 ***	0.2740 ***
	(0.0589)	(0.0612)	(0.0633)	(0.0647)	(0.0995)	(0.1009)	(0.0136)	(0.0130)	(0.0141)	(0.0134)	(0.0156)	(0.0150)
$[NPP_{it-1}]^2$					-0.0128 **	-0.0199 ***					-0.0055 ***	-0.0047 ***
					(0.0060)	(0.0065)					(0.0004)	(0.0004)
$ln(10^4 \times PBC_{it-2})$	0.5085 **	0.6269 **	0.7310 **	0.9616 ***	-0.0355	0.1088	0.0887	0.1149	0.4065 **	0.4350 ***	-0.0776	-0.0036
	(0.2305)	(0.2587)	(0.3184)	(0.3725)	(0.2118)	(0.2254)	(0.1166)	(0.1192)	(0.1653)	(0.1640)	(0.1522)	(0.1554)
$ln(10^4 \times ABC_{it-2})$	0.1650	0.2212 *	0.1695	0.2247 *	-0.0001	-0.1181	-0.1119	-0.0605	-0.0709	-0.0449	-0.0497	-0.0099
	(0.1093)	(0.1158)	(0.1122)	(0.1187)	(0.1296)	(0.1326)	(0.2413)	(0.2530)	(0.2387)	(0.2513)	(0.2495)	(0.2609)
$ln(10^3 \times PCC_{it-2})$	-0.0493	-0.0293	-0.0536	-0.0347	1.0086 ***	1.0506 ***	-0.0019	-0.0009	-0.0036	-0.0026	0.3728	0.2629
	(0.0391)	(0.0391)	(0.0396)	(0.0395)	(0.3567)	(0.3545)	(0.0147)	(0.0147)	(0.0149)	(0.0148)	(0.2308)	(0.2312)
$[ln(10^3 \times PCC_{it-2})]^2$					-0.1586 ***	-0.1611 ***					-0.0566 *	-0.0401
					(0.0530)	(0.0527)					(0.0337)	(0.0337)
$ln(10^3 \times ACC_{it-2})$	0.0179	0.0289	0.0152	0.0257	0.7979 ***	1.4445 ***	-0.0207	-0.0522 ***	-0.0206	-0.0516 ***	0.5505 *	0.7240 **
	(0.0326)	(0.0323)	(0.0328)	(0.0325)	(0.2805)	(0.3761)	(0.0162)	(0.0171)	(0.0162)	(0.0171)	(0.2996)	(0.3184)
$[ln(10^3 \times ACC_{it-2})]^2$					-0.1200 ***	-0.2149 ***					-0.0842 *	-0.1140 **
					(0.0420)	(0.0562)					(0.0438)	(0.0466)
$ln(10^4 \times PBC_{it-2}) \times NPP_{it-1}$			-0.2266 ***	-0.2937 ***					-0.0552 ***	-0.0554 ***		
			(0.0833)	(0.1033)					(0.0134)	(0.0133)		
$Residual(ln(F_{it-1}))$		0.2928 **		0.2904 **		0.4259 ***		-0.1950 ***		-0.1919 ***		-0.1749 ***
		(0.1390)		(0.1386)		(0.1551)		(0.0317)		(0.0314)		(0.0315)
Constant	0.3884	1.9930 **	0.4283	2.0215 **	0.4609	2.8346 ***	1.8040 ***	1.1190 ***	1.7953 ***	1.1222 ***	1.7564 ***	1.1478 ***
	(0.3276)	(0.8443)	(0.3292)	(0.8459)	(0.3322)	(0.9367)	(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)	3.2646 ***	3.2579 ***	3.2629 ***	3.2563 ***	3.2515 ***	3.2395 ***	2.3505 ***	2.3432 ***	2.3497 ***	2.3425 ***	2.3380 ***	2.3322 ***
	(0.0835)	(0.0831)	(0.0836)	(0.0832)	(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	-1535.08	-1534.02	-1534.8	-1533.8	-1533.05	-1531.2	-17890.2	-17876.5	-17888.6	-17875.2	-17865.9	-17855
Wald X^2	83.50 ***	79.41 ***	100.26 ***	94.70 ***	145.33 ***	142.83 ***	708453.7 ***	635920 ***	692853.7 ***	621759.4 ***	696163 ***	629545 ***

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 three years shows that this positive impact has a limit: the maximum threshold of the resulting inverted-U relationship corresponds to roughly 21 patents for Canada and 18 patents for the US. Contributing to more patents beyond these points is associated with a decreasing trend (Figure 5.1).

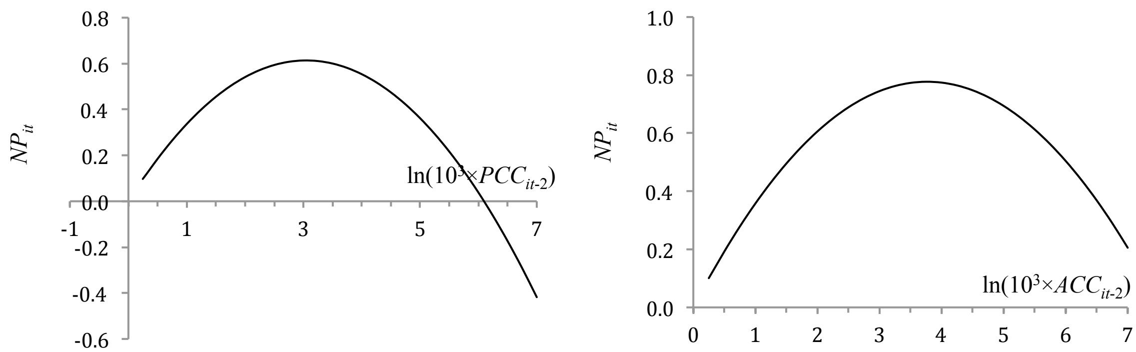


(a) (b)

Figure 5.1: Non-linear impact of the number of patents in past three years (*NPP*) on the number of patents in (a) Canada and (b) in the United States

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 except in Model 3. This is why we add quadratic terms in the regressions. 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 clustering coefficient measure of these two networks (*PCC*, *ACC*) including the nonlinear form of these 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 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 Figure 5.2). 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.



(a) (b)

Figure 5.2: 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)

The results as presented in Table 5.2 show a positive impact of the number of patenting activities in the past three 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 we consider is the number of claims (NCL_{it}) declared in patent documents. Table 5.3 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 (Figure 5.3a). Surprisingly, when we conducted this analysis for Canada, we found a negative impact of funding on the number of claims in our studied period. Past experience measured by the number of patents in the past three 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 (Figure 5.3b and Figure 5.4a).

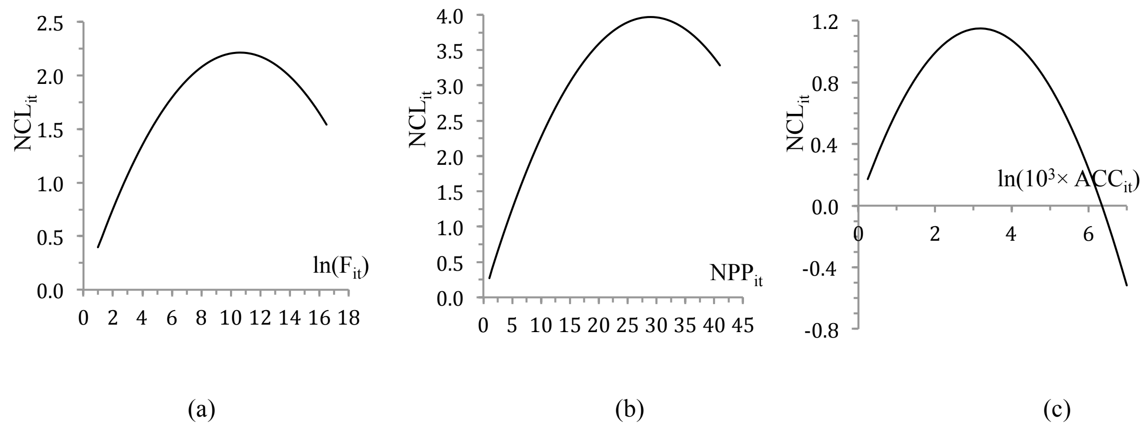
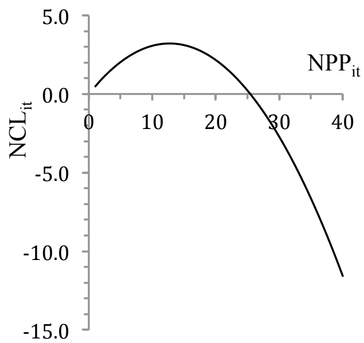
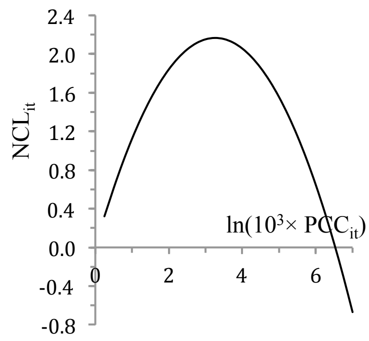
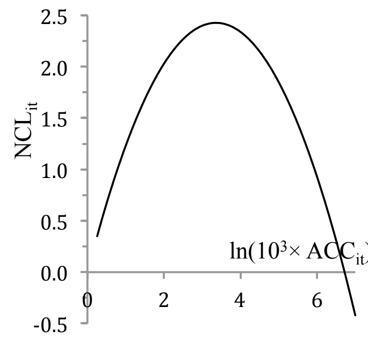


Figure 5.3:Non-linear impact of (a) funding (F), (b) the number of patents in past three years (NPP) and (c) the clustering coefficient in co-publication networks (ACC) on the number of claims in the United States (Model 6-2)

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 Figure 5.3c), while in Canada, both co-invention and co-publication networks boost patent quality (see Figure 5.4b and Figure 5.4c).







(a) (b) (c)

Figure 5.4:Non-linear impact of (a) the number of patents in past three 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)

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.

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 variables[26]. Table 5.4, Table 5.5 and Table 5.6 display the results for the Negative Binomial model and the Ordered Probit model for the pooled sample (both Canada and the United States).

In particular, these results provide further evidence that having previously patented has a stronger positive effect on increasing the number of patents in Canada compared to the US (Figure 5.5a). The intermediary position of researchers in co-invention networks is only significant when we do not consider the quadratic effects and seem to have more influence in Canada than in the US (Figure 5.5b). Although both Canada and the US have a positive slope, one unit increase in

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[26] Table C.8 in Appendix C compares the Canadian and US samples for all the variables of interest. 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. 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]). The results show that all variables except betweenness centrality in the co-invention network (*PCC*) are significantly different.

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, Figure 5.5c 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 (Figure 5.5d)[27].

Turning now to the patent quality indicators, 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 (Figure 5.6a). Additionally, the clustering coefficient in co-publication networks has a higher impact in Canada compared to the US, where the relationship is relatively flat (Figure 5.6b).

[27] 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.

Table 5.4 : Impact of government funding and collaborations on the number of patents in Canada and the United States together

NP_{it}	With dummy variables					
	(1)		(2)		(3)	
	1-1 (NO End.)	1-2 (2SRI)	2-1 (NO End.)	2-2 (2SRI)	3-1 (NO End.)	3-2 (2SRI)
$ln(F_{it-1})$	0.0227	0.1708 ***	0.0182	0.1678 ***	0.0118	0.1183 ***
	(0.0284)	(0.0348)	(0.0282)	(0.0348)	(0.0258)	(0.0328)
$[ln(F_{it-1})]^2$	-0.0011	-0.0022	-0.0007	-0.0019	-0.0003	-0.0012
	(0.0025)	(0.0025)	(0.0024)	(0.0025)	(0.0022)	(0.0022)
NPP_{it-1}	0.1704 ***	0.1580 ***	0.1748 ***	0.1627 ***	0.3109 ***	0.2934 ***
	(0.0071)	(0.0073)	(0.0073)	(0.0075)	(0.0297)	(0.0288)
$[NPP_{it-1}]^2$					-0.0086 ***	-0.0080 ***
					(0.0021)	(0.0020)
$ln(10^4 x\ PBC_{it-2})$	0.1132	0.1141	0.4720 ***	0.5150 ***	0.0900	0.1182
	(0.0922)	(0.1026)	(0.1303)	(0.1315)	(0.0944)	(0.1052)
$ln(10^4\ x\ ABC_{it-2})$	0.0437	-0.0272	0.0931	0.0137	0.0953	0.0230
	(0.1657)	(0.1856)	(0.1611)	(0.1763)	(0.1660)	(0.1827)
$ln(10^3\ x\ PCC_{it-2})$	0.0049	0.0063	0.0029	0.0042	-0.0625	-0.1295
	(0.0073)	(0.0072)	(0.0074)	(0.0072)	(0.0880)	(0.0898)
$[ln(10^3\ x\ PCC_{it-2})]^2$					0.0078	0.0180
					(0.0131)	(0.0134)
$ln(10^3\ x\ ACC_{it-2})$	-0.0243 ***	-0.0434 ***	-0.0234 **	-0.0428 ***	0.0446	0.0715
	(0.0092)	(0.0094)	(0.0091)	(0.0094)	(0.1258)	(0.1287)
$[ln(10^3\ x\ ACC_{it-2})]^2$					-0.0088	-0.0148
					(0.0187)	(0.0192)
$ln(10^4 xPBC_{it-2}) \times NPP_{it-1}$			-0.0439 ***	-0.0504 ***		
			(0.0103)	(0.0118)		
dCA	-0.8723 ***	-0.9564 ***	-0.8863 ***	-0.9692 ***	-0.6830 ***	-0.7455 ***
	(0.1459)	(0.1528)	(0.1472)	(0.1545)	(0.1518)	(0.1570)
$dCA \times ln(F_{it-1})$	-0.1661	-0.1714	-0.1423	-0.1497	-0.1575	-0.1656
	(0.1359)	(0.1362)	(0.1353)	(0.1360)	(0.1371)	(0.1369)
$dCA \times [ln(F_{it-1})]^2$	0.0184	0.0179	0.0161	0.0159	0.0176	0.0177
	(0.0136)	(0.0137)	(0.0135)	(0.0136)	(0.0138)	(0.0137)
$dCA \times NPP_{it-1}$	0.1506 ***	0.1682 ***	0.1934 ***	0.2008 ***	0.0199	0.0205
	(0.0261)	(0.0261)	(0.0371)	(0.0348)	(0.0732)	(0.0721)
$dCA \times [NPP_{it-1}]2$					0.0066	0.0079 *
					(0.0043)	(0.0042)
$dCA \times ln(10^4 \times PBC_{it-1})$	0.5693 **	0.4480 *	0.4079	0.2126	0.3268	0.2396
	(0.2662)	(0.2669)	(0.2612)	(0.2583)	(0.2712)	(0.2766)
$dCA \times ln(10^4 \times ABC_{it-1})$	0.0032	0.0538	-0.0480	0.0126	-0.1424	-0.0510
	(0.1874)	(0.2043)	(0.1826)	(0.1950)	(0.1963)	(0.2109)
$dCA \times ln(10^3 \times PCC_{it-2})$	-0.0397	-0.0518 **	-0.0482 *	-0.0587 **	0.4348 *	0.4290
	(0.0247)	(0.0248)	(0.0261)	(0.0261)	(0.2593)	(0.2649)
$dCA \times [ln(10^3 \times PCC_{it-2})]^2$					-0.0680 *	-0.0682 *
					(0.0378)	(0.0386)
$dCA \times ln(10^3 \times ACC_{it-2})$	0.0826 ***	0.0979 ***	0.0811 ***	0.0971 ***	0.3435	0.1949
	(0.0261)	(0.0266)	(0.0261)	(0.0265)	(0.2630)	(0.2675)
$dCA \times [ln(10^3 \times ACC_{it-2})]^2$					-0.0413	-0.0172
					(0.0396)	(0.0403)
$dCA \times ln(10^4 \times PBC_{it-2}) \times NPP_{it-1}$			-0.0865	-0.0518		
			(0.0715)	(0.0698)		
$residual(ln(F_{it-1}))$		-0.1395 ***		-0.1401 ***		-0.0991 ***
		(0.0216)		(0.0203)		(0.0218)
Constant	-1.1092 ***	-1.6714 ***	-1.1153 ***	-1.6795 ***	-1.2503 ***	-1.6444 ***
	(0.0680)	(0.1167)	(0.0678)	(0.1119)	(0.0814)	(0.1168)
Years	Yes	Yes	Yes	Yes	Yes	Yes
$ln(alpha)$	-0.2849 ***	-0.3381 ***	-0.2953 ***	-0.3535 ***	-0.5966 ***	-0.6215 ***
	(0.0842)	(0.0830)	(0.0839)	(0.0831)	(0.1108)	(0.1081)
Nb observations	10486	10486	10486	10486	10486	10486
Nb Groups	5913	5913	5913	5913	5913	5913
Loglikelihood	-7541.86	-7512.21	-7531.91	-7501.66	-7400.94	-7385.65
Wald X^2	1618.1 ***	1649.4 ***	1696.3 ***	1742.8 ***	2880.403 ***	2802.635 ***

Table 5.5 : Impact of government funding and collaborations on the number of claims in Canada and the United States together

NCL_{it}	With dummy variables					
	(1)		(2)		(3)	
	1-1 (NO End.)	1-2 (2SRI)	2-1 (NO End	2-2 (2SRI)	3-1 (NO End.)	3-2 (2SRI)
$ln(F_{it-1})$	0.2154 ***	0.2696 ***	0.2105 ***	0.2640 ***	0.2131 ***	0.2493 ***
	(0.0538)	(0.0678)	(0.0537)	(0.0677)	(0.0550)	(0.0688)
$[ln(F_{it-1})]^2$	-0.0171 ***	-0.0173 ***	-0.0166 ***	-0.0169 ***	-0.0170 ***	-0.0172 ***
	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0047)	(0.0047)
NPP_{it-1}	0.2600 ***	0.2519 ***	0.2673 ***	0.2594 ***	0.3279 ***	0.3210 ***
	(0.0138)	(0.0147)	(0.0143)	(0.0151)	(0.0157)	(0.0169)
$[NPP_{it-1}]^2$					-0.0058 ***	-0.0056 ***
					(0.0004)	(0.0004)
$ln(10^4 x\ PBC_{it-2})$	0.0564	0.0621	0.3634 **	0.3736 **	-0.0830	-0.0707
	(0.1122)	(0.1127)	(0.1589)	(0.1567)	(0.1430)	(0.1444)
$ln(10^4\ x\ ABC_{it-2})$	-0.0391	-0.0424	-0.0017	-0.0133	0.0139	0.0099
	(0.2245)	(0.2261)	(0.2222)	(0.2241)	(0.2313)	(0.2326)
$ln(10^3\ x\ PCC_{it-2})$	-0.0095	-0.0091	-0.0111	-0.0107	0.2994	0.2808
	(0.0135)	(0.0135)	(0.0136)	(0.0136)	(0.2098)	(0.2113)
$[ln(10^3\ x\ PCC_{it-2})]^2$					-0.0468	-0.0440
					(0.0306)	(0.0309)
$ln(10^3\ x\ ACC_{it-2})$	-0.0280 *	-0.0355 **	-0.0278 *	-0.0353 **	0.4628 *	0.4983 *
	(0.0149)	(0.0160)	(0.0149)	(0.0160)	(0.2798)	(0.2856)
$[ln(10^3\ x\ ACC_{it-2})]^2$					-0.0723 *	-0.0783 *
					(0.0410)	(0.0419)
$ln(10^4 xPBC_{it-2})$			-0.0555 ***	-0.0563 ***		
$x\ NPP_{it-1}$			(0.0135)	(0.0128)		
dCA	0.9910 **	1.0031 **	1.0005 **	1.0129 **	1.1982 ***	1.2036 ***
	(0.4408)	(0.4442)	(0.4408)	(0.4438)	(0.4270)	(0.4293)
$dCA \times ln(F_{it-1})$	-0.4791	-0.4822	-0.4741	-0.4776	-0.4874	-0.4881
	(0.3238)	(0.3235)	(0.3222)	(0.3219)	(0.3362)	(0.3355)
$dCA \times [ln(F_{it-1})]^2$	0.0490	0.0487	0.0486	0.0483	0.0478	0.0474
	(0.0304)	(0.0303)	(0.0302)	(0.0301)	(0.0318)	(0.0317)
$dCA \times NPP_{it-1}$	-0.0651	-0.0616	-0.0966	-0.0956	-0.2331	-0.2415
	(0.0692)	(0.0671)	(0.0864)	(0.0852)	(0.1832)	(0.1849)
$dCA \times [NPP_{it-1}]2$					0.0133	0.0143
					(0.0109)	(0.0112)
$dCA \times ln(10^4 \times PBC_{it-1})$	1.5121 ***	1.4443 ***	1.0225 **	0.9628 **	1.4964 **	1.4421 **
	(0.5611)	(0.5200)	(0.3984)	(0.3828)	(0.6295)	(0.6097)
$dCA \times ln(10^4 \times ABC_{it-1})$	-0.1576	-0.1785	-0.1942	-0.2066	-0.5531	-0.5451
	(0.2801)	(0.2814)	(0.2780)	(0.2790)	(0.3463)	(0.3473)
$dCA \times ln(10^3 \times PCC_{it-2})$	-0.0518	-0.0554	-0.0494	-0.0526	0.1647	0.1848
	(0.0738)	(0.0746)	(0.0738)	(0.0745)	(0.6770)	(0.6799)
$dCA \times [ln(10^3 \times PCC_{it-2})]^2$					-0.0313	-0.0344
					(0.1007)	(0.1010)
$dCA \times ln(10^3 \times ACC_{it-2})$	0.0117	0.0166	0.0168	0.0219	0.8504	0.7404
	(0.0750)	(0.0766)	(0.0755)	(0.0772)	(0.8402)	(0.8447)
$dCA \times [ln(10^3 \times ACC_{it-2})]^2$					-0.1280	-0.1109
					(0.1256)	(0.1263)
$dCA \times ln(10^4 \times PBC_{it-2})$			0.1741	0.1733		
$\times NPP_{it-1}$			(0.1593)	(0.1400)		
$residual(ln(F_{it-1}))$		-0.0532		-0.0523		-0.0351
		(0.0392)		(0.0385)		(0.0388)
Constant	1.7998 ***	1.6153 ***	1.7914 ***	1.6105 ***	1.7525 ***	1.6325 ***
	(0.0963)	(0.1701)	(0.0967)	(0.1684)	(0.0988)	(0.1696)
Years	Yes	Yes	Yes	Yes	Yes	Yes
$ln(alpha)$	2.5140 ***	2.5132 ***	2.5133 ***	2.5125 ***	2.5013 ***	2.5009 ***
	(0.0273)	(0.0274)	(0.0273)	(0.0274)	(0.0273)	(0.0273)
Nb observations	10486	10486	10486	10486	10486	10486
Nb Groups	5913	5913	5913	5913	5913	5913
Loglikelihood	-19698.8	-19697.5	-19697.2	-19695.9	-19671.2	-19670.6
Wald X^2	1825.5 ***	1836.9 ***	1872.5 ***	1890.7 ***	2220.2 ***	2232.4 ***

Table 5.6 :The Comparison of the impact of government funding and collaborations on the number of citations received by nanotechnology patents in Canada and the US with dummy variables

$C(NCi_{it})$	With dummy variables			
	(1)		(2)	
	1-1 (NO End.)	**1-2 (2SRI)**	**2-1 (NO End.)**	**2-2 (2SRI)**
$ln(F_{it-1})$	-0.0283 **	0.0777	0.0121	0.0647
	(0.0136)	(0.1908)	(0.1715)	(0.1909)
$[ln(F_{it-1})]^2$	-0.0041	-0.0045	-0.0034	-0.0040
	(0.0152)	(0.0155)	(0.0152)	(0.0155)
NPP_{it-1}	0.1145 ***	0.1082 ***	0.1156 ***	0.1102 ***
	(0.0192)	(0.0192)	(0.0191)	(0.0190)
$[NPP_{it-1}]^2$	-0.0017 ***	-0.0015 ***	-0.0017 ***	-0.0015 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$ln(10^4 x\ PBC_{it-2})$	-0.0598	-0.0624	0.0049	0.0124
	(0.1698)	(0.1626)	(0.1752)	(0.1742)
$ln(10^3\ x\ PCC_{it-2})$	0.0019	0.0042	-0.1213	-0.1626
	(0.0241)	(0.0240)	(0.2012)	(0.2089)
$[ln(10^3\ x\ PCC_{it-2})]^2$			0.0186	0.0250
			(0.0303)	(0.0315)
$ln(10^3\ x\ ACC_{it-2})$	0.0322	0.0322	0.0317	0.0315
	(0.0237)	(0.0243)	(0.0237)	(0.0240)
dCA	1.1882 ***	1.1868 ***	1.2177 ***	1.2059 ***
	(0.2762)	(0.2789)	(0.2758)	(0.2778)
$dCA \times ln(F_{it-1})$	-0.0171	-0.0711	-0.0489	-0.0574
	(0.1299)	(0.2198)	(0.2170)	(0.2208)
$dCA \times [ln(F_{it-1})]^2$	0.0026	0.0071	0.0051	0.0057
	(0.0123)	(0.0201)	(0.0199)	(0.0202)
$dCA \times NPP_{it-1}$	0.3091 ***	0.3227 ***	0.2914 ***	0.3038 ***
	(0.0939)	(0.0910)	(0.0940)	(0.0921)
$dCA \times [NPP_{it-1}]2$	-0.0160 **	-0.0160 **	-0.0155 **	-0.0156 **
	(0.0071)	(0.0069)	(0.0069)	(0.0067)
$dCA \times ln(10^4 \times PBC_{it-1})$	0.2212	0.2219	-0.0366	-0.0406
	(0.2455)	(0.2405)	(0.2843)	(0.2828)
$dCA \times ln(10^3 \times PCC_{it-2})$	0.1303 ***	0.1218 **	0.6672 *	0.6926 *
	(0.0482)	(0.0481)	(0.3797)	(0.3752)
$dCA \times [ln(10^3 \times PCC_{it-2})]^2$			-0.0803	-0.0851
			(0.0560)	(0.0555)
$dCA \times ln(10^3 \times ACC_{it-2})$	-0.0279	-0.0303	-0.0311	-0.0327
	(0.0431)	(0.0430)	(0.0432)	(0.0429)
$residual(ln(F_{it-1}))$		-0.0552		-0.0474
		(0.0554)		(0.0547)
Constantcut1	2.7246 ***	2.9655 ***	2.7315 ***	2.9345 ***
	(0.4391)	(0.5976)	(0.4412)	(0.5957)
Constantcut2	3.6277 ***	3.8721 ***	3.6405 ***	3.8458 ***
	(0.4883)	(0.6462)	(0.4907)	(0.6446)
Nb observations	2732	2732	2732	2732
Nb Groups	2121	2121	2121	2121
Loglikelihood	-277.251	-276.655	-276.174	-275.808
Wald X^2	1701.19 ***	1775.89 ***	1969.50 ***	1759.93 ***
Pseudo R^2	0.4309	0.4321	0.4339	0.4328

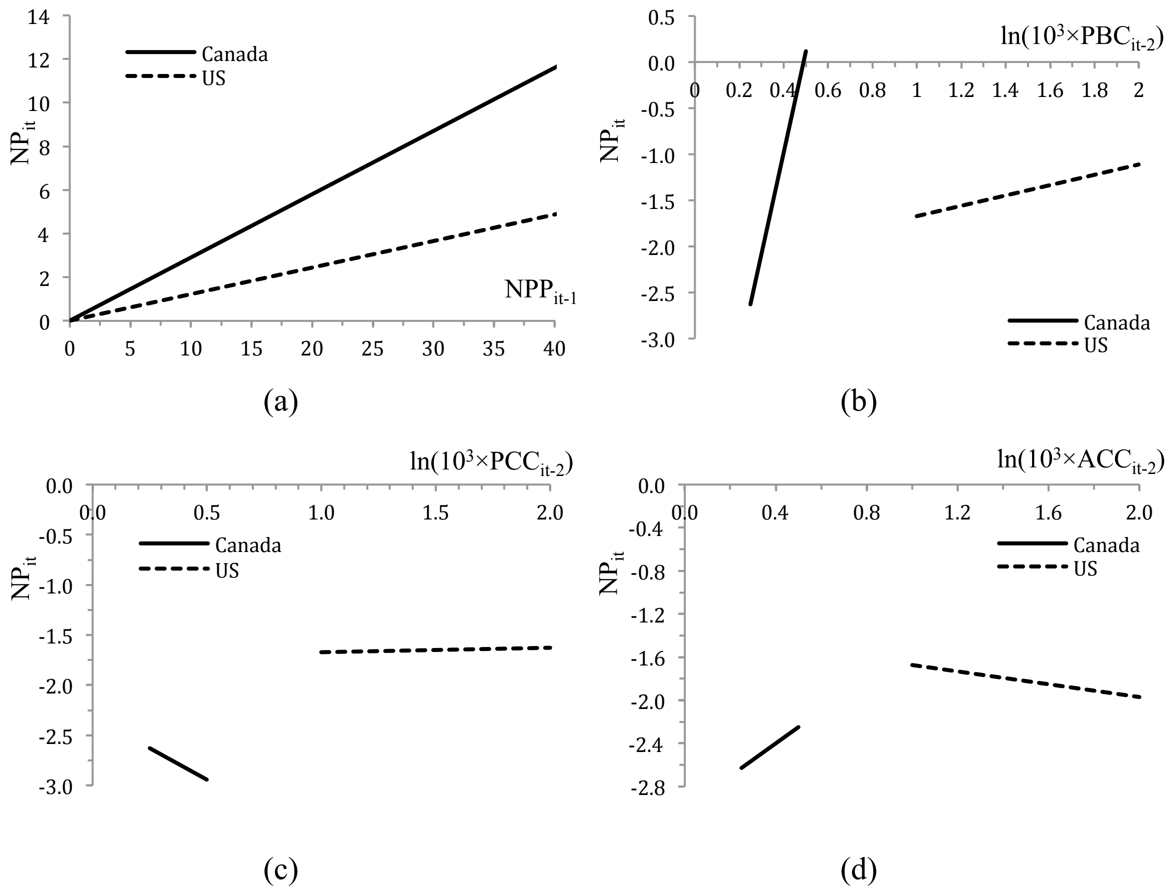


Figure 5.5: Comparison of the impact of (a) the number of patents in past three years (NPP), (b) betweenness centrality in the co-invention network (PBC), (c) the clustering coefficient in co-invention networks (PCC), and (d) the clustering coefficient in co-publication networks (ACC) on the number of nanotechnology patents in Canada and in the United States

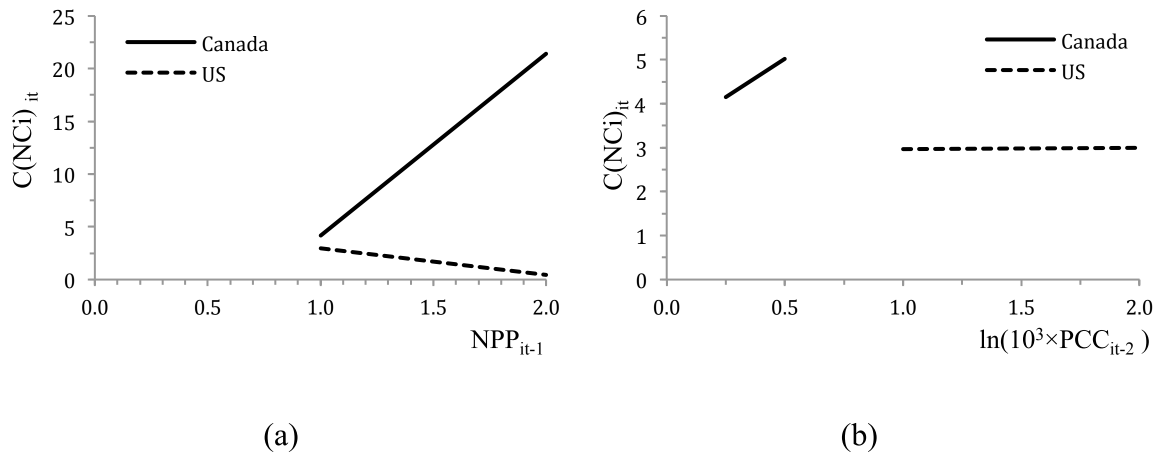


Figure 5.6: Comparison of the impact of (a) the number of patents in past three years (NPP), (b) the clustering coefficient in co-invention networks (PCC) on the number of citations in Canada and in the United States

Finally, 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 Figure 5.7). 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.

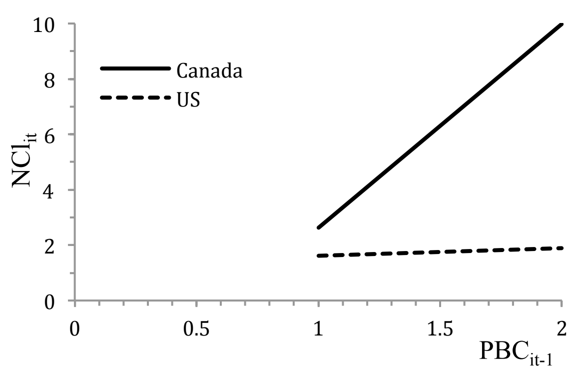


Figure 5.7: Comparison of the impact of betweenness centrality in the co-invention network (PBC) on the number of claims in Canada and in the United States

5.6 Conclusions

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. Four 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 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 limit to the increase in patent quality. This suggests that beyond a specific amount of funding (nearly 42 000 $), patent quality begins to decrease.

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 in 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. Although government funding plays an important role in technological productivity and patent quality in the US, we cannot capture this effect in the comparison analysis. 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. In particular, we cannot support *Hypothesis 4* as these comparison results were not significant to imply that government funds are more effective in the US comparing to Canada.

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 technological output. 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 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 missed 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.

CHAPTER 6 ARTICLE 5: COLLABORATIVE NETWORKS, PRODUCTIVITY, AND ACADEMIC RESEARCH: EVIDENCE AND IMPLICATIONS FOR THE FIELD OF NANOTECHNOLOGY

Leila Tahmooresnejad, Catherine Beaudry

6.1 Abstract

Research collaboration among academics and how these collaborative networks affect research output are controversial areas. Knowledge exchange that occurs between researchers reveals that collaborations are mainly realized through knowledge sharing within academic communities. In the academic realm, interconnected researchers in scientific and technological networks play a significant role in knowledge creation. In this study, we investigate co-author and co-inventor networks in a science-based high technology field, and measure the collaborative knowledge production by numbers of nanotechnology-related papers and patents. This paper considers how networks affect productivity of nanotechnology researchers and compares Quebec with the rest of Canada in this emerging technology. Our findings reveal that the number of publications is strongly associated with the position of scientists in co-authorship networks and the innovative productivity of researchers only increases with collaboration in a technological network. While scientific relationships do not have much significant impact on patents, technological relationships appear to have impact on publications.

Keywords: Collaboration, Scientific papers, Academic patents, Nanotechnology

6.2 Introduction

Knowledge networks play a strategic role in producing new knowledge. Academic researchers tend to cluster and collaborate in teams to reduce research infrastructure costs, share knowledge and benefit from the new ideas and tacit knowledge. Scientific and technological networks have attracted much attention in recent years and have emerged in various forms: joint 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.

Due to the competitive nature of high technologies such as nanotechnology, knowledge must be accessed and acquired quickly to stimulate economic development. Nanotechnology has experienced rapid growth over the last two decades and most countries have become interested in the economic benefits that nanotechnology development promises.

This study focuses on the influence of collaboration on academic scientists' research productivity. To this effect we consider two different types of collaboration in academic networks: while co-authorship is the most known indicator of an academic collaborative relationship, we also explore the effect of co-inventor relationships based upon the assumption that knowledge exchange is crucial, even in academic innovation activities. In such a multi-disciplinary field, we aim to identify whether the position of scientists in co-publication and co-invention networks increases the number of papers and the number of patents. The questions that arise in this context are: Which of these knowledge networks have central importance? Does only the co-publication network matter in terms of producing publications? Is co-invention of central importance in patent applications?

In recent years, collaborations among researchers and knowledge networks have become an interest in scientific community. Policy makers also consider scientist networks essential for the production of new knowledge and governments have initiated various programs to increase such collaborations. It is argued that the diffusion of knowledge depends on the direct and indirect connections between research actors (Katz, 1994; Katz and Martin, 1997).

There has been a recent growing interest in collaboration networks, but despite the substantial body of literature, more specifically on the collaboration between university and industry, producing the new knowledge underlying these networks requires further emphasis. This study contributes to existing related studies: first, using Social Network Analysis (SNA), we are able to investigate the different network structures for research outputs to enrich our understanding of the determinants that are more fruitful in 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 networks to develop a richer description of the scientific community in light of nanotechnology development.

Quebec is at the forefront of the nanotechnology revolution in Canada and the province has made efforts to promote R&D in this strategic technology. NanoQuebec, founded in 2001, has conducted several university-enterprise projects to facilitate the collaboration between universities and industry and has financed different innovative projects over the past decade (Allan et al. 2008; Dufour, 2005; Pelley and Saner 2009; Conseil de la science et de la technologie du Québec, 2002; NanoQuebec, 2010). In this paper, we therefore aim to shed light on the nanotechnology development in Quebec compared to other provinces in Canada.

In order to do so, we provide a detailed investigation of the network factors that influence academic research output, using public funding based on a systematic dataset compiled by the Ministry of Education as a control. More precisely, we characterize the types of links within the networks of nanotechnology-related researchers and investigate the explanatory power of scientific and innovative networks on academic productivity.

The outline of this paper is as follows. In Section 2, we introduce the theoretical background and main hypotheses for our empirical study. Section 3 provides the description of datasets, methodology and all the explanatory variables. Section 4 concentrates on the analysis of the results, and finally in Section 5 we conclude with a summary of the main findings and propose policy implications.

6.3 Conceptual framework

The focus of research has been a while shifted from lone scientists and inventors in laboratories towards distributed teamwork and collaboration networks in various institutions. The broader range of opportunities within networks accelerates the access to pool resources and skills to stimulate knowledge sharing and new knowledge creation (Bammer, 2008; Katz and Martin, 1997; Stokols et al., 2005). Since academic scholars must maintain their research productivity during their career and each lone scientist has limited capabilities, scientists highly benefit from collaboration to improve their productivity (Hauptman 2005). Collaborative research networks have expanded in various regions around the world, revealing the capacity of emerging research economies. A number of theoretical arguments have been put forward to examine scientific collaboration in terms of regional and geographical separation (Gao et al., 2011; Scherngell and Barber, 2011; Wanzenböck et al., 2013) or the impact of collaboration with industry (Baba *et al*., 2009; Balconi *et al*., 2004; Banal-Estañol et al., 2010).

6.3.1 Collaboration in co-authorship networks

Co-authorship is used as one of the most tangible indicators of collaboration and reliably assists in tracking almost every aspect of scientific collaboration networks. An increased level of collaboration influences research outputs besides 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 is noticeable from in the steady increase of 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) show that the majority of researchers involved in a publication do not appear in the paper as co-authors and Bellotti (2012) indicated that relationships between researchers involve a wider set of interactions rather than co-authorship, Glänzel and Schubert (2005) suggest that the positive correlation between collaboration and co-authorship gives insight into structural changes of collaboration. Thus, the question regarding whether or not these collaborations enhance a scholar's performance is of particular relevance.

Despite the good reasons that show collaboration enhances research productivity - such as access to tacit knowledge, equipment, new ideas, etc. (Bozeman and Corley 2004; Liberman and Wolf, 1998; Thorsteinsdottir 2000) - the general idea underlying this issue is that in a research community if scientists publish a paper together, the connection between researchers existed prior to the publication and remains for a period of time. They are therefore more likely to do research together and, to benefit from future joint research and improved scientific productivity. Some scholars show that research collaboration has a higher impact on the number of publications (Landry et al. 1996; Hollis, 2001) but others cannot find a positive correlation (McDowell and Smith 1992). In general, the relationship between scientific collaboration and research productivity is not obvious. Lee and Bozeman (2005) highlight the transaction costs, waiting a long time for others in teams to finish their research part, disappointing results, etc., as problems that scholars face in collaborative research. These difficulties will likely reduce the productivity in a research group.

To better understand the role of co-authorship in academia, we take two main scientific outputs into account, publications and patents, to explore the learning effect of teamwork on future productivity. 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) study network measures sourced from social network analysis to investigate how the network position of scientists affects research performance. We therefore propose two hypotheses:

Hypothesis 1*: Academic scientists with more central and cliquish* ***co-publication*** *network position contribute to more* ***publications*** *in the future.*

Hypothesis 2*: Academic scientists with more central and cliquish* ***co-publication*** *network position contribute to more* ***patents*** *in the future.*

6.3.2 Collaboration in co-invention networks

Academic patents can be a useful indicator of entrepreneurial activities in universities. University researchers have shown growing interest in patenting activities, since technological opportunities encourage academic researchers to proactively commercialize scientific findings. In some ways, research universities have been important for industrial progress. Some studies show a major increase in the number of university scientists listed as inventors and in university Technological Transfer Offices in the last quarter of the 20^{th} century (TTOs) (Crespi et al., 2011; Lissoni et al., 2008). More specifically, academic patents have become more economically important and experienced massive growth since the Bayh-Dole Act of 1980 in the United States caused changes in university patenting policies. (Sampat, 2006).

In recent years, there has been a growing interest in academic collaboration through co-invention networks. Creation and diffusion of ideas are widely important in technological innovation and induce 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 in these knowledge networks is the same as that of co-authorship given the fact that when two academic inventors work together on even one patent application, they 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 and indicated that a small number of links ensures 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 as a whole (Cowan and Jonard, 2004; Fleming et al., 2007). Based on co-invention patterns studied by Carayol and Roux (2007), these 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 collaborations within the network on the research productivity. Zhang et al. (2014a), for example, only observed significant impacts on patent productivity in provinces where a high number of patents were produced. Singh (2005) also showed that the connection among researchers in innovative networks contributes to a positive effect on knowledge flow. However, some scholars examined the network clustering and found that higher levels of clustering hinder innovation (Fowler, 2005; Chen and Guan, 2010). This paper will attempt to investigate the innovative relationships among scientists and address their effect on academic research performance in science-intense nanotechnology. Our last two hypotheses therefore go as follows:

Hypothesis 3*: Academic scientists with more central and cliquish* ***co-invention*** *network position contribute to more* ***publications*** *in the future.*

Hypothesis 4*: Academic scientists with more central and cliquish* ***co-invention*** *network position contribute to more* ***patents*** *in the future.*

Nanotechnology plays a crucial role in a wide range of high technology sectors and many countries have started investing in nanotechnology research and development. Promoting collaboration and sharing knowledge in such promising technology undoubtedly fosters efficient development.

6.4 Data sources and methodology

6.4.1 Data description

For this study, to investigate the issues discussed above we extracted data from two main publication and patent application databases in order to build a comprehensive dataset: Elsevier's Scopus and United States Patent and Trademark Office (USPTO). Scopus includes the list of articles by scientist and all other publication information such as title, publication date, abstract, etc., and considers a variety of publishers. We found that Scopus contains more publications than

Web of Science and also offers more thorough results compared to Web of Science and Google Scholar since it covers a wide diversity of fields and additional information.

In addition, we used USPTO data given that in such an emerging field, inventors prefer to protect their IP in a large market. Given the proximity of Canada to the United States, inventors submit their patent applications to both USPTO and the Canadian Intellectual Property Office (CIPO). The other reason to use USPTO is because we need addresses of researchers to distinguish whether two inventors with the same name are the same person, and therefore prevent ambiguity in merging data: CIPO does not provide this information in a consistent manner. We then used a nanotechnology-related keyword search based on that of Porter et al. (2008) for both publications and patents to find scientists conducting nanotechnology research. We first started with a 20-year time period (1985-2005) and then restricted our sample to 1996-2005 since nanotechnology research before 1996 is not sufficient and reliable for our analysis.

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 have changed their address over time. This involves manually checking the individual scientists and inventors against several sources of information (e.g., author and inventor affiliation) to eliminate similar researchers whose name have been spelled differently on papers or patent documents.

Once the scientists' names were disambiguated, we created two researchers networks based on their co-publication and co-invention ties. We then used three- and five-year time intervals to account for extended collaborations and to analyze the network connections among scientists and inventors. The construction of our dataset was then completed with matching all these databases with funding databases. Over the past two decades, the Natural Sciences and Engineering Research Council of Canada (NSERC) and the Canadian Institutes of Health Research (CIHR) have launched different nanotechnology programs that have influenced increasing the academic production of publications and patents (Dang et al., 2010). As we do not have easy and reliable access to other provincial funding information, only the data from these two funding agencies will be used in this paper for consistency purposes.

6.4.2 Variables and estimated model

We evaluate two dependent variables constructed for each scientist and each academic-inventor in a given year *t*: the number of articles (*NumPaper*) attributed to each scientist to validate *Hypothesis 1* and *Hypothesis 3,* and the number of patents (*NumPatent*) attributed to each academic inventor to validate *Hypothesis 2* and *Hypothesis 4.*

The network attribute measures on which we focus in this study are degree centrality, betweenness centrality, and individual cliquishness. By calculating these network measures in both co-publication and co-invention networks, we aim to examine whether the position of scientists/academic inventors in these two networks correlates with their research performance. The following paragraphs explain these three measures.

Because both dependent variables are count data with an excess of zeros (Vuong test was performed), we chose the Stata procedure zero-inflated Poisson (*zip*) model with the vce (cluster) option to analyze data in this empirical study (Vuong, 1989).

6.4.3 Degree centrality

Degree centrality of a researcher corresponds to the number of other researchers connected directly to that researcher; it can indicate local centrality in a network and a researcher's popularity. The normalized measure of researcher degree centrality R_k is given in Eq. (6-1) where n is the number of researchers in the network and $d(R_i,R_k)$ is a function that equals 1 if researcher R_i is connected to R_k, and 0 otherwise (Freeman, 1979; Chung and Hossain, 2009).

$$C_D(R_k) = \frac{\sum_{i=1}^{n} d(R_i, R_k)}{n-1} \tag{6-1}$$

6.4.4 Betweenness centrality

This measure proposed by Freeman (1979) is an indication of the number of times a researcher connects two other researchers in a network. The number of shortest paths (geodesics) between two researchers is considered in calculating this measure. Eq. (6-2) 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).

$$C_B(R_k) = \sum_{i}^{n} \sum_{j}^{n} \frac{g_{ij}(R_k)}{g_{ij}} \qquad where\ i \neq j \neq k \qquad (6\text{-}2)$$

6.4.5 Cliquishness

The clustering coefficient or cliquishness is commonly used to measure the tendency of researchers to cluster together. This indicator, introduced by Watts and Strogatz (1998), and is always a number between 0 and 1. Given three researchers (*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. (6-3) shows the clustering coefficient for a particular researcher (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).

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

In this study, these network indicators are calculated in two co-publication and co-invention networks and we chose 3-year intervals with a one-year lag to determine the importance of a researcher as a node in the networks. We define two sets of variables to account for each of these network measures: *DegCentPaper3*, *BetCentPaper3*, *CliquishnessPaper3* to explain the connections in co-authorship networks; and *DegCenPatent3*, *BetCentPatent3*, *CliquishnessPatent3* to account for co-invention ties in our models.

Prior studies show that knowledge diffusion is more efficient in clustered networks since collaboration among such network scientists facilitates the sharing of new knowledge (Cowan and Jonard, 2004; Cowan, 2005). One problem arises here, however: when scientists are more productive and produce more papers or patents, they are more likely to have higher clustered networks. This issue therefore gives rise to an endogeneity problem. To correct our model for endogeneity, we include instrumental variables to estimate an endogenous variable (the cliquishness of co-publication) using Two-Stage Residual Inclusion (2SRI) suggested by Terza et al. (2008) and Wooldridge (2002). For the first stage of the 2SRI model, we used an Ordinary Least Squares (OLS) regression with a cluster method. The residual of this regression is then added to the zero-inflated regression (second stage) as proposed by Stephan et al. (2007).

Well-connected scientists, who occupy central positions in their scientific networks, because of their higher involvement with other researchers are presumed to possess a greater ability to produce scientific outputs. In addition, a researcher with a more cliquish position is more likely to attract other researchers to his/her "clique" as additional co-authors or co-inventors by virtue of his/her reputation among other researchers.

For these reasons, we suspect that individual cliquishness is likely to be endogenous. To explain the individual cliquishness, we hence add a number of instrumental variables to correct for this endogeneity. First, we include the number of papers published by researchers in the past three years (*NumPaper3*). We also add the type of chair *(CanadaChair*) that these researchers occupied at some point in their career using an ordinal indicator that takes the value 0 for no chair, 1 if they occupy an industrial chair and also receive funding from NSERC or CIHR, and 2 for being a chair of the Canada Research Chair. We also added an ordered measure to our set of instruments for the type of funding (Award), which equals 1 if a researcher receives funding through an award and 0 otherwise. The granting of academic research can further act as a signal of scientist productivity and these scientists may attract additional funding in subsequent years. The literature generally finds that scientists with prestigious awards and public funding contribute to more scientific and technological outputs (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*) as an instrument in our models to explain the unobserved capabilities of researchers that may influence their position in scientific or technological networks. Furthermore, we create a proxy (*NanoAge*) for the nanotechnology experience of academic researchers, using their first publication/patent to account for the fact that scientists with more experience may be well connected in their networks.

To assess the impact of collaborations on academic publications and patenting, we develop the following model:

$$Y_{it} = \alpha + \beta_1 X_{it} + \beta_2 X_{it}^2 + \delta_t d_t + \nu_i + \varepsilon_{it} \qquad (i=1, \ldots N \text{ and } t=1, \ldots T) \qquad (6\text{-}4)$$

Where Y_{it} is a measure of academic 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, d_t is a dummy variable for years, v_i is an individual fixed effect to control unobserved scientist characteristics which is constant over time, and ε_{it} is an error term.

6.5 Regression Results

Using our data, we calculate the social network measures of co-publication and co-invention relationships with the software Pajek and for regression analysis we use STATA 12. Table 6.1 and Table 6.2 summarize the results for different model specifications on scientific (papers) and technological (patents) activities, respectively. We include various combinations of explanatory variables in the model and finally choose two models that yield the most consistent and significant results to present in these tables for each dataset. Columns (1-1), (2-1), (3-1), and (4-1) report the results for the model estimated using a zero-inflated Poisson regressions without controlling for endogeneity. The second column of each model accounts for the potential endogeneity.

Based on the results for the impact of collaborations on the number of papers, we capture the endogeneity, and the first stage results suggest that these instruments of *Age*, Age^2, and *NumPaper3* strongly address this potential endogeneity in all models and *CanadaChair* and *GrantAmount* in some models (the first stage regressions are presented in the appendix D).

Table 6.1 : Impact of collaborations on nanotech papers in Quebec and the rest of Canada – Regression results of zero-inflated Poisson model

$NumPaper_t$	Quebec				Rest of Canada			
	(1-1)	**(1-2)[a]**	**(2-1)**	**(2-2)[a]**	**(3-1)**	**(3-2)[a]**	**(4-1)**	**(4-2)[a]**
$\ln(10^4 \times DegCentPaper3_{t-2})$			0.5460***	0.3685 ***			0.5719 ***	0.3761 ***
			(0.0518)	(0.0553)			(0.0350)	(0.0453)
$\ln(10^4 \times BetCentPaper3_{t-2})$	0.3741***	0.1233***			0.3679***	0.0955 **		
	(0.0330)	(0.0396)			(0.0313)	(0.0454)		
$\ln(10^3 \times CliquishnessPaper3_{t-2})$	0.0593***	0.1825***	0.7709***	0.6647 ***	0.0544***	0.1728 ***	0.6863 ***	0.5567 ***
	(0.0109)	(0.0163)	(0.1161)	(0.0974)	(0.0072)	(0.0191)	(0.0929)	(0.0606)
$[\ln(10^3 \times CliquishnessPaper3_{t-2})]^2$			-0.1157***	-0.0837 ***			-0.1050 ***	-0.0685 ***
			(0.0189)	(0.0163)			(0.0164)	(0.0110)
$\ln(10^4 \times DegCentPatent3_{t-2})$			0.0002	-0.0156			0.0066	0.0019
			(0.0435)	(0.0424)			(0.0394)	(0.0352)
$\ln(10^4 \times BetCentPatent3_{t-2})$	-0.2759	-0.1072			0.0010	0.1147		
	(0.2134)	(0.1881)			(0.1256)	(0.1042)		
$\ln(10^3 \times CliquishnessPatent3_{t-2})$	0.0286**	0.0213*	0.1633	0.2453 **	0.0437***	0.0070	-0.0908	-0.0238
	(0.0142)	(0.0115)	(0.1270)	(0.1185)	(0.0140)	(0.0113)	(0.1302)	(0.1433)
$[\ln(10^3 \times CliquishnessPatent3_{t-2})]^2$			-0.0227	-0.0349 *			0.0159	0.0033
			(0.0195)	(0.0184)			(0.0188)	(0.0210)
$\ln(10^4 \times BetCentPatent3_{t-2}) \times \ln(10^3 \times CliquishnessPatent3_{t-2})$			-0.0879**	-0.0844 **			0.0138	0.0179
			(0.0424)	(0.0420)			(0.0172)	(0.0188)
$Res[\ln(10^3 \times CliquishnessPaper3_{t-2})]$		-0.1374***		-0.1148 ***		-0.1247 ***		-0.1127 ***
		(0.0144)		(0.0200)		(0.0214)		(0.0201)
Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.4374***	0.1571***	-0.5309***	-0.5444 ***	0.4686***	0.2811 ***	-0.4827 ***	-0.4319 ***
	(0.0565)	(0.0597)	(0.0961)	(0.0833)	(0.0374)	(0.0386)	(0.0752)	(0.0532)
Inflate								
$\ln(10^4 \times DegCentPaper3_{t-2})$			-2.5462***	-2.5856 ***			-3.3787 ***	-3.1844 ***
			(0.3662)	(0.3204)			(0.6217)	(0.2702)
$\ln(10^4 \times BetCentPaper3_{t-2})$	-0.6780***	-0.0641			-0.7800***	-0.0575		
	(0.0636)	(0.0668)			(0.0464)	(0.0581)		
$\ln(10^3 \times CliquishnessPaper3_{t-2})$	-0.1138***	-0.5996***	0.9808	0.8300 *	-0.1124***	-0.6276 ***	1.1321	0.6924 **
	(0.0111)	(0.0320)	(0.5978)	(0.4785)	(0.0071)	(0.0240)	(0.7581)	(0.2994)
$[\ln(10^3 \times CliquishnessPaper3_{t-2})]^2$			-0.1135	-0.0946			-0.1189	-0.0680
			(0.0900)	(0.0712)			(0.1143)	(0.0452)
$\ln(10^4 \times DegCentPatent3_{t-2})$			-0.2078	-0.2015			0.0194	0.0770
			(0.2046)	(0.2084)			(0.2159)	(0.2009)
$\ln(10^4 \times BetCentPatent3_{t-2})$	-0.2266	-0.0995			-0.3070**	-0.2683 *		
	(0.3208)	(0.2241)			(0.1471)	(0.1404)		
$\ln(10^3 \times CliquishnessPatent3_{t-2})$	-0.0661***	-0.0040	-1.0972	-1.0326	-0.0480***	0.0110	-0.0626	-0.0181
	(0.0179)	(0.0180)	(0.8691)	(0.9079)	(0.0142)	(0.0141)	(0.6226)	(0.5581)
$[\ln(10^3 \times CliquishnessPatent3_{t-2})]^2$			0.1649	0.1565			0.0192	0.0096
			(0.1286)	(0.1344)			(0.0917)	(0.0824)
$\ln(10^4 \times BetCentPatent3_{t-2}) \times \ln(10^3 \times CliquishnessPatent3_{t-2})$			-0.7260	-0.7171			0.0142	0.0092
			(0.4742)	(0.4952)			(0.1044)	(0.1029)
$Res[\ln(10^3 \times CliquishnessPaper3_{t-2})]$		0.5650***		0.0308		0.6042 ***		0.1246 **
		(0.0353)		(0.0733)		(0.0265)		(0.0548)
Constant	1.2721***	1.9707***	2.2623***	2.3782 ***	1.3791***	2.0094 ***	2.5535 ***	2.7083 ***
	(0.0434)	(0.0609)	(0.1607)	(0.1298)	(0.0289)	(0.0423)	(0.1634)	(0.0969)
Nb observations	12120	12120	12120	12120	37841	37841	37841	37841
Nb Groups	1164	1164	1164	1164	3722	3722	3722	3722
Loglikelihood	-10683.9	-10235.6	-8015.18	-7967.7	-29992.2	-28766.9	-21735.9	-21544.3
X^2	454.60***	1486.34***	1315.9***	1853.77 ***	759.43***	1582.12 ***	1490.49 ***	3840.95 ***
Vuong test	18.36***	18.36***	14.59***	14.59 ***	28.25***	28.25 ***	25.32 ***	25.32 ***

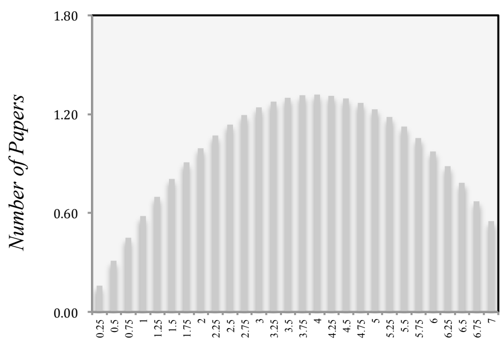
Note : ***, **, * show significance at the 1%, 5% and 10% levels and standard errors are presented in parentheses.
[a] Second Stage of 2SRI method

Table 6.2 : Impact of collaborations on nanotech patents in Quebec and the rest of Canada - Regression results of zero-inflated Poisson model

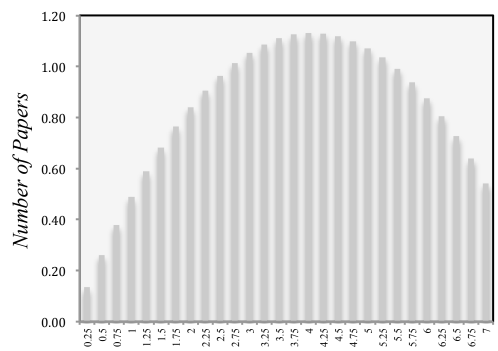
$NumPatent_t$	Quebec				Rest of Canada			
	(1-1)	**(1-2)[a]**	**(2-1)**	**(2-2)[a]**	**(3-1)**	**(3-2)[a]**	**(4-1)**	**(4-2)[a]**
$ln\ (10^4 \times DegCentPaper3_{t-2})$			0.0262	0.0964			0.0668	0.1488
			(0.0593)	(0.2713)			(0.0427)	(0.2735)
$ln(10^4 \times BetCentPaper3_{t-2})$	-0.1618	0.4571*			-0.0774	-0.1755		
	(0.1523)	(0.2775)			(0.0896)	(0.1765)		
$ln(10^3 \times CliquishnessPaper3_{t-2})$	-0.0439	-0.4177**	-0.1641	-0.1987	0.0006	0.0632	-0.3516 *	-0.3946 *
	(0.0512)	(0.1698)	(0.1805)	(0.2192)	(0.0343)	(0.0946)	(0.1839)	(0.2308)
$[ln\ (10^3 \times CliquishnessPaper3_{t-2})]^2$			0.0209	0.0187			0.0525 *	0.0505 *
			(0.0275)	(0.0290)			(0.0289)	(0.0296)
$ln\ (10^4 \times DegCentPatent3_{t-2})$			0.6018***	0.6050 ***			0.5664 ***	0.5703 ***
			(0.1168)	(0.1119)			(0.1011)	(0.0984)
$ln(10^4 \times BetCentPatent3_{t-2})$	-0.3678	-0.3289			0.1000	0.0918		
	(0.3139)	(0.3187)			(0.2043)	(0.2085)		
$ln(10^3 \times CliquishnessPatent3_{t-2})$	1.2083***	1.2732***	0.7958**	0.7828 **	0.9030***	0.8831 ***	0.4455 **	0.4521 **
	(0.3887)	(0.3673)	(0.3122)	(0.3059)	(0.2922)	(0.2899)	(0.1918)	(0.1914)
$[ln(10^3 \times CliquishnessPatent3_{t-2})]^2$	-0.1574**	-0.1600***	-0.1254***	-0.1234 ***	-0.1071**	-0.1047 **	-0.0712 **	-0.0719 **
	(0.0611)	(0.0560)	(0.0472)	(0.0462)	(0.0452)	(0.0449)	(0.0293)	(0.0292)
$Res[ln(10^3 \times CliquishnessPaper3_{t-2})]$		0.3955**		0.0496		-0.0644		0.0566
		(0.1794)		(0.1952)		(0.0950)		(0.1815)
Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.5822***	-1.1634***	-1.9037***	-1.8635 ***	-1.2041***	-1.2749 ***	-1.5708 ***	-1.5308 ***
	(0.2723)	(0.3344)	(0.3299)	(0.3604)	(0.1882)	(0.1997)	(0.2443)	(0.2702)
Inflate								
$ln\ (10^4 \times DegCentPaper3_{t-2})$			0.0556	-0.7678			0.0854	-1.0126
			(0.4231)	(2.3396)			(0.1747)	(1.3995)
$ln(10^4 \times BetCentPaper3_{t-2})$	-0.1916	0.6963*			-0.0390	-0.2184		
	(0.3010)	(0.4180)			(0.1062)	(0.2526)		
$ln(10^3 \times CliquishnessPaper3_{t-2})$	-0.0921	-0.6213**	0.5556	0.9254	-0.0867**	0.0258	-0.2762	0.2616
	(0.0588)	(0.2830)	(1.0797)	(1.6645)	(0.0380)	(0.1273)	(0.7125)	(1.2054)
$[ln(10^3 \times CliquishnessPaper3_{t-2})]^2$			-0.0919	-0.0583			0.0324	0.0631
			(0.1523)	(0.1588)			(0.1075)	(0.0998)
$ln\ (10^4 \times DegCentPatent3_{t-2})$			-60.3402***	-56.8985 ***			-53.6361 ***	-51.1800 ***
			(16.4894)	(15.6466)			(12.7598)	(10.5372)
$ln(10^4 \times BetCentPatent3_{t-2})$	-0.5205	-0.2640			0.1925	0.1848		
	(1.0811)	(0.6714)			(0.2491)	(0.2607)		
$ln(10^3 \times CliquishnessPatent3_{t-2})$	-1.2071*	-1.0326	-1.9062	-1.8766	-0.6495**	-0.6799 **	3.5865 ***	3.2591 ***
	(0.6660)	(0.6861)	(1.7037)	(1.6943)	(0.2837)	(0.2924)	(1.2691)	(1.2370)
$[ln(10^3 \times CliquishnessPatent3_{t-2})]^2$	0.1879*	0.1714*	0.2803	0.2740	0.1152***	0.1185 ***	-0.4961 ***	-0.4539 **
	(0.0976)	(0.0966)	(0.2531)	(0.2517)	(0.0424)	(0.0435)	(0.1883)	(0.1806)
$Res[ln(10^3 \times CliquishnessPaper3_{t-2})]$		0.5544*		-0.6025		-0.1163		-0.7604
		(0.2987)		(1.5450)		(0.1232)		(0.9945)
Constant	0.6610*	1.2317***	3.5331***	3.1147 ***	0.4383**	0.3183	3.0852 ***	2.7753 ***
	(0.3565)	(0.4489)	(0.3485)	(1.0470)	(0.1834)	(0.2242)	(0.2487)	(0.4498)
Nb observations	2854	2854	2854	2854	5482	5482	5482	5482
Nb Groups	288	288	288	288	592	592	592	592
Loglikelihood	-1503.52	-1499.55	-1152.39	-1152.11	-3180.3	-3179.7	-2552.63	-2551.72
X^2	200.88***	238.80***	117.28***	122.5 ***	136.177***	137.21 ***	79.040 ***	79.76 ***
Vuong test	2.32**	2.32**	11.64***	11.64 ***	4.81***	4.81 ***	14.78 ***	14.78 ***

Note : ***, **, * show significance at the 1%, 5% and 10% levels and standard errors are presented in parentheses.
[a] Second Stage of 2SRI method

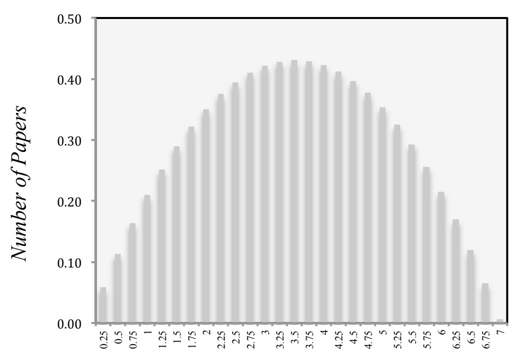
The results show that collaborative ties among scientists influence research performance. Positively significant correlations in Table 6.1 expose that in co-authorship relationships, scientists who have many collaborations with different researchers and those who frequently cross the collaboration paths of other scientists contribute to more publications. Further, maintaining collaborations within a group of scholars appears to have a positive impact on researcher productivity. This cliquishness can be said to have a positive effect, but we found that a too integrated network in co-publication relationships is not fruitful. Based on these results, the curve follows a non-linear inverted U-shaped relationship for productivity of a scholar in both Quebec and the rest of Canada (Figure 6.1a and Figure 6.1b). As such, some degree of integration can yield better results, but too integrated groups tend to have a negative impact on the number of papers.



(a) ln(10^3 x CliquishnessPaper3_{t-2}) - Quebec



(b) ln(10^3 x CliquishnessPaper3_{t-2}) - rest of Canada



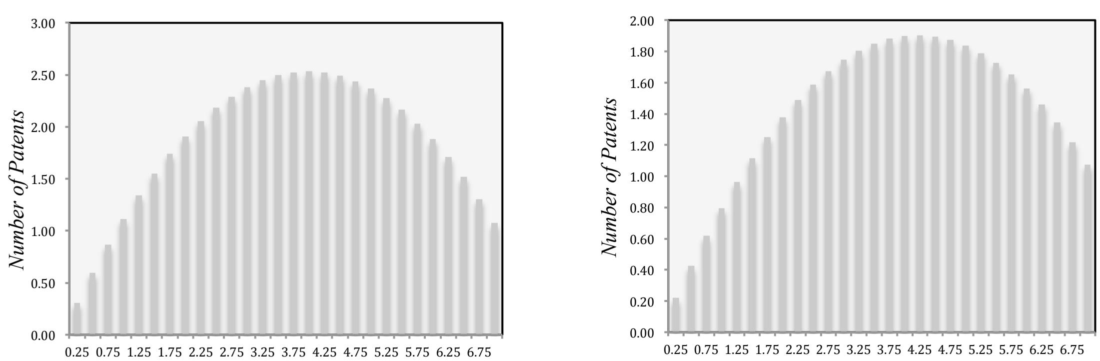
(c) ln(10^3 x CliquishnessPatent3_{t-2}) - Quebec

Figure 6.1: Non-linear effects of the cliquishness in co-authorship networks on the number of papers in (a) Quebec (2-2) and (b) the rest of Canada (2-2)

Whereas co-publication relationships reveal a positive influence on publication productivity, we also show a significant impact of co-invention relationships on publication productivity in Quebec. Cliquishness in the co-invention network has a positive influence on the number of papers, but similarly to what we have seen in the co-publication relationships, the curve follows an inverted U-shaped relationship (see Figure 6.1c). Thus, patenting collaborations show a consistently significant impact on the future scientific productivity of a scientist. Degree centrality or betweenness centrality in co-invention networks have neither a positive nor a negative effect on the number of papers.

Table 6.2 shows the importance of an academic inventor within co-invention relationships on his/her patenting activity. We observe a positive impact of degree centrality in co-invention networks indicating that the number of patents for each researcher rises if the number of other inventors directly connected to that researcher increases.

Our findings prove that highly cliquish networks based on co-patenting enhance the innovative performance of researchers, but when we examine the non-linear effect, the results are similar to those of co-authorship networks: too high cliquishness decreases innovation productivity. These empirical results in Table 6.2 however suggest a similar inverted U relationship curve for both Quebec and the rest of Canada (Figure 6.2a and Figure 6.2b). These curves demonstrate that too highly integrated clusters are associated with diminishing returns on scholarly productivity beyond a threshold that corresponds to the maximum of the curve.



(a) ln(10^3 x CliquishnessPatent3$_{t-2}$) - Quebec

(b) ln(10^3 x CliquishnessPatent3$_{t-2}$) - rest of Canada

Figure 6.2: Non-linear effects of the cliquishness in co-invention networks on the number of patents in (a) Quebec (2-2) and (b) the rest of Canada (2-2)

A further comparison of co-publication collaborations shows that these relationships are not efficient enough to influence. We only observe a weak positive impact of an intermediary position in a co-authorship network on the patenting activity of a researcher in Quebec; however, the clique structure in these co-publication communities does seem to influence the patent productivity. In this regard, our results reveal a U-shaped relationship between cliquishness and patenting. This indicator suggests that the structure of research groups in co-publication collaborations is more likely to influence the patenting performance of researchers in the rest of Canada.

The nature of interactions among academic scientists and academic inventors are different and their communication activity influences their scientific and technological efficiency. This fact may imply that a better co-authorship network position may increase publication productivity of a researcher, since patenting performance is correlated with the co-invention network position. Our examination, however, reveals that collaboration has the same impact on the scientific and technological performance of academic researchers in our two samples of Quebec and the rest of Canada. To our knowledge, this result is a novel and valuable contribution to the literature.

Our empirical analysis aims to estimate the marginal effect of independent variables on the scientific and technological productivity of researchers. Marginal effects present the change in the number of papers and patents given a one-unit change in the corresponding explanatory variable controlling the other independent variables. To compare the productivity of researchers in Quebec with the rest of Canada, we calculate the marginal effect at the means presented in Table 6.3.

Table 6.3 : Estimated Marginal Effects in Quebec and the rest of Canada

Variables	**Quebec Delta method (dy/dx)**				**The rest of Canada Delta method (dy/dx)**			
	$NumPaper_{it}$		**$NumPatent_{it}$**		**$NumPaper_{it}$**		**$NumPatent_{it}$**	
	Model (1)	**Model (2)**	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (3)**	**Model (4)**
$ln\ (10^4 \times DegCentPaper3_{t-2})$		0.4483 ***		0.0094		0.4237 ***		0.0294
		(0.0539)		(0.0221)		(0.0377)		(0.0191)
$ln(10^4 \times BetCentPaper3_{t-2})$	0.0637 ***		0.0058		0.0440 ***		-0.0110	
	(0.0206)		(0.0293)		(0.0140)		(0.0153)	
$ln(10^3 \times CliquishnessPaper3_{t-2})$	0.2332 ***	0.0106	-0.0069	-0.0688	0.2074 ***	0.0009	0.0115 ***	-0.1549 *
	(0.0133)	(0.0557)	(0.0204)	(0.0667)	(0.0081)	(0.0288)	(0.0044)	(0.0850)
$ln\ (10^4 \times DegCentPatent3_{t-2})$		0.0262		0.8781 ***		-0.0086		0.2711 ***
		(0.0312)		(0.1342)		(0.0220)		(0.0386)
$ln(10^4 \times BetCentPatent3_{t-2})$	-0.0126		-0.0296		0.1015 **		-0.0044	
	(0.0750)		(0.0453)		(0.0467)		(0.0429)	
$ln(10^3 \times CliquishnessPatent3_{t-2})$	0.0091 *	0.1984	0.3341 ***	0.3253 ***	-0.0005	-0.0014	0.2742 ***	0.1950 **
	(0.0055)	(0.1258)	(0.0758)	(0.1121)	(0.0040)	(0.0561)	(0.0570)	(0.0832)

Note: Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

Comparing the marginal effect, results show that a one unit change in the degree centrality variable in co-publication relationships, assuming all other variables constant, increases the number of papers; this increase is slightly higher in Quebec than the rest of Canada. Our findings in terms of betweenness centrality and cliquishness in co-authorship networks in Quebec and the rest of Canada also suggest that these indicators have more impact on publication productivity in

Quebec (see Figure 6.3). Our results also indicate that a one-unit increase in the clustering coefficient of co-publication networks has more effect on the number of patents in the rest of Canada. Based on our analysis of technological performance, we can state that particular degree centrality and clustering in co-invention networks have a higher impact on the number of patents in Quebec, as we observe in Figure 6.3.

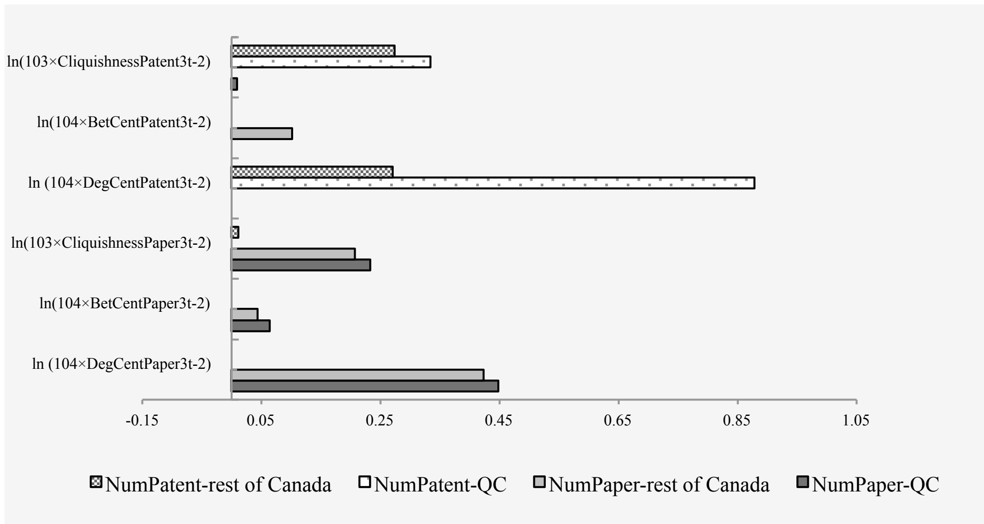


Figure 6.3: Comparison of marginal effects in Quebec and the rest of Canada

To better examining the difference between Quebec and the rest of Canada, we defined a dummy variable (*dQC*) taking the value 1 for Quebec scientists and the value 0 for scientists based in the other provinces. Our pooled sample regressions for all models are shown in Table 6.3. The results are only significant for the betweenness centrality in co-publication networks. The intermediary position of researchers in these networks has a stronger impact on the publication productivity in Quebec, which is in line with our comparison results of marginal effects.

Table 6.4 : Impact of collaborations on nanotech papers and patents in a pooled sample of Quebec and the rest of Canada - Regression results of zero-inflated Poisson model

Variable	***$NumPaper_t$***				***$NumPatent_t$***			
	(1-1)	**(1-2)[a]**	**(2-1)**	**(2-2)[a]**	**(3-1)**	**(3-2)[a]**	**(4-1)**	**(4-2)[a]**
$\ln(10^4 \times DegCentPaper3_{t-2})$			0.5781***	0.3797 ***			0.0713 *	0.1466
			(0.0371)	(0.0410)			(0.0426)	(0.2033)
$\ln(10^4 \times BetCentPaper3_{t-2})$	0.3694***	0.0895**			-0.0680	0.0241		
	(0.0311)	(0.0355)			(0.0893)	(0.1677)		
$\ln(10^3 \times CliquishnessPaper3_{t-2})$	0.0593***	0.1825***	0.6630***	0.5484 ***	-0.0002	-0.0617	-0.3421 *	-0.3821 *
	(0.0109)	(0.0163)	(0.0854)	(0.0579)	(0.0333)	(0.1057)	(0.1823)	(0.2079)
$[\ln(10^3 \times CliquishnessPaper3_{t-2})]^2$	0.0551***	0.1748***	-0.1010***	-0.0671 ***			0.0509 *	0.0493 *
	(0.0072)	(0.0153)	(0.0143)	(0.0100)			(0.0287)	(0.0291)
$\ln(10^4 \times DegCentPatent3_{t-2})$			0.0039	-0.0003			0.6085 ***	0.6143 ***
			(0.0392)	(0.0346)			(0.0905)	(0.0879)
$\ln(10^4 \times BetCentPatent3_{t-2})$	0.0039	0.1211			0.1260	0.1321		
	(0.1242)	(0.1037)			(0.2054)	(0.2004)		
$\ln(10^3 \times CliquishnessPatent3_{t-2})$	0.0435***	0.0057	-0.1163	-0.0437	0.8887***	0.9076 ***	0.4260 **	0.4306 **
	(0.0140)	(0.0111)	(0.1275)	(0.1441)	(0.3014)	(0.2979)	(0.1921)	(0.1922)
$[\ln(10^3 \times CliquishnessPatent3_{t-2})]^2$			0.0196	0.0062	-0.1065**	-0.1087 **	-0.0686 **	-0.0690 **
			(0.0184)	(0.0211)	(0.0463)	(0.0459)	(0.0293)	(0.0294)
$\ln(10^4 \times BetCentPatent3_{t-2}) \times \ln(10^3 \times CliquishnessPatent3_{t-2})$			0.0152	0.0193				
			(0.0168)	(0.0183)				
dQC	0.0160	-0.0810*	0.0279	-0.0389	-0.0406	-0.0300	0.0930	0.1180
	(0.0467)	(0.0464)	(0.0853)	(0.0733)	(0.1423)	(0.1443)	(0.1446)	(0.1450)
$dQC \times \ln(10^4 \times DegCentPaper3_{t-2})$			-0.0563	-0.0312			-0.0390	-0.0433
			(0.0490)	(0.0417)			(0.0706)	(0.0718)
$dQC \times \ln(10^4 \times BetCentPaper3_{t-2})$	0.0007	0.0539**			-0.0267	-0.0303		
	(0.0446)	(0.0236)			(0.1066)	(0.1065)		
$dQC \times \ln(10^3 \times CliquishnessPaper3_{t-2})$	0.0004	-0.0020	0.1217	0.1228	-0.0392	-0.0380	0.1421	0.1490
	(0.0119)	(0.0107)	(0.0901)	(0.0793)	(0.0392)	(0.0391)	(0.2571)	(0.2575)
$dQC \times [\ln(10^3 \times CliquishnessPaper3_{t-2})]^2$			-0.0167	-0.0175			-0.0245	-0.0255
			(0.0138)	(0.0120)			(0.0396)	(0.0396)
$dQC \times \ln(10^4 \times DegCentPatent3_{t-2})$			-0.0057	-0.0171			-0.1182	-0.1248
			(0.0574)	(0.0537)			(0.0865)	(0.0865)
$dQC \times \ln(10^4 \times BetCentPatent3_{t-2})$	-0.3018	-0.2636			-0.3432	-0.3573		
	(0.2463)	(0.2161)			(0.2667)	(0.2630)		
$dQC \times \ln(10^3 \times CliquishnessPatent3_{t-2})$	-0.0154	0.0152	0.2871*	0.2967	0.3683	0.3669	0.3850	0.3684
	(0.0193)	(0.0153)	(0.1738)	(0.1825)	(0.4135)	(0.4112)	(0.3902)	(0.3861)
$dQC \times [\ln(10^3 \times CliquishnessPatent3_{t-2})]^2$			-0.0428*	-0.0418	-0.0553	-0.0549	-0.0587	-0.0565
			(0.0257)	(0.0272)	(0.0636)	(0.0633)	(0.0588)	(0.0582)
$dQC \times \ln(10^4 \times BetCentPatent3_{t-2}) \times \ln(10^3 \times CliquishnessPatent3_{t-2})$			-0.0856*	-0.0844 *				
			(0.0454)	(0.0465)				
$Res[\ln(10^3 \times CliquishnessPaper3_{t-2})]$		-0.1271***		-0.1132 ***		0.0635		0.0513
		(0.0174)		(0.0169)		(0.1049)		(0.1331)

Table 6.4 : Impact of collaborations on nanotech papers and patents in a pooled sample of Quebec and the rest of Canada - Regression results of zero-inflated Poisson model (continued)

Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.4588***	0.2746***	-0.4957***	-0.4435 ***	-1.2902***	-1.2194 ***	-1.6961 ***	-1.6678 ***
	(0.0347)	(0.0361)	(0.0701)	(0.0494)	(0.1586)	(0.1740)	(0.2070)	(0.2255)
Inflate								
ln $(10^4 \times DegCentPaper3_{t-2})$			-3.0236***	-2.9639 ***			0.0802	-1.0514
			(0.3570)	(0.2059)			(0.1648)	(1.0536)
ln$(10^4 \times BetCentPaper3_{t-2})$	-0.7467***	-0.0513			-0.0285	0.0337		
	(0.0372)	(0.0440)			(0.0882)	(0.2035)		
ln$(10^3 \times CliquishnessPaper3_{t-2})$	-0.1141***	-0.6253***	0.9861**	0.7147 ***	-0.0875***	-0.1278	-0.1013	0.4165
	(0.0060)	(0.0193)	(0.4608)	(0.2496)	(0.0322)	(0.1242)	(0.5858)	(0.8916)
$[\ln(10^3 \times CliquishnessPaper3_{t-2})]^2$			-0.1029	-0.0740 **			0.0073	0.0465
			(0.0687)	(0.0375)			(0.0878)	(0.0858)
ln $(10^4 \times DegCentPatent3_{t-2})$			-0.1180	-0.0661	0.1603	0.1632	-53.7726 ***	-51.9677 ***
			(0.1563)	(0.1557)	(0.2302)	(0.2260)	(6.9306)	(5.9557)
ln$(10^4 \times BetCentPatent3_{t-2})$	-0.2855**	-0.2292*			0.1603	0.1632		
	(0.1344)	(0.1197)			(0.2302)	(0.2260)		
ln$(10^3 \times CliquishnessPatent3_{t-2})$	-0.0556***	0.0058	-0.5202	-0.4367	-0.7352***	-0.7226 ***	2.9953 **	2.6896 **
	(0.0111)	(0.0111)	(0.5379)	(0.5361)	(0.2699)	(0.2719)	(1.2617)	(1.2045)
$[\ln(10^3 \times CliquishnessPatent3_{t-2})]^2$			0.0843	0.0700	0.1246***	0.1233 ***	-0.4175 **	-0.3777 **
			(0.0792)	(0.0791)	(0.0398)	(0.0399)	(0.1842)	(0.1747)
ln$(10^4 \times BetCentPatent3_{t-2}) \times$ *ln*$(10^3 \times CliquishnessPatent3_{t-2})$			0.0462	0.0471				
			(0.0918)	(0.0950)				
Res$[\ln(10^3 \times CliquishnessPaper3_{t-2})]$		0.5989***		0.1003 **		0.0416		-0.7981
		(0.0214)		(0.0435)		(0.1222)		(0.7335)
Constant	1.3571***	2.0106***	2.4487***	2.6163 ***	0.5096***	0.5500 ***	3.2079 ***	2.8147 ***
	(0.0240)	(0.0348)	(0.1235)	(0.0801)	(0.1787)	(0.2129)	(0.2058)	(0.3969)
Nb observations	49961	49961	49961	49961	8336	8336	8336	8336
Nb Groups	9664	9664	9664	9664	1268	1268	1268	1268
Loglikelihood	-40693.7	-10235.6	-29779.2	-29539	-4706.31	-4705.9	-3724.44	-3722.84
X^2	1133.48***	1486.341***	2679.448***	5495.867 ***	241.55***	245.9 ***	124.81 ***	128.91 ***
Vuong test	33.52***	33.52***	29.16***	29.16 ***	5.3***	5.3 ***	18.4 ***	18.4 ***

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

[a] Second Stage of 2SRI method

6.6 Concluding Remarks

In order to investigate how research collaboration and research performance are correlated, we used co-authorship and co-invention data and considered nanotechnology-related papers and patents as two important scientific and technological research outputs. As social network analysis measures: degree centrality, betweenness centrality, and clustering coefficient (cliquishness) provide a promising avenue to analyze both these networks.

Our analysis results show that scientific performance is positively associated with the collaborations of scholars in a co-authorship network: scientists with strong connections yield a higher number of publications. Regarding the network measures, researchers with a higher number of direct connections, those who hold an intermediary position in a co-authorship network, and researchers who collaborate within a group of linked co-authors show higher scientific research performance than those with few connections.

Furthermore, our analysis of co-invention network measures shows no consistently positive and significant impact of degree centrality and betweenness centrality on the production of papers. We only observe a positive effect of cliquishness in Quebec, showing that collaboration within a fairly integrated group can be fruitful for scientific outcomes. Hence, we overwhelmingly accept our first hypothesis, which suggests that more collaboration between authors leads to more scientific papers, but the impact on technological performance is only partly acceptable (Hypothesis 3).

Regarding the influence of clustering on research performance, our findings show that although we observe a positive influence, we find that too high a value of individual cliquishness tends to have a negative impact once we account for the nonlinear effect. These results are the same for the positive impact of co-invention cliquishness on scientific performance. In the emerging field of nanotechnology, it appears to be critical that researchers develop their connections beyond a highly integrated cluster to share and diffuse knowledge, and to collaborate with researchers in various fields.

We extend our empirical study to examine whether the innovative performance of researchers improves with a better network position.

The results suggest that the co-authorship ties between researchers do not yield a convincing effect on the number of patents, but in particular, we found that academic inventors exchange their knowledge in co-invention relationships, thus their connections create opportunities for higher technological performance. This highlights the importance of direct links in such networks in order to enhance patenting activities.

Correspondingly, the relationship between clustering and the number of patents is positive. Indeed, similar to our results in co-publication networks, more cliquishness in these networks increases the technological performance, but we should expect a diminishing trend if scholars collaborate in a too integrated clique. Summing up, the impact of prominent positions in research networks on patenting performance of researchers is significantly positive, but to this effect, we need to encourage collaborations that involve innovation efforts. In this respect, our results accept *Hypothesis 4* and partly accept *Hypothesis 2*.

Our comparison results suggest that collaborations have a greater impact on nanotechnology research performance in Quebec and such a conclusion is consistent both with scientific and technological outputs. More co-authorship and co-invention relationships in Quebec are associated with higher research productivity and generate more publications and patents in the future.

Our study has revealed, however, that the network structure and level of clustering influences the extent of knowledge diffusion. Although clustering is important in an innovation network, it may also limit knowledge transmission. To mitigate the problems of very cliquish networks, it is necessary that the creation of links outside these integrated clusters is taken into account.

Since the growth of nanotechnology relates to technologies from various fields, researchers need to widen their connections within these domains in order to stimulate growth in this emerging high technology.

Finally, there are the numbers of limitations to this research. 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 it is entirely possible that we may have missed some nanotechnology related articles and patents. However, nanotechnology is an emerging field and some new keywords may have been missed in our careful canvassing of the scientific literature.

The other limitation is the mobility of scientists that can affect the affiliations and clearly the results of this research.

CHAPTER 7 GENERAL DISCUSSION

This research aimed to answer three sets of hypotheses that we discussed in previous chapters. The first set aimed at identifying the impact of public funding on the research performance of academic scientists; the second examined the influence of collaborative networks of scientists; and the third set of hypotheses compared this impact in Canada and the US. Publications and patents are the two main research outputs considered as scientific and technological outputs. We focused on nanotechnology which is of great importance for policy makers to further understand the factors that enhance the success of the development in such an emerging technology. The following sections in this chapter discuss these contributions.

7.1 The impact of Funding

Governments devote considerable amounts of funds towards basic and applied research and development (R&D). Given that academia accounts for a large proportion of research, it is important to study funding trends in universities and analyze the effectiveness of these government expenditures. We take publications and patents into account to examine the efficiency and productivity of government funding in this high technology.

In this research, we were concerned that there may exist a potential endogeneity problem regarding our funding and scientific output variables. We used the common instrumental variable techniques, 2SRI and 2SLS models, to control for potential endogeneity. Our instrumental variables were validated and verified by examining their correlation with other exogenous variables, with dependent variables and with our endogenous variable. We found these instrumental variables significant in the first stage of 2SRI and 2SLS models, which suggests that these are appropriate instruments to correct the potential endogeneity in our models.

Regarding the influence of funding on scientific production, the impact on the number of papers is overwhelmingly significant and positive in Canada and the US. The results that are presented in Paper 2 are supporting *Hypothesis 1.1a* in both Canada and the US and *Hypothesis 1.1b* only in the US, since the positive impact of government funding on the publication quality is only observed in the US and not Canada. Although, the links between government grants and academic research are complex and despite the fact that economists have recently paid much attention to research productivity, the effect of research expenditures on research output is not trivial in prior studies. Our results in the field of nanotechnology are in general accordance with the work of those scholars (Arora & Gambardella, 2005; McAllister and Narin, 1983; Payne and Siow, 2003; Peritz, 1990; Zucker et al., 2007) who observed receiving grants positively influences the production of scientific output.

This paper presents an empirical analysis of the impact of public funding on university technological outputs in the emerging science and technology domain, nanotechnology, on a sample of Canadian and American academic patents. We focus here on two relatively similar, yet very distinct countries and the results are a rather different. We find empirical evidence (see Paper 4) that government funding enhances the number of patents and patent quality in the US, but we are unable to find such a relationship in Canada. We hence accept *Hypothesis 1.2 a and Hypothesis 1.2 b* for the US, but reject this hypothesis for Canada. In order to examine the impact of public funding on patent quality, 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 limit to the increase in patent quality and beyond a specific amount of funding (nearly 42 000 $), patent quality begins to decrease. A limited number of studies have explored in details the influence of funding on academic innovative activity. The large body of literature generally focuses on the influence of funding on scientific productivity and these results expand the focus of research on academic patenting when scientists address industrial interests.

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.

Given the relationship between private funding and publications, the results of our investigation in Quebec (see Paper 3) show that paper quality decreases as industry funding increases. The efficacy of private funding for research purposes is an issue of much debate. Previous studies generally concentrate on government funding and the literature extensively suffers from a lack of data on the impact of private research financing in universities. Moreover the magnitude of this investment in new high technologies deserves as much consideration to understand the impact of funding sources on the quality of scientific production.

We also observed that while increased government funding is considered beneficial and a sign of a higher quality researcher, increased private funding is more likely to restrict the publication quality. Contracts with industrial firms have a negative non-linear effect on nanotechnology research quality. This problem highlights a concern about collaboration between two different scientific worlds of academic research and commercial innovation. There are concerns as to whether these interactions will decrease long-term research or change the culture of open science (Martin 2003; Van Looy 2004). As a consequence, since the amount of private research financing yields a negative effect in our analysis on the citation impact of scientific output, we reject *Hypothesis 1.3*

Prior studies on the impact of industry support on the scientific production are mixed. Gulbrandsen and Smeby (2005) explained that the publishing profile of an industry-funded academic researcher may be different from that of a government-funded researcher. An industry-funded researcher likely publishes more reports or files more academic patents instead of journal articles. Additionally, Geuna and Nesta (2006) also suggested a possible substitution effect between paper publication and patent application for university scientists with industrial support: academic researchers must sometimes withhold research results for months due to intellectual property rights. Our results, however, are in line with those studies (Beaudry and Allaoui, 2012; Boumahdi et al., 2003; Goldfarb, 2008) that found negative impact.

Moreover, the findings of this thesis generally confirm that government support for evolving research areas such as nanotechnology promises the highest socio-economical benefits and will result in higher performance research and efficient knowledge diffusion.

Our contribution shows that there is a high correlation between the amount of grants received and research outputs, but that the assumption that this funding yields higher quality research is not empirically verified in Canada.

This thesis contributes to the literature underlining the fact that grants may fail or not result in increasing research performance by providing more grants beyond a certain limit as we observed an inverted U-shaped curve. Our analysis of the non-linear relationships appears to show a negative impact at some point for our dependent variables. These findings are different from the prior studies that they found a positive, a negative or no impact of funding. These results show that government grants in smaller amounts can be more fruitful rather than larger grants in increasing the research output.

7.2 The impact of Collaborations and network

The other major findings from this research relate to the quantity of research output and the quality of their outputs given their position in scientific and technological networks. In the field of nanotechnology, we observe an increasing tendency of researchers to form research teams whose expertise span over a wide range of domains. Funding agencies thus commonly allocate financial resources to teams of scientists rather than individual researchers. In our second hypothesis we therefore focus on the way in which these collaborative teams are structured and shed some light on the impact of the network measures on the research output of the teams.

The evolution of collaborations between researchers over the years was analyzed using 3-year co-publication and co-invention sub-networks. We created these sub-networks for all the 3-year moving intervals by building one big network of Canada and the US for each co-publication and co-invention network.

In this research, we find a remarkably positive and significant impact of the researchers' collaboration in co-authorship networks on the quantity and quality of publications in both Canada and the US that enables us to accept *Hypothesis 2.1* (Paper 2). Our results tend to support the notion that clustered environments enhance the quantity of scientific output and confirm the efficiency of these collaborative networks in knowledge diffusion. We find that clustered networks increasingly augment scientific output and quality of research. We contribute to the literature by analyzing the position of scientists in their scientific networks. Prior studies have generally focused on the number of authors as a measure of collaboration in co-authored publications (Frenken et al., 2005; Hollis, 2001; Lee and Bozeman, 2005; Narin et al., 1991).

Our analysis results on a detailed study of collaborations and network measures in Paper 5 show that scientific performance is positively associated with the collaborations of scholars in a co-authorship network: scientists with strong connections yield a higher number of publications. Regarding the network measures, researchers with a higher number of direct connections, those who hold an intermediary position in a co-authorship network, and researchers who collaborate within a group of linked co-authors show higher scientific research performance than those with few connections.

This analysis further sheds light on our understanding of the influence that collaboration, within the network of science, has on enhancing commercial interests of academic researchers (Paper 4). In Canada we find that collaborations in co-authorship networks have a significant influence on the number and quality of patents. Our further analysis on more network measures in Quebec (Paper 5) shows that the co-authorship ties between researchers cannot yield a convincing effect on the number of patents. Hence, we partly accept *Hypothesis 2.2*.

Turning to the impact of co-invention networks, our analysis of co-invention network measures in Paper 5 shows no consistently positive and significant impact of degree centrality and betweenness centrality on the production of papers. We only observe a positive effect of cliquishness in Quebec, showing that collaboration within a fairly integrated group can be fruitful for scientific outcomes. Hence, the impact on technological performance is only partly acceptable (*Hypothesis 2.3*).

We also contribute to the literature in terms of a detailed analysis of the effect of co-invention collaborations on technological productivity. We accept *Hypothesis 2.4* for both Canada and partly for the US based on our findings in Paper 4. Our further focus on network metrics in Paper 5 also shows that academic inventors exchange their knowledge in co-invention relationships, thus their connections create opportunities for higher technological performance. This highlights the importance of direct links in such networks in order to enhance patenting activities.

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 such, a higher clustering coefficient decreases the efficiency of articles published implying that researchers working in more clustered collaborative environments become less productive and efficient. 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 the quantity and quality of research output. This may be explained by the possible inclination of authors in cliquish environments to cite scientists with whom they are linked in their network. It has proven critical that researchers develop their connections and share knowledge beyond a highly integrated cluster.

Very few papers have explored the role of collaboration in the technological performance of researchers. Previous studies have mostly analyzed the benefits of university-industry collaborations on commercial activities (see D'Este and Patel 2007; Hane 1999; Lee 2000; Perkmann and Walsh 2007; Robb1991) or have extensively studied the influence of academic patenting efforts on open science publications (Balconi et al. 2004; Meyer 2006; Van Looy et al. 2004). Using the network measures of academic researchers, we directly focus on the impact of innovative networks on university patents and contribute to the literature.

The findings of this thesis support the idea that collaborations yield more research outputs in emerging industries such as nanotechnology. Collaboration and knowledge sharing even in innovative networks appear to be fruitful and strengthen the publication performance of scientists.

Given the importance of collaborative linkages, particularly in a multidisciplinary field, this finding is of great importance, thus, scientists must be encouraged to develop their connections beyond their cliquish environments and cite new researchers. As for the importance of the scientific and technological network surrounding academic researchers, while these researchers build their network to have access to diverse knowledge of their community, in some fields such as nanotechnology, large multidisciplinary teams are required to benefit from knowledge of various sources. This would be necessary for an emerging field which is in its infancy to augment the research productivity and quality.

7.3 Comparison of Canada and the US

This thesis generates empirical evidence to compare the nanotechnology development of Canada and the US. We observe that government grants yield a greater effect on nanotechnology publications in the US, while network characteristics are more influential in Canada rather than in the US. Thus we reject *Hypothesis 3.1* in terms of the higher influence of government grants in Canada rather than in the US.

As a consequence, we capture similar results with respect to the technological performance of scientists. Government funding plays an important role in the US. In Canada on the other hand, the position of researchers in collaborative networks has been more effective. Although government funding plays an important role on technological productivity and patent quality in the US, we cannot capture this effect in the comparison analysis. Moreover, in Canada, if an academic inventor already holds a better intermediary position than other researchers and has a well-integrated clique with some level of fragmentation, this inventor contributes to more and higher quality technological output. These findings suggest that collaborations in Canada are effective in enhancing academic technological output. However, we cannot support *Hypothesis 3.2* as these comparison results were not significant to imply that government funds are more effective in the US comparing to Canada.

From this analysis, we realize that both funding and collaborations contribute to enhancing research output 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 technological output. 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.

Nanotechnology is a young field with considerable potential, but it is an emerging, knowledge-based technology which is risky and requires long-term research. Hence, given the influence of this technology on future economic development, it is vital to consider the impact of government funding and collaborations in order to enhance nanotechnology development.

Thus, purposeful research funding and strong relationships between nanotechnology researchers strengthens knowledge exchange and stimulates growth in this emerging high technology.

CONCLUSION

The findings of this thesis provide important contributions to nanotechnology development in academia. We first examined to what degree funding stimulates nanotechnology research in universities. There have been a number of studies which have investigated the impact of public funding in various fields and their results are conflicted: some reveal a positive relationship, others a negative impact, and others find no effect in some cases. This thesis has made a major contribution in identifying the impact of funding in an emerging nanotechnology.

This high and interdisciplinary technology holds the potential to yield considerable economic benefits and has the ability to generate new products, production processes and technology-intensive firms. Hence, it is of great importance to examine the factors that effectively influence the development of this new technology. Due to the substantial potential of nanotechnology, both public and private spending has consistently increased in the past two decades.

We developed non-linear econometric models to answer our research questions and found that the amount of funding allocated to scientists plays a fundamental role in enhancing nanotechnology research, particularly in the US. In addition, although we found a positive impact of government funding on research performance, in some cases we observed subtle differences; while more funding leads to higher research performance, the non-linear relationship shows that at some point, researchers experience a decrease since results suggest that this effect follows an inverted U shaped curve. The policy implication of these results could be that governments allocate various smaller grants to researchers in order to enhance the research output.

Furthermore, our results from Quebec appear to verify the general belief that industry funding negatively impacts the publication quality of academic researchers. This observation may be due to the industrial sectors which desire to protect their findings from being freely accessible for competitors. The empirical findings of this thesis suggest that government grants represent an essential gateway to nanotechnology research development and nanotechnology knowledge diffusion. While government research financing contributes to increasing the quality of knowledge being produced, and sharing it as open science for the benefit of society, the industry directs investment toward nanotechnology research to benefit from applied research and potential products and processes. Industry-supported research may lay the foundation for technological advancements and is protected by patents in patent offices. The collaboration of private companies in academic research, however, does not necessarily result in more patents, it may only provide consulting activities.

Publicly funded research contributes to the worldwide knowledge network and stimulates economic growth. The private sector is interested in short-term research; long-term and highly risky research, with a potential for greater impact, should accordingly be supported by government. This is not to say that academics should not seek private funding. One must recognize that in the filed of nanotechnology, private funding is complementary, but serves other purposes than high quality publications.

Nanotechnology is an interdisciplinary field which is increasingly necessary for scientists to research in teams and increase collaborations across disciplines to benefit from other scientists' knowledge to reap its full potential. Thus, the collaboration of researchers and the position that they occupy in their networks affect their performance. We indeed find a reinforcing effect between research collaboration and performance, particularly in Canada.

The policy implication of these findings is that governments encourage scientists to work in teams. We show that better network positions of scientists in co-authorship and co-invention networks affect their research outputs. Thus, this thesis underlines the strong relationship between the scientific and technological performance of academic scientists and their collaborative behavior in networks. Since the growth of nanotechnology relates to technologies from various fields, researchers need to widen their connections within these domains in order to stimulate growth in this emerging high technology.

This thesis uncovers an interesting issue regarding network characteristics. Although a positive correlation exists between the structure of research teams measured by the clustering coefficient (cliquishness) and research outputs, the maximum clustering coefficient exhibits diminishing returns and researchers therefore do not benefit from highly integrated teams and more cliquish networks. Scientists are more likely to become less efficient in such clustered collaborative environments and need some fragmentation to network in this multidisciplinary field. To mitigate the problems of very cliquish networks, it is necessary that the creation of links outside these integrated clusters is taken into account.

The results of this thesis are of great importance for Canada as this research concentrates on nanotechnology, which can foster significant economic development. We study this technology in order to understand two important factors that enhance such development: funding and collaboration.

Given these results, we recommend that the Canadian government support nanotechnology development by financing academic research, given the crucial role we found financing has played in the US. We also recommend the government invest in the development of collaborative networks, as we have observed that such networking considerably increases research performance in Canada. According to our findings, we suggest that government allocate various smaller amounts of grants to teams of researchers in order to enhance the quantity and quality of research. In the filed of nanotechnology, large multidisciplinary teams would be more fruitful.

This research has greatly contributed to the understanding of the impact of government funding and scientific and innovation networks on research. It has analyzed not only the quantity, but also the quality of scientific and technological outputs in nanotechnology.

Limitations

An inherent limit of this thesis is that nanotechnology is a rather narrow field. Despite our efforts to extract the papers and patents most relevant to the field, it is possible some were not included due to our narrow definition of nanotechnology. However, nanotechnology is an emerging field and some new keywords may have been missed in our careful canvassing of the scientific literature. Also, our study does not take into consideration articles written in languages other than English, which may affect the difference in productivity between French-speaking and English-speaking parts of Canada.

Another limitation of this study was the ambiguity of scientists' names in merging different publishing, patenting and funding databases. Although we performed a check of individuals' name to avoid this bias, it may have caused some deterioration or loss of the data.

The other limitation resides in the mobility of researchers across the US and Canada. Given the main purpose of this study is to compare outputs from researchers affiliated with either Canadian or American institutions, the mobility of these researchers between institutions clearly affects the results. This issue however could not be addressed in this study.

Another limitation of this thesis is that we could not measure the impact that graduate students have on the production of research teams, since they are not academic professors and therefore not included in our funding databases.

Moreover, nanotechnology is an emerging field and not only has the number of patents and publications been rapidly growing, but funding has also been increasing to develop this new technology. However, the collaborative structure of researchers has been rapidly changing over time that can affect the findings we found in this thesis.

Finally, our study is limited to nanotechnology-related publications and patents, but funding is generally granted to researchers and we are not able to separate the amount of funding that is only allocated for nanotechnology research of scientists.

Recommendations for future research

This thesis can be extended by gathering industry funding data for other provinces in Canada and the US. This will allow for a broader understanding of the innovative productivity and patent quality of researchers especially since industry partners appear to value the innovative performance over publication productivity.

Furthermore, there is a need for more investigations on how industry funding can affect research collaborations.

Given the role of graduate students in the production of papers and patents, future studies can address this knowledge gap. Scholarships and international funds can also be taken into consideration in studying the impact of funding on research output. Furthermore, the study can also be extended by analyzing the size of grants. Such investigations would reveal further insight on the relationship between funding and research outputs, the quality of research outputs, and also raise some interesting questions about research teams and co-author/co-inventor relationships that can shed some light on the need for further networking policies.

A final recommendation for future research is to study the economic value of patents contributed to academic research. This investigation would further our understanding of patent quality indicators and allow us to measure the returns for patent inventors or assignees.

Numerous opportunities exist for researchers to further our understanding of the funding and collaborations due to the great importance of nanotechnology. We hope to observe rich and diverse discussions on the subject in the near future that will provide overarching benefits of further study in this field.

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APPENDIX A – TABLES AND FIGURES of ARTICLE 2

Table A.1: First stage regressions results –The US (Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1)

The US	nbPaper (FS-reg)				nbCitation5 (FS-reg)			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
$nbPast3Pat_{it-1}$	0.0315 ***	0.1174 ***	0.1172 ***	0.1172 ***	0.0315 ***	0.1174 ***	0.1172 ***	0.1172 ***
	(0.0041)	(0.0099)	(0.0099)	(0.0099)	(0.0041)	(0.0099)	(0.0099)	(0.0099)
$[nbPast3Pat_{it}]^2$		-0.0049 ***	-0.0049 ***	-0.0049 ***		-0.0049 ***	-0.0049 ***	-0.0049 ***
		(0.0005)	(0.0005)	(0.0005)		(0.0005)	(0.0005)	(0.0005)
$\ln(10^4 \times BetweenCent_{it-2})$	-0.0201	-0.0083	0.0142	0.0142	-0.0201	-0.0083	0.0142	0.0142
	(0.2238)	(0.2232)	(0.2232)	(0.2232)	(0.2238)	(0.2232)	(0.2232)	(0.2232)
$\ln(10^3 \times Cliquishness_{it-2})$	-0.1912 ***	-0.1874 ***	-0.7074 ***	-0.7074 ***	-0.1912 ***	-0.1874 ***	-0.7074 ***	-0.7074 ***
	(0.0133)	(0.0133)	(0.1985)	(0.1985)	(0.0133)	(0.0133)	(0.1985)	(0.1985)
$[\ln(10^3 \times Cliquishness_{it-2})]^2$			0.0769 ***	0.0769 ***			0.0769 ***	0.0769 ***
			(0.0293)	(0.0293)			(0.0293)	(0.0293)
CareerAge	1.1155 ***	1.1148 ***	1.1153 ***	1.1153 ***	1.1155 ***	1.1148 ***	1.1153 ***	1.1153 ***
	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)
$[CareerAge]^2$	-0.0585 ***	-0.0584 ***	-0.0584 ***	-0.0584 ***	-0.0585 ***	-0.0584 ***	-0.0584 ***	-0.0584 ***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
$nbAvgPaper3_{t-1}$	0.1879 ***	0.1895 ***	0.1920 ***	0.1920 ***	0.1879 ***	0.1895 ***	0.1920 ***	0.1920 ***
	(0.0370)	(0.0367)	(0.0366)	(0.0366)	(0.0370)	(0.0367)	(0.0366)	(0.0366)
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes **
Constant	1.2424 ***	1.1643 ***	1.1623 ***	1.1623 ***	1.2424 ***	1.1643 ***	1.1623 ***	1.1623 ***
	(0.0900)	(0.0905)	(0.0905)	(0.0905)	(0.0900)	(0.0905)	(0.0905)	(0.0905)
Nb-observations	56511	56511	56511	56511	56511	56511	56511	56511
Nb-groups	33655	33655	33655	33655	33655	33655	33655	33655
Loglikelihood	-171712	-171636	-171632	-171632	-171712	-171636	-171632	-171632
R^2	0.1634	0.1656	0.1658	0.1658	0.1634	0.1656	0.1658	0.1658

Table A.2: First stage regressions results –Canada (Standard errors in parentheses and *** $p<0.01$, ** $p<0.05$, * $p<0.1$)

Canada	nbPaper (FS-reg)				nbCitation5 (FS-reg)			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
$nbPast3Pat_{it-1}$	0.0102	0.2081	0.2034	0.2034	0.0102	0.2081	0.2034	0.2034
	(0.0749)	(0.1464)	(0.1477)	(0.1477)	(0.0749)	(0.1464)	(0.1477)	(0.1477)
$[nbPast3Pat_{it}]^2$		-0.0238 *	-0.0238 *	-0.0238 *		-0.0238 *	-0.0238 *	-0.0238 *
		(0.0140)	(0.0142)	(0.0142)		(0.0140)	(0.0142)	(0.0142)
$\ln(10^4 \times BetweenCent_{it-2})$	-0.0881	-0.0890	-0.2045	-0.2045	-0.0881	-0.0890	-0.2045	-0.2045
	(0.1255)	(0.1257)	(0.1473)	(0.1473)	(0.1255)	(0.1257)	(0.1473)	(0.1473)
$\ln(10^3 \times Cliquishness_{it-2})$	-0.0654 ***	-0.0670 ***	0.4253	0.4253	-0.0654 ***	-0.0670 ***	0.4253	0.4253
	(0.0216)	(0.0217)	(0.3408)	(0.3408)	(0.0216)	(0.0217)	(0.3408)	(0.3408)
$[\ln(10^3 \times Cliquishness_{it-2})]^2$			-0.0724	-0.0724			-0.0724	-0.0724
			(0.0501)	(0.0501)			(0.0501)	(0.0501)
CareerAge	0.7714 ***	0.7721 ***	0.7705 ***	0.7705 ***	0.7714 ***	0.7721 ***	0.7705 ***	0.7705 ***
	(0.0342)	(0.0342)	(0.0341)	(0.0341)	(0.0342)	(0.0342)	(0.0341)	(0.0341)
$[CareerAge]^2$	-0.0393 ***	-0.0394 ***	-0.0394 ***	-0.0394 ***	-0.0393 ***	-0.0394 ***	-0.0394 ***	-0.0394 ***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
$nbAvgPaper3_{t-1}$	0.0250	0.0196	-0.0036	-0.0036	0.0250	0.0196	-0.0036	-0.0036
	(0.0493)	(0.0497)	(0.0545)	(0.0545)	(0.0493)	(0.0497)	(0.0545)	(0.0545)
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.9853 ***	-0.9918 ***	-0.9854 ***	-0.9854 ***	-0.9853 ***	-0.9918 ***	-0.9854 ***	-0.9854 ***
	(0.0800)	(0.0802)	(0.0799)	(0.0799)	(0.0800)	(0.0802)	(0.0799)	(0.0799)
Nb-observations	8180	8180	8180	8180	56511	56511	56511	56511
Nb-groups	3684	3684	3684	3684	3684	3684	3684	3684
Loglikelihood	-23680	-23678	-23677	-23677	-23680	-23678	-23677	-23677
R^2	0.2254	0.2258	0.2260	0.2260	0.2254	0.2258	0.2260	0.2260

Table A.3: Descriptive statistics

	Canada					United States				
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
$nbPaper_t$	8180	1	2	0	44	56511	0	1	0	44
$nbCitation5_t$	8180	8	39	0	985	56511	2	24	0	1766
$\ln(GovGrant3_{t-1})$	8180	10	1	4	15	56511	11	1	0	17
$nbPast3Pat_{it-1}$	8180	0	1	0	40	56511	3	5	0	53
$\ln(10^4 \times BetweenCent_{it-2})$	8180	0	1	0	5	56511	0	0	0	4
$\ln(10^3 \times Cliquishness_{it-2})$	8180	2	3	0	7	56511	1	3	0	7
CareerAge	8180	6	5	1	21	56511	5	5	1	21
$nbAvgPaper3_{t-1}$	8180	0	1	0	37	56511	0	1	0	40

Table A.4: Correlation Matrix – Canada

Variable		1	2	3	4	5	6	7	8
$nbPaper_t$	1	1							
$nbCitation5_t$	2	0.7545	1						
$\ln(GovGrant3_{t-1})$	3	0.0143	0.0162	1					
$nbPast3Pat_{it-1}$	4	0.084	0.0906	0.0086	1				
$\ln(10^4 \times BetweenCent_{it-2})$	5	0.5736	0.4333	0.0305	0.0801	1			
$\ln(10^3 \times Cliquishness_{it-2})$	6	0.3435	0.2421	0.027	0.0717	0.3096	1		
CareerAge	7	0.1225	0.0866	0.1216	0.0634	0.1569	0.1055	1	
$nbAvgPaper3_{t-1}$	8	0.8679	0.6565	0.0253	0.0915	0.6669	0.3879	0.153	1

Table A.5: Correlation Matrix – The US

Variable		1	2	3	4	5	6	7	8
$nbPaper_t$	1	1							
$nbCitation5_t$	2	0.4706	1						
$\ln(GovGrant3_{t-1})$	3	0.0494	0.0361	1					
$nbPast3Pat_{it-1}$	4	-0.0622	-0.0187	-0.0115	1				
$\ln(10^4 \times BetweenCent_{it-2})$	5	0.1030	0.0410	0.0088	-0.0331	1			
$\ln(10^3 \times Cliquishness_{it-2})$	6	0.3845	0.1385	0.0338	-0.1133	0.1943	1		
CareerAge	7	0.2097	0.0837	0.1669	-0.0949	0.0674	0.2643	1	
$nbAvgPaper3_{t-1}$	8	0.8967	0.4532	0.0537	-0.0685	0.1123	0.4224	0.2481	1

Table A.6: Second Stage of regression results of Poisson model – Impact of public funding on the number of papers and the number of citations in Canada and the US (Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1)

Variable	nbPaper				nbCitation5			
	Canada Model (1)		The US Model (1)		Canada Model (1)		The US Model (1)	
	W/O Endog	2SLS	W/O Endog	2SLS	W/O Endog	2SLS	W/O Endog	2SLS
ln(*GovGrant3*$_{it-1}$)	-0.0005		0.0377 ***		0.0072		0.0538***	
	(0.0081)		(0.0036)		(0.0114)		(0.0105)	
nbPast3Pat$_{it-1}$	0.1567***	0.1484***	-0.0331 ***	-0.0352***	0.1892***	0.1837***	-0.0358	-0.0430
	(0.0197)	(0.0197)	(0.0087)	(0.0079)	(0.0237)	(0.0238)	(0.0308)	(0.0266)
ln(10^4×*BetweenCent*$_{it-2}$)	0.6327***	0.6137***	0.3414 ***	0.3404***	0.6316***	0.6200***	0.5031***	0.5296 ***
	(0.0480)	(0.0460)	(0.0585)	(0.0553)	(0.0789)	(0.0766)	(0.1185)	(0.1212)
ln(10^3×*Cliquishness*$_{it-2}$)	0.1226***	0.1195***	0.3138 ***	0.3097***	0.1105***	0.1089***	0.3380***	0.3468 ***
	(0.0117)	(0.0117)	(0.0063)	(0.0063)	(0.0190)	(0.0190)	(0.0184)	(0.0209)
Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prediction(*GovGrant3*$_{it-1}$)-2SLS		(0.1002)***		0.3491***		0.0696		0.5329 ***
		0.0319		(0.0219)		(0.0500)		(0.0863)
Constant	-0.7651***	-1.3227***	-1.6618 ***	-2.9757***	2.0338***	1.6903***	0.3458*	-1.8670 ***
	(0.0848)	(0.1998)	(0.0842)	(0.1349)	(0.1240)	(0.3038)	(0.2053)	(0.5276)
Nb observations	8180	8180	56511	56511	8180	8180	56511	56511
Nb Groups	3684	3684	33655	33655	3684	3684	33655	33655
Loglikelihood	-8625	-8601	-41322	-38924	-133895	-133755	-413909	-382311
χ^2	714.6***	675.9***	5104 ***	5266***	636.89***	631.12***	968.10***	788.54 ***

Table A.7: Second Stage of regression results of xtpoisson model – Impact of public funding on the number of papers and the number of citations in Canada and the US (Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1)

Variable	nbPaper				nbCitation5			
	Canada Model (1)		The US Model (1)		Canada Model (1)		The US Model (1)	
	W/O Endog	2SLS	W/O Endog	2SLS	W/O Endog	2SLS	W/O Endog	2SLS
ln(*GovGrant3*$_{it-1}$)	-0.0145 ***		0.0171 ***		0.0003		0.0019**	
	(0.0049)		(0.0019)		(0.0015)		(0.0008)	
nbPast3Pat$_{it-1}$	0.2196***	0.2156***	-0.0338 ***	-0.0406***	0.2248***	0.2385***	-0.0082***	-0.0189 ***
	(0.0314)	(0.0319)	(0.0033)	(0.0033)	(0.0094)	(0.0095)	(0.0017)	(0.0018)
ln(10^4×*BetweenCent*$_{it-2}$)	0.1642***	0.1382***	0.2207 ***	0.1534***	-0.1501***	-0.1507***	0.4149***	0.4100 ***
	(0.0229)	(0.0231)	(0.0431)	(0.0433)	(0.0077)	(0.0076)	(0.0138)	(0.0138)
ln(10^3×*Cliquishness*$_{it-2}$)	0.0108	0.0008	0.0954 ***	0.1221***	-0.0874***	-0.0810***	-0.0223***	-0.0099 ***
	(0.0084)	(0.0083)	(0.0040)	(0.0039)	(0.0025)	(0.0025)	(0.0015)	(0.0015)
Years (1996-2005)	Yes	Yes		Yes	Yes	Yes	Yes	
Prediction(*GovGrant3*$_{it-1}$)-2SLS		0.1770***		0.2420***		0.1457***		0.0863 ***
		(0.0217)		(0.0062)		(0.0073)		(0.0031)
Constant	-0.3677***	-1.3967***	-1.7050 ***	-2.7025***	3.0109***	2.1255***	0.0643	-0.3056 ***
	(0.0633)	(0.1290)	(0.0523)	(0.0593)	(0.0728)	(0.0835)	(0.0613)	(0.0617)
ln(*alpha*)	1.3243***	1.3317***	2.0456 ***	1.8212***	2.8822***	2.8617***	4.7488***	4.7103 ***
	(0.0510)	(0.0502)	(0.0240)	(0.0246)	(0.0360)	(0.0361)	(0.0276)	(0.0278)
Nb observations	8180	8180	56511	56511	8180	8180	56511	56511
Nb Groups	3684	3684	33655	33655	3684	3684	33655	33655
Loglikelihood	-6647.69	-6618.4	-28720.8	-27992.3	-39780.8	-39578.7	-76589.6	-76193.1
χ^2	496.26***	545.68***	2185.0 ***	3586.8***	8692.9***	8914.9***	6384.3***	7102.7 ***

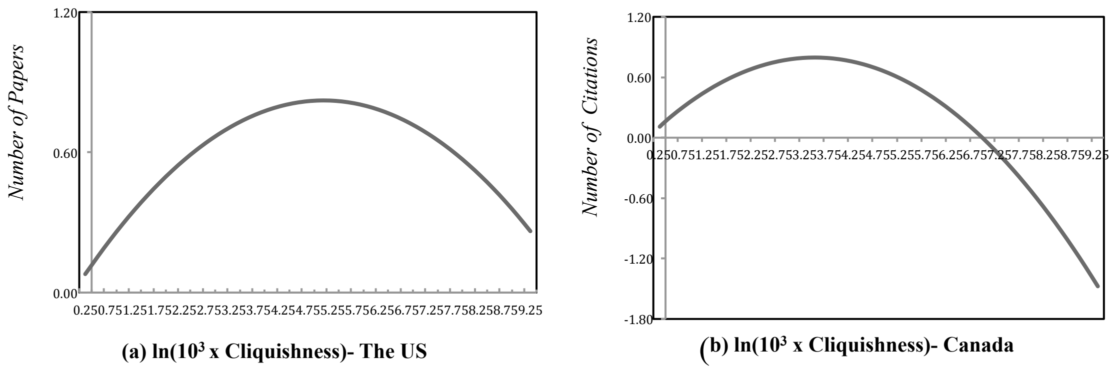

Figure A.1: A Quadratic effect of past individual cliquishness of scientists, Cliquishness, on (a) the number of papers in the US and (b) the number of citations in Canada

APPENDIX B – TABLES OF ARTICLE 3

Table B.1 : Description of dependent and explanatory variables

Variable	Variable Type	Description
$nbArtCit5_t$	D	Number of forward citations received by the papers of each scientist up to five years after publication
ln($AvgGrant3_{t-1}$)	En	Average yearly amount of grants received in the past 3 years lagged one year
ln($AvgContract3_{t-1}$)	Ex	Average yearly amount of contracts received in the past 3 years lagged one year
ln(10^4x$BtwCent3_{t-2}$)	Ex	Betweenness centrality of scientists in the three-year co-publication subnetwork lagged two years
ln(10^3x$Cliqness3_{t-2}$)	Ex	Cliquishness centrality of scientists in the three-year co-publication subnetwork lagged two years
Age_t	In	Career age of each scientist defined as the number of years since the first paper publication
Chair	In	Ordinal indicator that takes the value 0 if a researcher has no chair, the value 1 if he holds an industrial chair, the value 2 if being a chair of one of two Canadian federal granting councils, and the value 3 for a scientist who is a Canadian Research chair at some point in his career
$nbArticle3_{t-1}$	In	Average number of articles over the past 3 years lagged one year
$nbPatent3_{t-1}$	Ex	Number of patents over past three years lagged one year
d1997-d2005	Ex	Year dummy variables

Notes: D: Dependent Variable, En: Endogenous Variable, Ex: Exogenous variable, In: Instrumental Variable

Table B.2 : Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$nbArtCit5_t$	8319	6.6875	34.3190	0.0000	878.0000
ln($AvgGrant3_{t-1}$)	8319	11.1988	1.4135	2.9337	16.5820
ln($AvgContract3_{t-1}$)	8319	3.6895	4.9457	0.0000	16.2668
$nbPatent3_{t-1}$	8319	0.1543	0.9919	0.0000	43.0000
ln(10^4x$BtwCent3_{t-2}$)	8319	0.1350	0.5664	0.0000	4.8911
ln(10^3x$Cliqness3_{t-2}$)	8319	1.8369	2.9486	0.0000	6.9088
Chair	8319	0.0030	0.0855	0.0000	3.0000
Age_t	8319	16.6497	2.8822	12.0000	21.0000
Avg($nbArticle3_{t-1}$)	8319	0.4310	1.2274	0	18.6666

Table B.3 : Correlation matrix

Variable		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
$nbArtCit5_t$	**1**	1.0000								
ln($AvgGrant3_{t-1}$)	**2**	0.0896	1.0000							
ln($AvgContract3_{t-1}$)	**3**	0.0114	0.2580	1.0000						
$nbPatent3_{t-1}$	**4**	0.0455	0.0632	0.0769	1.0000					
ln(10^4x$BtwCent3_{t-2}$)	**5**	0.4210	0.0897	0.0482	0.0793	1.0000				
ln(10^3x$Cliqness3_{t-2}$)	**6**	0.2361	0.1126	0.0404	0.0701	0.3148	1.0000			
Chair	**7**	-0.0031	0.0134	-0.0097	0.0016	-0.0084	-0.0054	1.0000		
Age_t	**8**	0.0738	0.1578	-0.0250	0.0037	0.0469	0.1035	0.0476	1.0000	
Avg($nbArticle3_{t-1}$)	**9**	0.6045	0.1166	0.0324	0.0825	0.7002	0.4352	-0.0062	0.0938	1.0000

Table B.4 : First stage regressions results

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
ln(*AvgContract3*$_{t-1}$)	0.1650 ***	0.0603	0.0606	0.0604	0.0604	0.0633	0.0650
	(0.0082)	(0.0410)	(0.0411)	(0.0412)	(0.0412)	(0.0404)	(0.0403)
[ln(*AvgContract*$_{t-1}$)]^2		0.0098 **	0.0097 **	0.0097 **	0.0097 **	0.0095 **	0.0092 **
		(0.0038)	(0.0038)	(0.0039)	(0.0039)	(0.0038)	(0.0038)
nbPatent3$_{t-1}$	0.0569	0.0430	0.0528	0.0469	0.0469	0.0766	0.1213
	(0.0615)	(0.0589)	(0.0989)	(0.0995)	(0.0995)	(0.0554)	(0.0994)
[*nbPatent3t*$_{t-1}$]^2			-0.0005	-0.0004	-0.0004		-0.0021
			(0.0025)	(0.0025)	(0.0025)		(0.0026)
ln(10^4x*BtwCent3*$_{t-2}$)	0.0278	0.0258	0.0255	-0.1105	-0.1105	-0.3480	-0.1955 *
	(0.0877)	(0.0875)	(0.0876)	(0.0939)	(0.0939)	(0.4767)	(0.1003)
ln(10^3x*Cliqness3*$_{t-2}$)	0.0240	0.0247	0.0246	0.6679 ***	0.6679 ***	0.0218	0.7329 ***
	(0.0154)	(0.0154)	(0.0154)	(0.2241)	(0.2241)	(0.0155)	(0.2181)
[ln(10^3x*Cliqness3*$_{t-2}$)]^2				-0.0944 ***	-0.0944 ***		-0.1044 ***
				(0.0330)	(0.0330)		(0.0321)
ln(10^4x*BtwCent3*$_{t-2}$) x *NbPatent3*$_{t-1}$						-0.1503 **	0.0278
						(0.0691)	(0.0702)
[ln(10^4x*BtwCent3*$_{t-2}$) x NbPatent3$_{t-1}$]^2							-0.0293 ***
							(0.0080)
ln(10^4x*BtwCent3*$_{t-2}$) x ln(10^3x*Cliqness3*$_{t-2}$)						0.0747	-0.0853
						(0.0845)	(0.1828)
[ln(10^4x*BtwCent3*$_{t-2}$) x ln(10^3x*Cliqness3*$_{t-2}$)]^2							0.0176
							(0.0301)
Chair	0.0287	0.0315	0.0304	0.0453	0.0453	0.0277	0.0382
	(0.3447)	(0.3415)	(0.3419)	(0.3401)	(0.3401)	(0.3422)	(0.3413)
Age$_t$	0.0639 ***	0.0647 ***	0.0646 ***	0.0651 ***	0.0651 ***	0.0645 ***	0.0645 ***
	(0.0144)	(0.0144)	(0.0144)	(0.0144)	(0.0144)	(0.0144)	(0.0144)
Avg(*nbArticle3*$_{t-1}$)	0.1561 ***	0.1580 ***	0.1575 ***	0.1082 ***	0.1082 ***	0.1734 ***	0.1143 ***
	(0.0379)	(0.0380)	(0.0381)	(0.0392)	(0.0392)	(0.0384)	(0.0408)
Constant	8.9899 ***	8.9913 ***	8.9921 ***	8.9873 ***	8.9873 ***	8.9900 ***	8.9923 ***
	(0.2416)	(0.2418)	(0.2419)	(0.2420)	(0.2420)	(0.2418)	(0.2421)
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb observations	8319	8319	8319	8319	8319	8319	8319
Nb groups	1382	1382	1382	1382	1382	1382	1382
R^2	0.1014	0.1023	0.1023	0.1031	0.1031	0.1031	0.1046
F-statistics	40.22 ***	38.68 ***	36.55 ***	35.19 ***	35.20 ***	34.23 ***	31.39 ***

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

APPENDIX C – TABLES OF ARTICLE 4

Table C.1 : 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 five 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 three years (*t*-3 to *t*-1)
NPP_{it-1}	Number of applied patents of an academic-inventor *i* over past three years (*t*-3 to *t*-1)
PBC_{it-2}	Betweenness centrality of an academic-inventor *i* in the three-year **co-invention** subnetwork lagged two years.
PCC_{it-2}	Clustering coefficient of an academic-inventor *i* in the three-year **co-invention** subnetwork lagged two years.
ABC_{it-2}	Betweenness centrality of an academic-inventor *i* in the three-year **co-publication** subnetwork lagged two years.
ACC_{it-2}	Clustering coefficient of an academic-inventor *i* in the three-year **co-publication** subnetwork lagged two years.
D_t	Dummy variables for different years (*t* = 1985, …, 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 three years.

Table C.2 : First stage regression results – Number of patents – Canada and the United States

	NP_{it}					
	Canada (1)	**US (4)**	**Canada (2)**	**US (5)**	**Canada (3)**	**US (6)**
NPP_{it-1}	-0.0820	-0.0090	-0.0327	-0.0118	-0.0012	0.0073
	(0.0768)	(0.0243)	(0.1002)	(0.0254)	(0.1742)	(0.0353)
$[NPP_{it-1}]^2$					-0.0095	-0.0012
					(0.0134)	(0.0009)
$ln(10^4 \times PBC_{it-2})$	0.3518	-0.0562	0.6387 *	-0.2338	0.2875	-0.3689
	(0.3143)	(0.2250)	(0.3424)	(0.3500)	(0.4836)	(0.2327)
$ln(10^4 \times ABC_{it-2})$	-0.0513	0.1183	-0.0542	0.1119	-0.2706	0.1799
	(0.2082)	(0.5653)	(0.2088)	(0.5656)	(0.2223)	(0.5636)
$ln(10^3 \times PCC_{it-2})$	0.0426	0.0023	0.0375	0.0033	0.1087	0.6898 **
	(0.0420)	(0.0205)	(0.0424)	(0.0206)	(0.7611)	(0.3131)
$[ln(10^3 \times PCC_{it-2})]^2$					-0.0106	-0.1022 **
					(0.1114)	(0.0462)
$ln(10^3 \times ACC_{it-2})$	-0.0273	0.0781 ***	-0.0285	0.0778 ***	0.9590 *	-0.7427
	(0.0463)	(0.0281)	(0.0463)	(0.0281)	(0.4918)	(0.4646)
$[ln(10^3 \times ACC_{it-2})]^2$					-0.1467 **	0.1209 *
					(0.0736)	(0.0684)
$ln(10^4 \times PBC_{it-2}) \times NPP_{it-1}$			-0.2156	0.0261		
			(0.1567)	(0.0370)		
Age_{it}	0.3161 ***	0.3847 ***	0.3131 ***	0.3849 ***	0.3107 ***	0.3805 ***
	(0.0849)	(0.0389)	(0.0850)	(0.0389)	(0.0848)	(0.0391)
$[Age_{it}]^2$	-0.0112 **	-0.0119 ***	-0.0110 **	-0.0119 ***	-0.0113 **	-0.0118 ***
	(0.0048)	(0.0021)	(0.0048)	(0.0021)	(0.0048)	(0.0021)
NA_{it}	0.0925	0.2650 ***	0.0925	0.2641 ***	0.0502	0.2627 ***
	(0.0584)	(0.0329)	(0.0586)	(0.0330)	(0.0589)	(0.0330)
Constant	5.4334 ***	2.0645 ***	5.4327 ***	2.0652 ***	5.4682 ***	2.0798 ***
	(0.5056)	(0.2445)	(0.5055)	(0.2445)	(0.5061)	(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	0.2245	0.0432	0.2252	0.0432	0.2266	0.0443

Notes: ***, **, * show significance at the 1%, 5% and 10% levels. Standard errors are presented at parentheses.

Table C.3 : 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}	-0.0820	-0.0090	-0.0327	-0.0118	-0.0012	0.0073
	(0.0768)	(0.0243)	(0.1002)	(0.0254)	(0.1742)	(0.0353)
$[NPP_{it-1}]^2$					-0.0095	-0.0012
					(0.0134)	(0.0009)
$ln(10^4 \times PBC_{it-2})$	0.3518	-0.0562	0.6387 *	-0.2338	0.2875	-0.3689
	(0.3143)	(0.2250)	(0.3424)	(0.3500)	(0.4836)	(0.2327)
$ln(10^4 \times ABC_{it-2})$	-0.0513	0.1183	-0.0542	0.1119	-0.2706	0.1799
	(0.2082)	(0.5653)	(0.2088)	(0.5656)	(0.2223)	(0.5636)
$ln(10^3 \times PCC_{it-2})$	0.0426	0.0023	0.0375	0.0033	0.1087	0.6898 **
	(0.0420)	(0.0205)	(0.0424)	(0.0206)	(0.7611)	(0.3131)
$[ln(10^3 \times PCC_{it-2})]^2$					-0.0106	-0.1022 **
					(0.1114)	(0.0462)
$ln(10^3 \times ACC_{it-2})$	-0.0273	0.0781 ***	-0.0285	0.0778 ***	0.9590 *	-0.7427
	(0.0463)	(0.0281)	(0.0463)	(0.0281)	(0.4918)	(0.4646)
$[ln(10^3 \times ACC_{it-2})]^2$					-0.1467 **	0.1209 *
					(0.0736)	(0.0684)
$ln(10^4 \times PBC_{it-2}) \times NPP_{it-1}$			-0.2156	0.0261		
			(0.1567)	(0.0370)		
Age_{it}	0.3161 ***	0.3847 ***	0.3131 ***	0.3849 ***	0.3107 ***	0.3805 ***
	(0.0849)	(0.0389)	(0.0850)	(0.0389)	(0.0848)	(0.0391)
$[Age_{it}]^2$	-0.0112 **	-0.0119 ***	-0.0110 **	-0.0119 ***	-0.0113 **	-0.0118 ***
	(0.0048)	(0.0021)	(0.0048)	(0.0021)	(0.0048)	(0.0021)
NA_{it}	0.0925	0.2650 ***	0.0925	0.2641 ***	0.0502	0.2627 ***
	(0.0584)	(0.0329)	(0.0586)	(0.0330)	(0.0589)	(0.0330)
Constant	5.4334 ***	2.0645 ***	5.4327 ***	2.0652 ***	5.4682 ***	2.0798 ***
	(0.5056)	(0.2445)	(0.5055)	(0.2445)	(0.5061)	(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	0.2245	0.0432	0.2252	0.0432	0.2266	0.0443

Notes: ***, **, * show significance at the 1%, 5% and 10% levels. Standard errors are presented at parentheses.

Table C.4 : 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

Notes: ***, **, * show significance at the 1%, 5% and 10% levels. Standard errors are presented at parentheses.

Table C.5 : First stage regressions – Number of patents, number of claims, and citations – Canada and the United States together

Variables	**NP_{it}**			**NCL_{it}**			**$C(NCi_{it})$**	
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**
NPP_{it-1}	-0.0115	-0.0141	0.0085	-0.0115	-0.0141	0.0085	0.0469	0.0366
	(0.0243)	(0.0253)	(0.0352)	(0.0243)	(0.0253)	(0.0352)	(0.0461)	(0.0461)
$[NPP_{it-1}]^2$			-0.0014			-0.0014	-0.0015	-0.0016
			(0.0008)			(0.0008)	(0.0013)	(0.0014)
$ln(10^4 \times PBC_{it-2})$	-0.1304	-0.2978	-0.4217 *	-0.1304	-0.2978	-0.4217 *	0.1477	-0.2645
	(0.2256)	(0.3515)	(0.2329)	(0.2256)	(0.3515)	(0.2329)	(0.3723)	(0.4088)
$ln(10^4 \times ABC_{it-2})$	0.0859	0.0797	0.1457	0.0859	0.0797	0.1457		
	(0.5554)	(0.5557)	(0.5541)	(0.5554)	(0.5557)	(0.5541)		
$ln(10^3 \times PCC_{it-2})$	-0.0110	-0.0101	0.6237 **	-0.0110	-0.0101	0.6237 **	-0.0298	0.9360 *
	(0.0204)	(0.0205)	(0.3147)	(0.0204)	(0.0205)	(0.3147)	(0.0387)	(0.4936)
$[ln(10^3 \times PCC_{it-2})]^2$			-0.0944 **			-0.0944 **		-0.1442 **
			(0.0465)			(0.0465)		(0.0734)
$ln(10^3 \times ACC_{it-2})$	0.0781 ***	0.0778 ***	-0.6873	0.0781 ***	0.0778 ***	-0.6873	-0.0230	-0.0258
	(0.0280)	(0.0280)	(0.4653)	(0.0280)	(0.0280)	(0.4653)	(0.0542)	(0.0541)
$[ln(10^3 \times ACC_{it-2})]^2$			0.1128 *			0.1128 *		
			(0.0684)			(0.0684)		
$ln(10^4 \times PBC_{it-2}) \times NPP_{it-1}$		0.0246			0.0246			
		(0.0369)			(0.0369)			
Age_{it}	0.4428 ***	0.4432 ***	0.4372 ***	0.4428 ***	0.4432 ***	0.4372 ***	0.5391 ***	0.5412 ***
	(0.0348)	(0.0349)	(0.0351)	(0.0348)	(0.0349)	(0.0351)	(0.0789)	(0.0789)
$[Age_{it}]^2$	-0.0166 ***	-0.0167 ***	-0.0165 ***	-0.0166 ***	-0.0167 ***	-0.0165 ***	-0.0205 ***	-0.0207 ***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0047)	(0.0047)
NA_{it}	0.2889 ***	0.2882 ***	0.2858 ***	0.2889 ***	0.2882 ***	0.2858 ***	0.1641 ***	0.1649 ***
	(0.0330)	(0.0331)	(0.0332)	(0.0330)	(0.0331)	(0.0332)	(0.0525)	(0.0518)
dCA	1.1173 ***	1.1149 ***	1.0681 ***	1.1173 ***	1.1149 ***	1.0681 ***	0.7120	0.6521
	(0.2396)	(0.2396)	(0.2410)	(0.2396)	(0.2396)	(0.2410)	(0.6015)	(0.6047)
$dCA \times NPP_{it-1}$	-0.1247	-0.1023	-0.1005	-0.1247	-0.1023	-0.1005	-0.5123 *	-0.4872
	(0.0774)	(0.1014)	(0.1763)	(0.0774)	(0.1014)	(0.1763)	(0.3003)	(0.2967)
$dCA \times [NPP_{it-1}]2$			-0.0031			-0.0031	0.0154	0.0157
			(0.0128)			(0.0128)	(0.0184)	(0.0182)
$dCA \times ln(10^4 \times PBC_{it-1})$	0.4545	0.7390	0.8130	0.4545	0.7390	0.8130	-0.8367	-0.1250
	(0.4356)	(0.5210)	(0.5842)	(0.4356)	(0.5210)	(0.5842)	(0.6240)	(0.7723)
$dCA \times ln(10^4 \times ABC_{it-1})$	-0.1501	-0.1454	-0.5174	-0.1501	-0.1454	-0.5174		
	(0.6028)	(0.6033)	(0.6070)	(0.6028)	(0.6033)	(0.6070)		
$dCA \times ln(10^3 \times PCC_{it-2})$	0.0079	0.0052	-0.8982	0.0079	0.0052	-0.8982	0.0590	-1.6833
	(0.0493)	(0.0495)	(0.8776)	(0.0493)	(0.0495)	(0.8776)	(0.1328)	(1.2832)

Table C.5: First stage regressions – Number of patents, number of claims, and citations – Canada and the United States together (Continued)

dCA × [ln(10³ × PCC$_{it-2}$)]²			0.1339			0.1339		0.2603
			(0.1285)			(0.1285)		(0.1905)
dCA × ln(10³ × ACC$_{it-2}$)	-0.0608	-0.0610	2.0723 ***	-0.0608	-0.0610	2.0723 ***	0.0716	0.0802
	(0.0538)	(0.0539)	(0.6885)	(0.0538)	(0.0539)	(0.6885)	(0.1270)	(0.1264)
dCA × [ln(10³ × ACC$_{it-2}$)]²			-0.3160 ***			-0.3160 ***		
			(0.1021)			(0.1021)		
dCA × ln(10⁴ × PBC$_{it-2}$) × NPP$_{it-1}$		-0.1118			-0.1118			
		(0.1841)			(0.1841)			
dCA × Age$_{it}$	0.5377 ***	0.5345 ***	0.5512 ***	0.5377 ***	0.5345 ***	0.5512 ***	0.7224 ***	0.7242 ***
	(0.0939)	(0.0952)	(0.0947)	(0.0939)	(0.0952)	(0.0947)	(0.2706)	(0.2718)
dCA × [Age$_{it}$]²	-0.0327 ***	-0.0325 ***	-0.0335 ***	-0.0327 ***	-0.0325 ***	-0.0335 ***	-0.0476 ***	-0.0463 ***
	(0.0069)	(0.0070)	(0.0070)	(0.0069)	(0.0070)	(0.0070)	(0.0178)	(0.0177)
dCA × NA$_{it}$	-0.1733 **	-0.1726 **	-0.2276 ***	-0.1733 **	-0.1726 **	-0.2276 ***	-0.1266	-0.1343
	(0.0750)	(0.0751)	(0.0750)	(0.0750)	(0.0751)	(0.0750)	(0.1048)	(0.1030)
Constant	2.2512 ***	2.2518 ***	2.2632 ***	2.2512 ***	2.2518 ***	2.2632 ***	2.1194 ***	2.1380 ***
	(0.2245)	(0.2246)	(0.2256)	(0.2245)	(0.2246)	(0.2256)	(0.4316)	(0.4323)
Years	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Nb observations	10486	10486	10486	10486	10486	10486	2732	2732
Nb Groups	5913	5913	5913	5913	5913	5913	2121	2121
F	36.62 ***	34.11 ***	30.59 ***	36.62 ***	34.11 ***	30.59 ***	9.73 ***	9.12 ***
R^2	0.0640	0.0640	0.0653	0.0640	0.0640	0.0653	0.0633	0.0649

Notes: ***, **, * show significance at the 1%, 5% and 10% levels. Standard errors are presented at parentheses.

Table C.6 : Correlation Matrix – Canada

Variable	Obs	Mean	Std. Dev.	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	0.829	0.3767	0.7017	-0.0075	1						
PBC_t	1329	0.0403	(0.2842)	0.00	4.89	6	0.067	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 C.7: Correlation Matrix – United States

Variable	Obs	Mean	Std. Dev.	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	0.04	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 C.8: Mean comparison between Canada and five similarly-sized random subsamples for the United States

								Two-sided p-values					
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**	**Canada vs US**	**Canada vs US-s1**	**Canada vs US-s2**	**Canada vs US-s3**	**Canada vs US-s4**	**Canada vs 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)	(02423)	(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)						

Notes: Standard deviation in parentheses.

APPENDIX D – TABLES OF ARTICLE 5

Table D.1: First stage of regressions results

Variables	**Quebec**				**Rest of Canada**			
	NumPaper	**NumPaper**	**NumPatent**	**NumPatents**	**NumPaper**	**NumPaper**	**NumPatent**	**NumPatents**
	(1)	**(2)**	**(1)**	**(2)**	**(3)**	**(4)**	**(3)**	**(4)**
ln (10^4×DegCentPaper3$_{t-2}$)		0.9921***		1.3322 ***		0.9583 ***		1.4125 ***
		(0.0414)		(0.0717)		(0.0381)		(0.0579)
ln(10^4×BetCentPaper3$_{t-2}$)	0.4582***		0.7448***		0.6534***		1.0314 ***	
	(0.0738)		(0.1055)		(0.0960)		(0.1266)	
ln (10^4×DegCentPatent3$_{t-2}$)		0.1638		0.1159		0.2245 **		0.0995
		(0.1323)		(0.0988)		(0.0952)		(0.0642)
ln(10^4×BetCentPatent3$_{t-2}$)	0.0417		0.0338		-0.1181		0.1661	
	(0.2665)		(0.2864)		(0.2575)		(0.1930)	
ln(10^3×CliquishnessPatent3$_{t-2}$)	0.0696***	-0.7354	0.0218	-0.3480	0.0801***	-0.1572	0.0494 ***	0.0300
	(0.0240)	(0.4841)	(0.0223)	(0.3028)	(0.0182)	(0.2441)	(0.0162)	(0.1993)
[ln(10^3×CliquishnessPatent3$_{t-2}$)]^2		0.1119		0.0516		0.0291		-0.0006
		(0.0706)		(0.0441)		(0.0359)		(0.0292)
CanadaChair$_{it}$	0.1973 *	0.1331	0.5986 **	0.4425 *	0.1018	0.0622	0.3725 **	0.3235 **
	(0.1021)	(0.0917)	(0.2827)	(0.2597)	(0.0663)	(0.0585)	(0.1750)	(0.1463)
Award$_{it}$	0.1595	0.0936	0.7407	0.6086	0.1486	0.0920	0.1075	-0.0303
	(0.2822)	(0.2324)	(0.6186)	(0.4874)	(0.1727)	(0.1469)	(0.4133)	(0.3046)
NanoAge$_{it}$	0.3777***	0.3189***	0.1455***	0.1109 ***	0.3840***	0.3343 ***	0.0643 **	0.0663 ***
	(0.0208)	(0.0169)	(0.0460)	(0.0342)	(0.0134)	(0.0108)	(0.0325)	(0.0246)
[NanoAge$_{it}$]^2	-0.0192***	-0.0158***	-0.0072***	-0.0046 **	-0.0210***	-0.0178 ***	-0.0022	-0.0025
	(0.0013)	(0.0011)	(0.0028)	(0.0022)	(0.0009)	(0.0007)	(0.0024)	(0.0018)
NumPaper3$_{it}$	0.6728***	0.3800***	0.4250***	0.1440 **	0.5686***	0.3474 ***	0.2570 **	0.0612
	(0.0982)	(0.0728)	(0.1001)	(0.0576)	(0.1168)	(0.0800)	(0.1137)	(0.0565)
GrantAmount$_{it-1}$	-0.0145 *	-0.0189***	0.0012	-0.0097	-0.0055	-0.0075 *	0.0338 ***	0.0306 ***
	(0.0081)	(0.0070)	(0.0178)	(0.0145)	(0.0047)	(0.0042)	(0.0118)	(0.0101)
ln(10^4×BetCentPatent3$_{t-2}$) × ln(10^3×CliquishnessPatent3$_{t-2}$)		0.0610				-0.0325		
		(0.0711)				(0.0459)		
Years (1996-2005)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.3847***	0.0493	0.9938***	0.3611 ***	0.4401***	0.1132 ***	0.8817 ***	0.2780 ***
	(0.0583)	(0.0512)	(0.1674)	(0.1260)	(0.0366)	(0.0295)	(0.1087)	(0.0755)
Nb observations	13968	13968	3456	3456	44664	44664	7104	7104
Nb Groups	1164	1164	288	288	3722	3722	592	592
Loglikelihood	-32477.9	-31774.8	-8300.95	-7963.16	-100851	-98882.5	-16529.1	-15759.4
F Statistics	61.72***	204.3***	15.00***	55.81 ***	175.02***	450.83 ***	26.68 ***	106.65 ***

Table D.2 : NumPaper-Quebec

Variable		1	2	3	4	5	6	7	8	9	10	11	12
NumPapert	1	1											
DegCentPaper3$_{t-2}$	2	0.5482	1										
BetCentPaper3$_{t-2}$	3	0.4757	0.4212	1									
CliquishnessPaper3$_{t-2}$	4	0.2455	0.4775	0.31	1								
DegCentPatent3$_{t-2}$	5	0.1199	0.1333	0.1582	0.1029	1							
BetCentPatent3$_{t-2}$	6	0.045	0.0607	0.1057	0.0386	0.2092	1						
CliquishnessPatent3$_{t-2}$	7	0.1306	0.1515	0.15	0.1175	0.4723	0.207	1					
GrantAmount$_{t-1}$	8	0.0965	0.0882	0.0502	0.0862	0.0348	0.0268	0.0467	1				
CanadaChair$_t$	9	0.0241	0.0539	0.0154	0.0564	0.0204	0.0304	0.0212	0.1467	1			
Award$_t$	10	0.0448	0.0487	0.0354	0.0442	0.0239	0.006	0.0184	0.1251	0.1024	1		
NanoAge$_t$	11	0.1736	0.1582	0.1573	0.2189	0.078	0.0366	0.0907	0.2704	0.0987	0.0935	1	
NumPaper3$_t$	12	0.6228	0.5488	0.644	0.3879	0.1287	0.0399	0.1413	0.089	0.0415	0.0553	0.1901	1

Table D.3 : NumPatent-Quebec

Variable		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
$NumPatent_t$	1	1											
$DegCentPatent3_{t-2}$	2	0.2664	1										
$BetCentPatent3_{t-2}$	3	0.0936	0.1588	1									
$CliquishnessPatent3_{t-2}$	4	0.1067	0.3534	0.168	1								
$DegCentPaper3_{t-2}$	5	0.0444	0.1055	0.0689	0.1147	1							
$BetCentPaper3_{t-2}$	6	0.0093	0.1441	0.1218	0.1226	0.5162	1						
$CliquishnessPaper3_{t-2}$	7	0.0239	0.087	0.0436	0.0954	0.5585	0.3651	1					
$GrantAmount_{t-1}$	8	0.0046	0.0567	0.0497	0.1039	0.1023	0.0803	0.0893	1				
$CanadaChair_t$	9	-0.0106	0.0446	0.0656	0.0524	0.0517	0.0026	0.078	0.1733	1			
$Award_t$	10	-0.0056	0.0505	0.0137	0.0437	0.0493	0.0441	0.0638	0.0979	0.1288	1		
$NanoAge_t$	11	0.0071	0.0939	0.0419	0.1224	0.0994	0.1248	0.1287	0.2982	0.1196	0.0914	1	
$NumPaper3_t$	12	0.0137	0.0966	0.032	0.1014	0.5855	0.6995	0.388	0.1086	0.0324	0.0418	0.1428	1

Table D.4 : NumPaper-The rest of Canada

Variable		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
NumPapert	1	1											
DegCentPaper3$_{t-2}$	2	0.5418	1										
BetCentPaper3$_{t-2}$	3	0.4441	0.3908	1									
CliquishnessPaper3$_{t-2}$	4	0.2216	0.4524	0.3007	1								
DegCentPatent3$_{t-2}$	5	0.1292	0.1265	0.1521	0.0969	1							
BetCentPatent3$_{t-2}$	6	0.0827	0.0703	0.1174	0.042	0.2725	1						
CliquishnessPatent3$_{t-2}$	7	0.126	0.1356	0.146	0.1074	0.4491	0.1766	1					
GrantAmount$_{t-1}$	8	0.0863	0.0983	0.0583	0.1087	0.027	0.0099	0.0486	1				
CanadaChair$_{t}$	9	0.0312	0.0492	0.039	0.0477	0.0208	-0.0014	0.0078	0.113	1			
Award$_{t}$	10	0.0085	0.0316	0.0303	0.0282	0.013	-0.0038	0.0061	0.1321	0.094	1		
NanoAge$_{t}$	11	0.1969	0.1668	0.1794	0.2297	0.0768	0.0293	0.0824	0.2976	0.0969	0.0591	1	
NumPaper3$_{t}$	12	0.6165	0.5174	0.6233	0.3594	0.1355	0.0732	0.1513	0.0886	0.0455	0.0191	0.2034	1

Table D.5 : NumPatent- The rest of Canada

Variable		1	2	3	4	5	6	7	8	9	10	11	12
NumPatent$_{t}$	1	1											
DegCentPatent3$_{t-2}$	2	0.3097	1										
BetCentPatent3$_{t-2}$	3	0.1061	0.2051	1									
CliquishnessPatent3$_{t-2}$	4	0.1171	0.304	0.1324	1								
DegCentPaper3$_{t-2}$	5	0.0709	0.1188	0.1208	0.119	1							
BetCentPaper3$_{t-2}$	6	0.0366	0.1319	0.1588	0.1123	0.5257	1						
CliquishnessPaper3$_{t-2}$	7	0.0665	0.1063	0.0801	0.1169	0.5791	0.3912	1					
GrantAmount$_{t-1}$	8	-0.0031	0.0316	0.0244	0.0832	0.0796	0.0728	0.12	1				
CanadaChair$_{t}$	9	-0.0148	0.0491	-0.0042	0.0147	0.0382	0.0388	0.0633	0.1223	1			
Award$_{t}$	10	-0.0195	0.0165	-0.0103	0.0034	0.0386	0.0427	0.0339	0.1323	0.0983	1		
NanoAge$_{t}$	11	0.0191	0.0481	0.0428	0.0856	0.092	0.0792	0.1254	0.3036	0.0689	0.0519	1	
NumPaper3$_{t}$	12	0.054	0.0944	0.0836	0.1037	0.5711	0.6561	0.367	0.0967	0.0345	0.0193	0.1029	1

APPENDIX E – NANOTECHNOLOGY KEYWORDS

Search Term	Search Queries
Nano* terms	"nano assembly", "nano computer", "nano cubic technology", "nano molecular machine", "nano optic", "nano optical tweezers", "nano warfare", “nanoarray”, "nanoassembler", "nanobarcode", "nanobarcodes particle", "nanobioprocess", "nanobot", "nanobotics", "nanobots", "nanobubble", "nanobusiness alliance", "nanobusiness company", "nanocatalysis", "nanoceramic", "nanochemistry", "nanochip", "nanocircle", "nanocluster", "nanocomputer", "nanocone", "nanocontact", "nanocrystal", "nanocrystal antenna", "nanodefense", "nanodentistry", "nanodetect", "nanodevice", "nanodiamond", "nanodisaster", "nanodot", "nanoelectrospray", "nanoengineering", "nanofacture", "nanofacty", "nanofiber", "nanofibre", "nanofiltration", "nanofluidic", "nanofoam", "nanogate", "nanogear", "nanogenomic", "nanoimaging", "nanoimprint lithography", "nanoimprint machine", "nanoimprinting", "nanolabel", "nanolithography", "nanomachine", "nanomagnet", "nanomanipulat", "nanomanipulation", "nanomanufacturing", "nanomaterial", "nanomechanical", "nanomot", "nanoparticles”,nanowire", "nanope", "nanope", "nanopharmaceutical", "nanophotonic", "nanophysic", "nanoplumbing", "nanoprism", "nano-ring", "nanoscale self assembly", "nanoscale synthesis", "nanoscience", "nanoscopic scale", "nanoscopic scale", "nanosens", "nanosheet", "nanoshell", "nanosource", "nanostructure", "nanostructured", "nanosurgery", "nanosystem", "nanotechism", "nanotechnology", "nanotube", "nanotube bundle", "nanowalker", "nanowetting"
Quantum terms	"quantum cascade laser", "quantum coherence", "quantum

	computation", "quantum compute", "quantum computer", "quantum computing", "quantum conduct", "quantum conductance", "quantum conductivity", "quantum confine", "quantum device", "quantum dot", "quantum gate", "quantum information", "quantum information process", "quantum mirage", "quantum nanophysics", "quantum nanomechanics", "quantum system", "quantum well"
Molecular* terms	"molecular assembler", "molecular machine", "molecular nanogenerat", "molecular nanotechnology", "molecular robotic", "molecular scale manufacturing", "molecular systems engineering", "molecular technology"
Self assembly terms	"fluidic self assembly", "nanoscale self assembly", "self assembled"
Atomic terms	"atomic manipulation", "atomic nanostructure"
Other terms	"biofabrication", "biomedical nanotechnology", "biomimetic synthesis", "biomolecular assembly", "biomolecular nanoscale computing", "biomolecular nanotechnology", "bionems", "brownian assembly", "buckminsterfullerene", "buckyball", "buckytube", "c60 molecule", "carbon nanotubes", "conductance quantization", "dna chip", "electron beam lithography", "epitaxial film", "epitaxy", "fat fingers problem", "ganic led", "glyconanotechnology", "grey.goo", "immune machine", "khaki goo", "laser tweezer", "limited assembler", "military nanotech.", "moletronic", "naneplicat", "nanite", "optical trapping", "protein design", "protein engineering", "proximal probe", "rotaxane", "single cell manipulation", "spin coating", "stewart platfm", "sticky fingers problem", "textronic", "universal assembler", "utility fog", "zettatechnology"