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IMPACT OF UNIVERSITY–INDUSTRY COLLABORATION ON THE QUALITY OF BIOTECHNOLOGY AND NANOTECHNOLOGY PATENTS IN CANADA

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DEDICATION

I would like to dedicate this thesis to my husband and my family, especially my mother. I offer great appreciation for their help, inspiration, and support. Living far away from one's family is quite a challenge; yet they always encourage me to work hard for my achievements. I would like to thank my beloved husband who has allowed me to be far away from him for five months to be able to accomplish my thesis. I would like to dedicate this thesis also to my father, who has passed away; I am sure his soul is always with me. I would like to thank my brothers, who always encourage me, and who have taught me my goals are much closer than I imagine; I should just turn and look around carefully to find my goals and to reach them, instead of looking far in the distance.

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RÉSUMÉ

Cette thèse vise à explorer le rôle et l'impact de la collaboration au niveau des activités liées à la protection de la propriété intellectuelle par le biais de brevets sur la « qualité » de ces derniers dans les domaines de la biotechnologie et de la nanotechnologie au Québec. Nous examinons ici plusieurs mesures ou proxy normalement associés à la « qualité » des brevets. La thèse vise à répondre à la question suivante : *Existe-t-il des associations possibles entre les attributs de la collaboration université/industrie et la qualité d'un brevet?* Le réseau de collaboration regroupe des scientifiques œuvrant au sein des universités et des industries (Motohashi & Muramatsu, 2012). De plus, la propriété de brevets d'origine "universitaire" par les entreprises est souvent considérée comme l'un des canaux essentiels des *liens université-industrie* (Bray & Lee, 2000; Bulut & Moschini, 2009; Y. Wang, Hu, Li, Li, & Li, 2015; Y. Wang, Huang, Chen, Pan, & Chen, 2013; Y. Wang, Pan, Chen, & Gu, 2013). Selon des études exploratoires antécédentes en matière de brevets et de propriété intellectuelle, on recense relativement peu d'articles portant sur l'impact des réseaux de collaboration sur les activités de brevetage et sur la « qualité » des brevets au Canada. Dans cette thèse, nous examinons l'impact de ces réseaux, représentés par les liens entre des inventeurs et détenteurs de brevets avec les universités et les entreprises. Des facteurs tels le financement, le nombre d'années d'expérience de l'inventeur, les caractéristiques des réseaux de co-invention et de co-publication sont considérés afin d'estimer la « qualité » des brevets issus de la collaboration université/industrie au Canada. Sterzi (2013) a constaté que les brevets universitaires appartenant à des entreprises sont d'une qualité supérieure lorsqu'ils sont initialement assignés aux universités. Cette thèse vise donc aussi à mesurer l'impact des divers types de cessionnaires de brevets sur la « qualité » de ceux-ci, tout en considérant les liens université-entreprise.

Nos travaux ont étudié la « qualité » des brevets générés par les inventeurs universitaires au Canada et qui ont été assignés à une université ou au gouvernement et les ont comparés à la qualité des brevets détenus uniquement par l'industrie. La première question que cette thèse aborde est la suivante: *les brevets qui sont générés par au moins un inventeur issu du milieu universitaire (résidant au Canada) et assignés à une université sont-ils d'une « qualité » moindre que ceux appartenant seulement à une entreprise*? Également, en considérant le rôle du gouvernement en tant qu'entité du secteur public, nous posons la seconde question suivante : *les*

brevets qui sont générés par au moins un inventeur issu du milieu universitaire (résidant au Canada) et assignés au gouvernement sont-ils d'une « qualité » moindre que ceux appartenant seulement à une entreprise? Nous posons également des questions similaires afin de mesurer l'impact des cessionnaires gouvernementaux et universitaires sur la « qualité » des brevets, afin de comparer les impacts des cessionnaires publics par rapport aux cessionnaires industriels sur la « qualité » de l'invention.

En outre, cette thèse cherche à expliquer comment les caractéristiques spécifiques des inventeurs influencent la qualité des brevets issus de la collaboration université/industrie. Par conséquent, cette thèse vise également à répondre à la question suivante : *comment les caractéristiques des chercheurs affectent leur capacité à générer des brevets de meilleure « qualité »*? Des variables telles que le nombre d'années d'expérience et la collaboration avec de prestigieux inventeurs détendeurs de brevets sont considérées. De plus, nous avons observé l'impact des caractéristiques du réseau de co-invention et de co-publication sur la « qualité » des brevets. Nous avons donc mesuré si les brevets générés par les inventeurs situés dans des réseaux de co-inventeurs ou de co-auteurs très centraux sont d'une « qualité » supérieure à celle des brevets générés par les inventeurs moins centraux. En outre, cette recherche vise à déterminer si les brevets issus d'une combinaison brevet-article ou d'une combinaison brevet-subvention sont d'une « qualité » supérieure à ceux qui n'ont pas de telles combinaisons, soit des articles et brevets publiés par les mêmes équipes sur les mêmes thèmes de recherche et objets d'application.

Pour évaluer l'impact des attributs de la relation université-industrie sur la « qualité » des brevets, notre méthodologie consiste en l'estimation de régressions binomiales négatives classiques et à zéro-augmenté, Tobit, et à variables instrumentales pour les moindre carrés ordinaires (2SLS) afin de prendre en considération l'endogénéité potentielle de nos modèles. Nos mesures ou proxy de la « qualité » des brevets comprennent le nombre de citations, le nombre de revendications, un indice de type Herfindahl des citations en amont, et un indice de type Herfindahl des citations en aval. Ce type d'indice mesure la diversité des documents cités par un brevet en particulier et la diversité des brevets qui citent ce brevet.

Nos résultats montrent que les brevets générés par au moins un inventeur universitaire et appartenant au secteur public (gouvernement et université) citent une moins grande diversité de documents et sont moins cités que ceux issus du secteur privé (industriels). Nos résultats

montrent aussi que les brevets détenus par les institutions publiques sont moins diversifiés que les brevets détenus par le secteur privé. Par conséquent, les brevets attribués aux firmes sont susceptibles d'avoir obtenu plus de citations que les brevets de sources publiques (Popp, 2006; Popp, Santen, Fisher-Vanden, & Webster, 2013). Nos résultats sont cohérents avec les études antérieures de Popp (2006) and Popp et al. (2013).

Nous avons utilisé la méthode « fréquence de termes et fréquence de documents inverse » (TF-IDF) qui est une technique d'exploration de données classique permettant de mesurer la similitude entre les différentes combinaisons de paires de brevets et d'articles, afin d'identifier les paires brevet-article que nous allons utiliser. Nos résultats démontrent que l'impact des paires brevet-article sur la « qualité » des brevets est négatif pour les variables nombre de citations et nombre de revendications.

De même, nous avons utilisé la méthode TF-IDF pour mesurer la similitude des brevets et des subventions pour trouver les paires brevet-subvention. Nos résultats suggèrent qu'il n'y a un effet négatif des paires brevet-subvention sur le nombre de citations. Cependant, les paires brevet-subvention affectent positivement l'indice Herfindahl des citations obtenues.

Mots clés : collaboration université–industrie, qualité des brevets, propriété des brevets, cessionnaires universitaires, cessionnaires gouvernementaux, cessionnaires industriels, paires brevet-article, paires brevet–subvention, biotechnologie, nanotechnologie

ABSTRACT

This thesis aims to explore the role and impact of collaborative patenting on the "quality" of Biotechnology and Nanotechnology patents in Quebec. We examine a number of measures or proxy measures that are normally associated with the "quality" of patents. This study seeks to answer the following question: *Is there any association between university–industry collaboration attributes and a patent's quality?* The collaboration network includes university and industrial researchers and scientists (Motohashi & Muramatsu, 2012). Furthermore, the ownership of academic patents by corporations is often addressed as one of the essential channels of *university–industry ties* (Bray & Lee, 2000; Bulut & Moschini, 2009; Y. Wang et al., 2015; Y. Wang, Huang, et al., 2013; Y. Wang, Pan, et al., 2013). According to prior exploratory studies in patenting and intellectual property, there is a lack of attention given to the impact of the co-patenting network on the patent "quality" in Canada. In this research we explore the impact of these networks, represented by inventors' and assignees' ties to universities and corporations. Furthermore, particular factors including funding, inventors' career age, characteristics of the inventors' co-network, and publications are used to estimate the "quality" of joint patents granted to Canadian inventors and/or organisations. Sterzi (2013) found that academic patents owned by firms are of a higher quality when initially assigned to the universities. This study aims to measure the impact of the patent ownership structure on patent "quality", when the university–industry linkage is considered.

We investigated the "quality" of patents generated by academic inventors in Canada and assigned to the university or the government and compared it with the "quality" of patents privately held by industry. The first question that this research addresses is: *Are patents generated by at least one academic inventor (residing in Canada) and assigned to the university of a lesser "quality" than those owned by a firm?* Likewise, in regard to the role of government, as an entity of the public sector, we pose the following question: *Are patents generated by at least one academic inventor (residing in Canada) and assigned to the government of a lesser "quality" than those owned by an industry firm?* To answer the above questions we estimated the impact of government assignees and academic assignees on patent "quality", in order to compare the impacts of the public assignees and industrial assignees on invention "quality".

Furthermore, this study seeks to explain how the inventors' specific characteristics influence the "quality" of patents that stem from university–industry collaboration. Therefore, this thesis also aims to answer the following question: *How do the researchers' characteristics affect their opportunities to generate patents of a higher "quality"*? Variables such as career age and collaboration with prestigious patent inventors are considered. Moreover, we observed the impact of the co-invention and co-authorship network characteristics on patent "quality". We therefore measured whether patents generated by inventors that are highly centralized in the co-inventor or co-authorship networks are of a higher "quality" than patents created by inventors that occupy less centralized positions. Furthermore, this research aims to assess whether patents issued from a patent–paper pair or patent–grant pair are of a higher "quality" than those without such a link, i.e. articles and patents published by the same teams and on the same research topics and application objects.

To assess the impact of university–industry linkage attributes on patent "quality", our methodology uses classic and zero-inflated negative binomial regressions, Tobit, and two-stage least-squares regressions (2SLS) to account for potential endogeneity problems. Our measures or proxies of patent "quality" include the number of forward citations, the number of claims, a Herfindahl index of backward citations, and a Herfindahl index of forward citations. This type of index measures the diversity of documents cited by the patent, and the diversity of patents that cite this particular patent.

Our findings show that patents generated by at least one academic inventor and owned by the public sector (government and university) are of a lesser "quality" measured by both number of forward citations and a Herfindahl index of backward citations, than those of private (industrial) assignees. Our findings also reveal that patents owned by public institutions are less diversified than privately held patents. Therefore, the patents assigned to the corporations are likely to have obtained more citations than public patents (Popp, 2006; Popp et al., 2013). Our results are consistent with the former studies of Popp (2006) and Popp et al. (2013).

We used the Term Frequency and Inverse Document Frequency (TF-IDF) method as a classic data mining technique to measure the similarity between patents and papers, in order to identify the patent–paper pairs. Our results show that the impact of patent–paper pairs on patent "quality" is negative for the number of forward citations and number of claims variables.

Likewise, we used the TF-IDF method to measure the similarity of patents and grants to find the patent–grant pairs. Our results suggest there is a negative effect of patent–grant pairs on the number of forward citations. In contrast, patent–grant pairs positively affect the Herfindahl index of forward citations.

Keywords: University–Industry Collaboration, Patent Quality, Patent Ownership, Academic Assignees, Government Assignees, Industrial Assignees, Patent–Paper Pairs, Patent–Grant Pairs, Biotechnology, Nanotechnology

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LIST OF SYMBOLS AND ABBREVIATIONS

UILs	University–Industry Linkages
CIPO	Canadian Intellectual Property Office
USPTO	United States Patent and Trademark Office
SNA	Social Network Analysis
TLOs	Technology Licensing Offices
SIRU	Quebec University Research Information System
TCT	Technology Cycle Time
CII	Current Impact Index
SL	Science Linkage
NPRs	Non-Patent References
CI	Citation Index
IPC	International Patent Classifications

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CHAPTER 1 INTRODUCTION

Both biotechnology and nanotechnology are strongly science-based and useful in various other technologies (Motoyama, 2014). In this research, both the biotechnology and nanotechnology industry in Canada are examined.

The biotechnology sector has been rapidly growing, with a market of $200 billion in 2009, showing an annual growth rate of 10.2% during the period 2005 to 2009 (Soh & Subramanian, 2014). The health care and medical domains are the largest biotechnology application sectors, covering 66.2% of total biotechnology market value (Silber, 2010; Soh & Subramanian, 2014). The majority of the biotechnology firms located in Canada have been established from spin-offs of the regional universities and research facilities, such as the University of British Columbia (UBC). The annual research funding assigned to UBC reached CAD$350 million, an increase of over 250% over the previous 5 years (Groote & Gee, 2005). The provincial government in BC allocated over CAD$450 million for life-science researches in BC, showing the high priority of the governmental sector in developing biotechnology in that province (Groote & Gee, 2005). Canadian biotechnology firms are however predominantly located in Quebec and Ontario (L. A. Hall & Bagchi-Sen, 2002).

Regarding nanotechnology, Genet, Errabi, and Gauthier (2012) found that 90% of all nanotechnology SME firms are located in Europe, the US and Canada. Large and very large nanotechnology firms are mostly situated in Europe (48%), US/Canada (24%), and Asia (21%) (Genet et al., 2012). The US, as a leader of nanotechnology among the world, considers nanotechnology as one of the “22 National Key Technologies and Strategic Technologies in 2005” (Liu & Guan, 2016, p. 222). More than ten government agencies in the US supported the World Technology Evaluation Center at Loyola College to work on nanotechnology projects during 1996–1998 (Liu & Guan, 2016). Liu and Guan (2016) analyzed inter-organizational partnership in the field of nanoenergy in the US, and found collaboration between nanotechnology partners was fragmented across various integrated inter-institutional collaboration network components. The authors investigated the collaboration between different players engaging in small components as a salient factor. They found that particular universities and corporations are located in the center of the network, serving as a bridge between different entities. The components are highly integrated and all of the partners can reach each other directly and indirectly. Thus, information exchange can span the network widely and very fast (Liu & Guan, 2016). According to the network observations, the University of California and Massachusetts Institute of Technology (MIT) were located in the center and served as a bridge to diffuse the knowledge across the network (Liu & Guan, 2016).

Like nanotechnology, biotechnology as a science-based industry is an interesting, multidisciplinary field of study in the university–industry linkages (UILs) literature (Soh & Subramanian, 2014). UILs significantly affect economic growth in science and technology-based sectors (Cohen, Nelson, & Walsh, 2002; Mansfield, 1992; Soh & Subramanian, 2014). Transferring universities' discoveries to industry is essential in the life sciences, in order for inventions to be commercialized (George, Zahra, & Wood Jr, 2002; Murray, 2002; Soh & Subramanian, 2014). Scholars have found that university–industry collaboration leads to new product development as well as generating patents (Deeds & Hill, 1996; Shan, Walker, & Kogut, 1994; Soh & Subramanian, 2014). Particularly in the biotechnology sector, firms and universities can gain important benefits from their alliances, especially as biotechnology firms have a considerable experience in engaging in UILs (Rothaermel & Deeds, 2006; Soh & Subramanian, 2014). Various studies show that collaboration with industry and among academic scientists is crucial to develop and maintain a strong biotechnology domain (Liebeskind, Oliver, Zucker, & Brewer, 1996; Oliver, 2004; Zucker, Darby, & Armstrong, 2002). Different kinds of collaboration are required, including the participation between academic scholars at the same university, collaboration of academic scientists between different universities, and the alliance between academic scientists and their industrial partners (Oliver, 2004).

Zavale and Macamo (2016) assessed the kind of knowledge university and industry transfers through the UILs in low-income and developing countries, and how it is transferred. They categorized the interaction channels in three groups: embodied knowledge, disembodied knowledge and resources (Zavale & Macamo, 2016). *Embodied knowledge* is structured according to informal and personal interaction of scientists at universities with their partners within firms (Zavale & Macamo, 2016). This knowledge is mostly shaped through informal meetings, academic consultation and student internships in companies (Zavale & Macamo, 2016). *Disembodied knowledge* is science-based and produces codified knowledge such as patents (Zavale & Macamo, 2016). This knowledge enables the licensing of academic patents by corporations, as well as co-authorship of articles by academic and industrial scientists (Zavale &

Macamo, 2016). As a third channel, *resources* include funding and contracting to universities for research projects, or assigning grants for equipment and infrastructure to universities and academic research facilities (Zavale & Macamo, 2016).

Researchers have found that in low-income and developing countries, UILs are essentially structured by embodied knowledge transfer involving informal and personal interaction rather than disembodied knowledge (Kruss, Adeoti, & Nabudere, 2012; Zavale & Macamo, 2016). The low-income countries lack sufficient infrastructure, policies to protect university and industry interactions, and resources to build UILs. Therefore, the developing and less developed countries hardly engage in UILs as a knowledge-intensive process, and university and industry participation instead is based on informal interactions (Kruss et al., 2012; Zavale & Macamo, 2016). According to (Zavale & Macamo, 2016), government intervention is crucial to build effective UILs. Government can take action by defining specific rules and policies by which to engage and to connect all partners and networks to shape the embodied, disembodied and resource knowledge-based UILs (Zavale & Macamo, 2016).

Likewise, various scholars have explored different university and industry partnership channels and their scope in most developed countries (Hershberg, Nabeshima, & Yusuf, 2007; Veugelers & Del Rey, 2015; Zavale & Macamo, 2016). The licensing of academic scientists' patents by industry is considered as one of university and industry interaction channels (Bray & Lee, 2000; Bulut & Moschini, 2009; Y. Wang et al., 2015; Y. Wang, Huang, et al., 2013; Y. Wang, Pan, et al., 2013).

The aforementioned studies show there is no sole university–industry collaboration channel. Some scholars divided the UILs as market-based or non-market-based. Cases where corporations contracted universities, or where industry licensed patents, were associated with the market-based view (Mowery & Ziedonis, 2015). Various scholars analyzed the impact of UILs on the academic performance of the universities in terms of number of publications and number of article citations (Salimi, Bekkers, & Frenken, 2015). Some former scientists measured the impact of university–industry collaboration on the performance of the corporations (Chai & Shih, 2016; George et al., 2002; Motohashi, 2005). The university–industry interaction can be studied as a dual interaction, with effects on both sides (Chai & Shih, 2016). A university is not an entity that is exogenous to industry, i.e. it can be considered as an endogenous variable which can be influenced by industry (Chai & Shih, 2016). In the literature on UILs, some researchers have observed the impact of university and industry linkage on innovation outcomes (Motohashi & Muramatsu, 2012).

There is extensive literature that measures innovation performance, patent quality, patent value, and innovation importance using various proxy measures; there are overlaps among mentioned domains and the boundaries are blurred (Hagedoorn & Cloodt, 2003). Significant numbers of researchers use patent citation as a measure of innovation performance (Hagedoorn & Cloodt, 2003). Patent citation is also commonly used as a proxy to measure patent quality (Hagedoorn & Cloodt, 2003). Likewise, Petruzzelli, Rotolo, and Albino (2015) measured innovation importance according to the number of forward patent citations. Scholars found that there is a positive association between patent importance and the number of patent citations (Briggs, 2015; Hagedoorn & Cloodt, 2003; Harhoff, Narin, Scherer, & Vopel, 1999). Therefore, a patent citation seems to be the preferred and most commonly used indicator to measure patent quality and importance (Briggs, 2015; Mariani & Romanelli, 2007; Schettino, Sterlacchini, & Venturini, 2013).

Petruzzelli et al. (2015) assessed patent importance using various drivers, including the number of claims and technology scope, leading a patent to have a strong influence in subsequent innovation development (Petruzzelli et al., 2015). Scholars have investigated the influence of firms engaged in several technology domains on patent quality, and patent importance in subsequent technologies, bearing in mind the overlaps in the existent literature regarding patent quality and importance (Petruzzelli et al., 2015; Singh, 2008). Scientists have used the breadth of technology measured by 1 minus the Herfindahl index of backward citations to calculate the technological variety of patents as another patent quality indicator (Petruzzelli et al., 2015; Singh, 2008).

Researchers reveal the ability to extensively search the information from different domains to provide knowledge accumulation for firms and scientists (Fleming, 2001), leading to the generation of patents of outstanding importance (Petruzzelli et al., 2015). Singh (2008) also measured the impact of the Herfindahl index of the regional distribution of patents across different geographical locations on patent quality. Singh's (2008) investigations showed that cross-regional R&D collaboration has a moderating effect on R&D distribution, which is negatively related to innovation quality. The lack of cross-regional knowledge integration is a potential explanation for lower innovation value for distributed patenting activities across various geographical locations (Singh, 2008). Petruzzelli et al. (2015) showed that a greater technology scope is associated with a greater number of forward citations from subsequent non-biotechnology patents.

Bonaccorsi and Thoma (2007) used the number of claims to measure patent quality. Inventors have to demonstrate the novel aspect of their invention in the claims in order to be highly legally protected. A higher number of claims increases the probability that scientists can rely on the patent, leading the patent to be cited more by subsequent patents (Petruzzelli et al., 2015).

Considerable efforts have also been undertaken to examine U–I collaboration, with the result that there is no single channel observed and used to transfer knowledge: University–industry knowledge interactions, licensing of academic patents by corporations, and patent–publication links, are all highlighted as science-based UILs. The Bayh–Dole Act passed during the 1980s gives permission to federal contractors including universities to claim the patents funded by the government, providing more authority for universities to keep their intellectual property rights (Kenney & Patton, 2009). Moreover, it standardizes procedures for the researches funded by government, to better control and clarify the process of the projects (Kenney & Patton, 2009; Sampat, Mowery, & Nelson, 2004). Through granting licensing authority to the universities, the number of patents emanating from universities and research facilities increased, although the quality of patents held by universities is less known (Motohashi & Muramatsu, 2012). The measurement of innovation quality varies across different regions and technology domains (Petruzzelli et al., 2015; Popp, 2006; Popp et al., 2013). For instance, Petruzzelli et al. (2015) examined how determinant factors of patent quality differently influence patent citations across different domains. Petruzzelli et al. (2015) used six factors to analyze patent importance, including: technology breadth, novelty, number of claims, scope, use of the scientific knowledge in generating the patents, and the existence of collaboration for the invention. Their study revealed that the number of claims positively affects an invention's influence as measured by the patent's number of forward citations in non-biotechnology fields, while this factor has an inverted U-shaped effect in the biotechnology field.

We found no adequate literature that measures the impact of university and industry linkages on patent quality in biotechnology and nanotechnology in Canada, while controlling for the patent ownership structure and patent–publication links. Magerman, Looy, and Debackere (2011) reported no significant difference between the forward citations of patents belonging to patent–publication pairs and those of patents that are not associated with these pairs. In this research we measure, or proxy for, the "quality" of patents using different factors including forward patent citations, number of backward citations, and number of claims (Dang & Motohashi, 2015; Hirschey & Richardson, 2004; Narin, Noma, & Perry, 1987; Schettino et al., 2013; Wu, Chang, Tsao, & Fan, 2016). We also contribute to the measurement of patent "quality" by using the patents' technological breadth identified by 1 minus the Herfindahl index of technological concentration.

In addition, we sought to answer whether academic patents that are privately held by corporations are of a higher quality than that owned by public assignees. The ownership of academic patents by corporations is one of the UILs channels examined in this study. We compared the impact of patents assigned to universities and government with that of industrial assignees for patents generated by academic inventors residing in Canada. The novel method in the technology-science literature coined "patent–paper pairs" was used to investigate the link between patents and scientific publication. "Patent–paper pairs" were associated with the inventor(s) of a patent listed as the author(s) of the article(s) in a similar subject within a short time frame after a patent was granted (Lissoni & Montobbio, 2006; Magerman et al., 2011; Magerman, Looy, & Debackere, 2015; Murray, 2002).

The remainder of this thesis is structured as follows: Section 2 describes the conceptual framework of this study, including a literature review on the patent ownership structure, patent–paper pairs, UILs, and patent quality which justifies the proposed hypotheses of this investigation; Section 3 explains the research questions and proposed hypotheses; Section 4 describes the data and methodology; in Section 5, the data's descriptive statistics are presented; Section 6 summarizes the results; Section 7 shows the general discussion; and finally in Section 8, the conclusions are highlighted.

CHAPTER 2 LITERATURE REVIEW

2.1 Biotechnology and nanotechnology in Canada

This section is focused on Canadian biotechnology and nanotechnology. Biotechnology started in laboratories in 1970 in universities with the support of public research institutions, and then this industry started to expand to include small science-based corporations (Gilding, 2008). This technology was especially the target of research institutes and universities, venture capital firms and multinational pharmaceutical corporations, benefiting from collaborations across regions and countries in drug discovery and the creation of commercial products (Gilding, 2008). Biotechnology is an enabling technology involved in several domains. A large number of scientists are working in biotechnology firms' R&D divisions to initiate new products aimed at generating more revenues (Traore & Rose, 2003). The number of biotechnology firms located in Canada increased from 282 in 1997 to 385 in 1999, rising 27% for this period, and their revenues more than doubled (Traore & Rose, 2003). Their revenues increased from CAD$813 million to CAD$1.9 billion (Traore & Rose, 2003). The latest data for the biotechnology domain in Canada was gathered in 2005. Statistics Canada revealed Canada gained CAD$4.2 billion in revenue and employed 13,000 people, of which 8,391 of employees hired in the private and public sector worked in R&D in the biotechnology domain in 2005 (BiotecCanada, 2015).

Biotechnology is a process that works on living organisms to produce products; therefore, it represents the integration of life science and technology (Dorockis & Boguś, 2014). The technology has applications ranging from food starter cultures and genetic modification to pharmaceuticals and detergents, as well as products for agriculture and forestry (Dorockis & Boguś, 2014). Biotechnology requires high-quality research infrastructure with qualified scientists, taking a high investment risk to accomplish biotechnology projects (Dorockis & Boguś, 2014). While the US, Canada and specific Western European countries, as developed countries, hold an outstanding position in the biotechnology domain, many developing countries have also recently started to invest in the biotechnology domain; for instance, China, Malaysia, India, Singapore and the Philippines (Dorockis & Boguś, 2014). In terms of biotechnology, the US holds the largest and most diversified position in the world. Canada is 5 years behind the US in terms of development in the biotechnology sector (L. A. Hall & Bagchi-Sen, 2002). The biotechnology industry in Canada has doubled in size between 1994 and 1997 and the number of firms has increased from 121 to approximately 300; while revenues for biotechnology increased from CAD$353 million to CAD$1.1 billion (L. A. Hall & Bagchi-Sen, 2002). Today, the biotechnology sector in Canada contributes CAD$40 billion to the economy (BiotecCanada, 2015).

The strategic collaboration of universities, industries and government in Quebec (especially Montreal and Quebec City) position the province as a leader in the bio-pharmaceutical sector in Canada, with a strong technological infrastructure is also in place in Ontario (especially Toronto), while British Columbia (mainly Vancouver) contributes valuable university–industry research (L. A. Hall & Bagchi-Sen, 2002). Biotechnology is a science-based, multidisciplinary industry. There are various studies that show the collaboration between academic and industry scientists is crucial in biotechnology to develop and maintain the technology. Therefore, different kinds of collaboration are required, including the participation between academic scholars at the same university, collaboration of academic scientists between different universities, and the alliance between the academic scientists and their industrial partners (Oliver, 2004).

Nanotechnology is an emerging technology that enables the manufacture of new products and tools. Considering the impact of this technology on economic improvement, over CAD$3 billion of government funding was assigned to nanotechnology up to 2007 (Niosi & Reid, 2007). Nanotechnology is a technology entailing work at the 0.1–100 nm scale (Niosi & Reid, 2007). “Nanotechnology involves the intentional manufacture of large-scale objects whose discrete components are less than a few hundred nanometers wide” (Niosi & Reid, 2007, p. 432). As such, the technology depends upon research and tools from diverse fields including molecular biology, electronics, materials science, and physics (Niosi & Reid, 2007), using engineered nano-materials in engineering, space, medicine and technology applications (Bera & Belhaj, 2016).

2.2 Biotechnology and nanotechnology patents

The Canadian Intellectual Property Office (CIPO) is a Special Operating Agency (SOA) of Industry Canada and it has two goals: (a) administrating the Intellectual Property (IP) rights including patents, industrial designs, and trademarks; and (b) facilitating the use of the intellectual property system and its utilization (McMaster, 2007). About 7% of all firms located in Canada use intellectual property to keep the novelty rights of their innovations (McMaster, 2007). Among the 39,600 patent applications filed in Canada (including foreign inventors), only 2% were filed only in Canada, while 95% were also filed in the US (McMaster, 2007). Canadians filed 8,200 patent applications in the US in 2004, 50% more than the patents filed in Canada (McMaster, 2007), and corresponding to the sixth rank in the world after the US (190,600), Japan (65,000), Germany (20,000), China (17,000) and South Korea (17,000) (McMaster, 2007). During the period 1963 to 2015, Canada filed a total of 124,000 patents in the US, ranking eighth after the US (6 million including U.S. and foreign origin inventors and 3 million generated by U.S. based inventors), Japan (1 million), Germany (408,000), the United Kingdom (165,000), France (153,000), South Korea (152,000), and Taiwan (139,000) (US Patent and Trademark Office, 2015).

2.2.1 Patent Quality

In large-scale patent-econometric studies, scholars use different indicators to measure or to proxy for patent quality. For instance, Narin et al. (1987) used the number of backward citations to measure patent quality, i.e., the number of previous patents that are quoted as references in a focal patent document (Narin et al., 1987). Other scholars use number of backward citations in the non-patent literature to examine patent quality (Carpenter, Cooper, & Narin, 1980; Hirschey & Richardson, 2004). Because the non-patent literature is scientific in nature, this measure indicates the scientific grounding of a patent. Taking a different approach, Manuel Trajtenberg (1990) applied incremental forward citations as an attribute to estimate patent quality. The number of patent forward citations tallies the number of times that a focal patent is cited in subsequent patents within a period of 5–10 years after the patent application year (Manuel Trajtenberg, 1990).

Hirschey and Richardson (2001) used the Current Impact Index (CII), Science Linkage (SL), and Technology Cycle Time (TCT) indicators to examine patent quality. The CII identifies the number of citations that a corporation has received in the most recent 5 years divided by the expected average number of citations that similar high technology companies received (Hirschey & Richardson, 2001). SL is a measure to analyze the link between a patent (as technology) to science through scientific publications that are listed on the front page of a patent document as "other references cited" (Hirschey & Richardson, 2001). The TCT measures the time that has passed between the current patent and the previous generation of the patent, thus calculating the length of the cycle between the current technology and the prior stage of the technology (Hirschey & Richardson, 2001, 2004). New emerging technologies have a short cycle time (4 or 5 years), while mature technologies have a long cycle time (average 15 years or more) (Hirschey & Richardson, 2004).

In a later work by the same authors, Non-Patent References (NPRs), Citation Index (CI), and TCT are used by Hirschey and Richardson (2004) to assess patent quality. The NPR variable links to scientific publications cited on the front page of the patent application and includes books, articles, and brochures (Hirschey & Richardson, 2004). The NPR variable determines how close the patent is to scientific publications in a given year (Hirschey & Richardson, 2004). The CI measures the number of forward citations obtained in patent applications in a current year, for patents granted to the corporation in the most recent 5 years (Hirschey & Richardson, 2004).

Goetze (2010) used three indicators to assess patent quality. First, the author used the number of International Patent Classifications (IPC) in which a patent is filed to build and assess an indicator of patent quality. Second, he also used patent net citation measured as the cumulative number of citations that inventor *i* obtains from subsequent patents (issued by inventor *j*) minus self-citations associated to patents generated by the same inventor *i*. Finally, the authors used an indicator that identifies the portion of foreign inventors (indicated by dissimilar country location) among all co-inventors for jointly generated patents to assess patent quality.

Motohashi and Muramatsu (2012) measured patent quality by the number of inventors, patent forward citations (number of forward self-citations and number of forward non-self citations), number of claims, and a generality index. Generality index determines the breadth of the domains in which patent is cited, measured by the number of forward citations (Motohashi & Muramatsu, 2012).

Schettino et al. (2013) also constructed a composite patent quality indicator as suggested by Lanjouw and Schankerman (2004). Schettino et al. (2013) used family size, patent forward citation, patent backward citation, and number of claims to construct a composite metric to measure patent quality. Family size calculates the number of jurisdictions that are required to protect the same innovation activity; it also measures the patent survival span. For instance, the time between a patent's expiration and application is highly associated with the family size (Harhoff, Scherer, & Vopel, 2003).

Patent quality is also often measured by patent renewal information, number of citations, and number of claims (Dang & Motohashi, 2015). However, patent renewal information has a shortcoming in terms of timeliness and does not reflect recent changes in patent quality (Dang & Motohashi, 2015). Dang and Motohashi (2015) therefore used number of claims to measure patent quality.

Thompson (2016) analyzed patent quality metrics and found the inventiveness of the patent application's claims to be associated to patent quality. He therefore used patent number of claims as a metric to measure patent quality (Thompson, 2016). The author also states that typical research investigates the prior art of each patent. Thus, the use of the number of backward citations exclusively is not a sufficient metric for patent quality, because it does not show the fact that patents with a high number of claims obtain more backward citations (Thompson, 2016).

Patent application is based on a "first to invent" philosophy and as such the legal status of previous patents is fundamental to analyze the novelty of patents (Wu et al., 2016). Patent quality indicators are related to legal status (LS) of patents evaluated by number of claims (Wu et al., 2016). Essentially, patent quality measures the potential future value of patents and offers valuable direction for policy makers to better monitor the market (Wu et al., 2016). Lawyers, by contrast, consider legal consistency and certainty to assess patent quality. For lawyers, legal certainty is a main priority whereas patentability requirements and novelty are secondary concerns (Burke & Reitzig, 2007). There is extensive literature regarding patent quality; a summary is presented below in Table 2.1.

Table 2.1 : Patent quality indicators

Variable	**Detailed description of measure**
Number of backward citations to the non-patent literature (Non-Patent References, NPR) (Carpenter et al., 1980)	• Shows the number of non-patent references that are actively quoted by patent, and refers to scientific citations in patent document.
Number of backward citations to patent literature (Narin et al., 1987)	• Identifies the number of patent references that are actively quoted by a patent.
Incremental forward citations (Manuel Trajtenberg, 1990)	• Demonstrates the number of times that a focal patent is quoted as a relevant state during an examination of subsequent patent applications filed within a period of 5–10 years after the focal patent application.
Current Impact Index (CII) Science Linkage (SL) Technology Cycle Time (TCT) (Hirschey & Richardson, 2001)	• CII shows the number of patent citations that a company has obtained during the most recent 5 years divided by anticipated number of patent citations that similar high-tech companies gained. • SL links patents to scientific publications through the “other references cited” on the front page of the patent document. • Technology Cycle Time (TCT) demonstrates the time that has passed between current patent and previous generation of the patent.

Table 2.1 : Patent quality indicators (Cont'd)

Variable	**Detailed description of measure**
Citation Index (CI) Technology Cycle Time (TCT) Non-Patent References (NPR) (Hirschey & Richardson, 2004)	• CI measures the number of citations received in subsequent patents in the current year, for patents granted to a company in the most recent 5-year period. • TCT determines the time that has passed between current patent and previous generation of the patent. • NPR is associated to the scientific citations in patent document.
Number of International Patent Classification (IPC) subclasses Net citations Inventor co-location (Goetze, 2010)	• Number of IPC subclasses is the number of international classification subclasses in which a patent is filed. • Net citations indicates the cumulative number of citations that inventor *i* received from subsequent patents (generated by other inventors *j*) minus patent self-citations (issued by inventor *i*). • Inventor co-location identifies the share of foreign inventors, identified by dissimilar country location, among all co-inventors.
Number of inventors Patent forward citations (number of forward self-citations and number of forward non-self citations) Number of claims Generality index (Motohashi & Muramatsu, 2012)	• Patent forward citations was measured by the number of forward self-citations and number of forward non-self citations

Table 2.1 : Patent quality indicators (Cont'd and end)

Variable	**Detailed description of measure**
Number of claims Backward citations Forward citations Family size (Schettino et al., 2013; Seol, Lee, & Kim, 2011)	• Number of claims contained in the patent. • Number of backward citations shows the number of prior patents cited in a focal patent. Number of forward citations identifies the number of times a focal patent is cited in subsequent patents. • Family size calculates the number of jurisdictions that are required to protect the same innovation activity, and the time between patent application and expiration (Harhoff et al., 2003).
Patent number of claims (Dang & Motohashi, 2015; B. Wang & Hsieh, 2015; Wu et al., 2016)	• Number of claims contained in a patent.

Patent quality has attracted the attention of numerous scholars, who have used the terms patent *quality*, *value*, *importance*, and *influence* interchangeably (Petruzzelli et al., 2015; Singh, 2008). Among the antecedent factors of patent quality, patent citation is the most common measure quality (Hagedoorn & Cloodt, 2003; Jung & Lee, 2014). As patent citation is a noisy proxy to measure patent quality, there are some considerations regarding using citation to measure quality. Factors affecting patent citations include proximity of the inventors (Gittelman, 2007), and the rigor of decision making by subsequent patent examiners to cite prior art of the patent (Gress, 2010). Whether or not we know about the patent examiner's decision and qualification, the existence of citations shows the prior art of patents (Jung & Lee, 2014).

2.2.2 Patent Value

Many methodologies have been proposed to evaluate the monetary value of each patent (Harhoff et al., 1999; Harhoff et al., 2003). Patent value identifies the present value assessed by patent examiners on a patent value scale (Reitzig, 2003). Some scholars count patent forward citations to measure patent value (Lerner, 1994), as they did for patent quality (see the previous section). Other researchers examine the probability of patents being granted to investigate patent value (Ernst, Legler, & Lichtenthaler, 2010). Harhoff et al. (2003) posit that patent value can be considered as a firm's asset value. Therefore, to assess patent value, the observable effects of patents on pricing, costs, and also number of products being patented are observed. Simultaneously, unobservable effects of patents on owners' competitors are examined (Ernst et al., 2010; Reitzig, 2004).

Several approaches to assessing patent value have been developed. These methodologies, which can be categorized as the contemporary approaches, include cost-based, market-based, design-around-based, and income-based approaches (Reitzig, 2004). Among the contemporary approaches, cost-based methodology concentrates on the costs required to develop the products being patented (Ernst et al., 2010; Sherry & Teece, 2004). The market-based approach compares a patent with similar patents previously sold in the market (Takalo, 2002). The design-around-based method computes the costs to develop equivalent products according to the patent claims. It identifies the costs required to design a product having the same results as a patented product (Gallini, 1992). The income-based approach estimates the patent contribution as the economic benefits of a patent for a company including its cash flow. The future cash flow of a company is therefore counted in this methodology (Ernst et al., 2010).

Hsieh (2013) stressed that it is difficult to measure patent value before the patent's commercialization. Hsieh (2013) suggested four independent variables from the factor analysis to assess patent value in the early stage of the commercialization process: General Management Benefit, General Management Risks, Offensive Benefits, and Cost-Related Risks. Essentially, the author observed both benefit and risk indicators to assess patent value. The variable General Management Benefits contains indicators that bring benefits for corporations, for instance increased revenues, increased business diversification, facilitating welfare progress, and offering new business opportunities (Hsieh, 2013). The component General Management Risks includes increased market risks, boosted production and development risks, and increased charges for litigation. Offensive Benefits are associated to increased market share, increased citation, and increased litigation. As a fourth component, Cost-Related Risks relates to patent maintenance costs and patent application expenses (Hsieh, 2013). Finally, according to the patent value assessment, Hsieh (2013) proposed short-term and long-term further commercialization strategies for each group of patents, considering a combined benefits and risks approach.

B. Wang and Hsieh (2015) used a fuzzy method to measure patent value according to 10 criteria categorized into three groups: patent strategic value, patent protection value, and patent commercialization value. The first group, patent strategic value, includes competiveness and innovativeness of a patent, business potential, and organization growth (B. Wang & Hsieh, 2015). The second group, patent protection value, includes patent quality indicators and patent residual life cycle time (B. Wang & Hsieh, 2015). According to B. Wang and Hsieh (2015), patent quality indicators are associated to patent number of claims and licensing status of patents. The third group, patent commercialization value, relates to obtaining revenue from a patent application in a relevant-industry domain (B. Wang & Hsieh, 2015). It is essential for firms to have an intellectual property valuation when they engage in an acquisition process or strategic appliances (Phillips, McGlaughlin, Ruth, Jager, & Soldan, 2015). Patent valuation therefore has a significant impact on certain business activities due to firms' alliances or acquisitions (Breitzman & Thomas, 2002; B. Wang & Hsieh, 2015).

2.3 University–Industry Linkage

A review of the literature on university and industry collaboration reveals a number of different paradigms that can appropriately be used to investigate UILs. For instance, joint R&D activities, co-patenting, and co-authorship of scholars at universities and at firms are all defined as factors in university and industry participation (Abramo, D'Angelo, Di Costa, & Solazzi, 2009; Baba, Shichijo, & Sedita, 2009; Motohashi, 2005).

George et al. (2002) examined the impact of university-industry (U–I) alliances on the firm's number of patents as well as financial performance and R&D expenses of the corporation. They considered all alliances (formal agreements) that the firm had entered into by the end of 1995, horizontal linkages including joint R&D, patent swaps, technology transfers, and joint ventures, as well as vertical links including outsourcing and distribution links. The results of that study demonstrated that corporations with UILs generate more patents than firms without university assistance. Furthermore, firms engaging in UILs have lower R&D expenses than companies without such a link (George et al., 2002). However, according to George et al.'s (2002) research, U–I participation does not enhance the companies' financial performance.

Motohashi (2005) analyzed the impact of UILs on the performance of both small and large corporations. He found that small firms tend to exhibit better performance than larger companies when collaborating with universities. Small firms and young companies cannot compete with large corporations in terms of tangible assets (Motohashi, 2005). Therefore, small companies can employ UILs as a practical means to develop new products. In Motohashi (2005) survey, UILs included both formal (for instance, joint R&D activities, training, and patent licensing) and informal activities (consultation services). Motohashi (2005) found the objectives of U–I collaboration to include the development of new products, licensing technology, paper publication, enhancement of human resource management, discovering the potential for joint R&D participation, and improving the skills required for project management.

Balconi and Laboranti (2006) used Social Network Analysis (SNA) to structure the collaboration between the various players in a mutual network. They considered each professor as a vertex to collaborate with other partners. They built a UILs network using cases where professors were listed as inventors of patents, but patents were assigned to firms. The impact of UILs on professors' scientific performance was measured by the number of article citations. Balconi and Laboranti (2006) found that UILs offered the opportunity for professors to increase their publication citations. Further, Balconi and Laboranti (2006) constructed a U–I co-inventor network, where there was at least one academic scientist listed among industrial inventors' names. Their research revealed two common patterns for situations where patents generated by academics are assigned to companies (Balconi & Laboranti, 2006). In the first pattern, patents are issued as a result of collaboration between academic inventors and industrial assignees (Balconi & Laboranti, 2006). In the second, the corporation defines a project that is then accomplished by the university (Balconi & Laboranti, 2006).

Various scholars measured the co-authorship of publications to reconstruct university and industry participation (Abramo et al., 2009; Balconi & Laboranti, 2006). Abramo et al. (2009) examined the impact of co-authorship of university researchers with their industry colleagues on research performance. They found that academic researchers who jointly published articles with their industrial partners attained a higher research performance than scholars without such a link. Research performance was rated by number of articles published, together with publication contribution calculated by number of co-authors (Abramo et al., 2009). However, Abramo et al. (2009) found that the impact factor of journals containing articles by U–I researchers was generally lower than for those containing articles co-authored by other players. Moreover, university–private publications did not demonstrate a higher multidisciplinary value than other publications (Abramo et al., 2009).

Baba et al. (2009) tested the impact of mutual patenting on firm's innovation performance, measured by number of patents generated. To that end, they studied the impact of co-invention networks of both "Pasteur scientists" and "Star scientists" on the number of registered patents. "Pasteur scientists" are academic scientists who have published a large number of articles as well as generating patents. According to the examination conducted by Baba et al. (2009), the inclusion of "Pasteur scientists" in collaborative networks has a significantly positive impact on the number of patents. The impact of "Star scientists" on firm's performance is more modest, compared to "Pasteur scientists" (Baba et al., 2009).

Several scholars have examined how UILs affect patent value (Belderbos, Cassiman, Faems, Leten, & Van Looy, 2014; Motohashi & Muramatsu, 2012). They proposed different hypotheses to measure the impact of UILs on innovation performance, and found that patents with UILs obtain greater value than those not linked to corporations.

Motohashi and Muramatsu (2012) categorized UIL patents as jointly invented or joint-application UIL patents. In joint application, university and industry jointly file the patent application, while joint invention is related to the inventors from university and industry who jointly generate patents; it is essentially concentrated on the inventors (Motohashi & Muramatsu, 2012). Motohashi & Muramastsu's (2012) results highlight that jointly invented patents have higher value, measured by patent forward self-citation and non-self citation, than jointly applied patents. Motohashi and Muramatsu (2012) constantly swapped patent quality and value terms containing the same concept and measures.

Motohashi and Muramatsu (2012) learned that UIL patents obtain a higher number of forward non-self citations than patents solely generated by either companies or universities. Furthermore, jointly invented patents achieve more generality than patents issued without corporation assistance, on a generality index referring to the range of the citing patent, measured by the number of forward citations (Motohashi & Muramatsu, 2012). Comparing small and large firms, Motohashi and Muramatsu (2012) found that patents generated by small firms through UILs have higher quality than those issued by large corporations. As we described in Section 2.2.1, Motohashi and Muramatsu (2012) measured patent quality by the number of inventors, patent forward citations (number of forward self-citations and number of forward non-self citations), number of claims, and a generality index. This difference could be attributed to the many high technology start-up companies that receive more UILs patent non-self citations (Motohashi & Muramatsu, 2012).

A number of scholars have investigated the impact of co-patenting and co-ownership on innovation performance (Belderbos et al., 2014; Belderbos, Faems, Leten, & Looy, 2010; Hagedoorn, 2003). A survey of the innovation management literature highlights an open innovation system. Such a system offers opportunities for partners to receive information via a variety of internal and external channels (Belderbos et al., 2014; Cassiman & Veugelers, 2006; Chesbrough, Vanhaverbeke, West, Eds., & 2006). Partners can then integrate knowledge from these sources and allocate information to innovation processes to develop new products (Belderbos et al., 2014; Cassiman & Veugelers, 2006). The debate on co-patenting addresses the complexities of collaboration with external partners (Belderbos et al., 2010; Hagedoorn, 2003). Belderbos et al. (2010) found a negative link between co-patenting share and corporate financial performance. Similarly, Hagedoorn (2003) earlier cited co-patenting as a policy that corporations tend to avoid. However, the investigations carried out by Belderbos et al. (2014) focused on the ownership aspect of co-patenting and the complexities of how to share intellectual property among partners, ultimately revealing the effects of co-ownership on the value creation process of firms.

Chai and Shih (2016) assessed the impact of U–I co-funding on corporations' innovative outcomes performance. They analyzed projects supported by the Danish National Advanced Technology Foundation (DNATF) that were co-funded by universities and companies. Their sample was sorted according to small and medium sized corporations (SMEs), young corporations, and project size. Chai and Shih's (2016) study reveal two perspectives for U–I participation. According to the first view, the university is considered as an exogenous entity that has a linear effect on corporations' performance (Chai & Shih, 2016; Mansfield, 1995). As a second perspective, U–I participation entails more complexities, in a bidirectional relation (Chai & Shih, 2016; Murray, 2002). Thus, science can be affected by technology, and the university is an entity endogenous to the technology (Chai & Shih, 2016). Chai and Shih (2016) measured three dimensions of firm's performance: number of patents, number of publications, and number of cross-institutional publications. They found that for SMEs and large projects, funded corporations issued more publications than unfunded firms. For young corporations as well as firms involved in large projects, companies issued significantly more patents up to 4 years after corporation funding (Chai & Shih, 2016). For all three samples, the number of cross-institutional publications was significantly enhanced for corporations that obtained funding as compared to unfunded companies, observed 3 years after funding (Chai & Shih, 2016). Bearing in mind the massive amount of literature on UILs, a summary of the research is highlighted in Table 2.2.

Table 2.2 : University–Industry Linkage

Title	**University–Industry Collaboration**	**Results**
The effects of business–university alliances on innovation output and financial performance Domain: Publicly traded biotechnology companies (George et al., 2002)	Includes all alliances (formal agreements) that the firm has entered into by the end of 1995; horizontal linkages include joint R&D, patent swaps, technology transfers, and joint ventures, whereas vertical links include outsourcing and distribution links Indicator of innovative output: Number of patents issued to the firm under USPTO, number of products on the market, and number of products under development	- Companies with UILs generate more patents than firms without university assistance - Firms with U–I collaboration have lower R&D expenses than companies without such a link - U–I participation does not enhance the firm's financial performance

Table 2.2 : University–Industry Linkage (Cont'd)

Title	**University–Industry Collaboration**	**Results**
Assess the impact of U–I collaboration on new technology-based firms' performance Domain: Small startup firms in Japan (Motohashi, 2005)	Joint R&D activities, training, technology licensing, consultation Objective of U–I collaboration is development of new products, licensing the technology, paper publication, enhancement of human resource management, discovering potential for joint R&D participation, and improving the skills required for project management	- Small firms tend to exhibit better performance than large corporations through UILs
University–Industry interactions in applied research: Domain: The case of microelectronics (academic centers for electronics in Italy) (Balconi & Laboranti, 2006)	- Patents generated by professors at universities and assigned to corporations - Co-invention of academic and industrial inventors (at least one academic scientist is listed among industrial inventors' names for a patent)	- Academic inventors can perform better in terms of scientific publications by building relations with industry

Table 2.2 : University–Industry Linkage (Cont'd)

Title	University–Industry Collaboration	Results
Assess the role of "Pasteur scientists" and "Star scientists" co-invention network on firms' R&D outcome, measured by number of registered patents Domain:Advanced materials field(Baba et al., 2009)	Co-invention of "Pasteur scientists" and "Star scientists"	- Mutual patenting network of "Pasteur scientists" increases the number of registered patents, while the impact of "Star scientists" co-patenting on number of patents is more modest in comparison
Assess the impact of university and private sector collaboration to jointly publish articles (co-authorship) on research performance, journal impact factor, and multidisciplinary of publication (Abramo et al., 2009) Domains: Polymer materials science and technology, industrial chemistry, electronics, applied physical chemistry, chemical fundaments of technology, principles of chemical engineering, molecular biology, applied pharmaceutical technology	Co-authorship of articles in international journals	-Researchers who jointly publish articles with their industrial partners have better research performance than scholars without such a link -Research performance examined by number of articles published by scientists and sum of publication contributions calculated by number of co-authors - The impact factor of journals containing collaborative articles (published by U–I researchers) is generally lower than those co-authored by other players - University–private publications do not demonstrate a higher multidisciplinary value than other publications

Table 2.2 : University–Industry Linkage (Cont'd)

Title	**University–Industry Collaboration**	**Results**
Assess the impact of UILs on patent value and compare the value of jointly invented and joint-application UIL patents. (Motohashi & Muramatsu, 2012)	UILs joint-invention and UILs joint-application of patent Indicators to evaluate patent value: Number of patents, patent forward citations (number of forward self-citations and number of forward non-self citations), number of claims, and a generality index	- Jointly invented patents have greater technological value in terms of UILs patent forward self-citation and non-self citation than jointly applied patents - UIL patents gain a higher number of forward non-self citations than those patents solely generated by companies or universities - Jointly invented patents achieve more generality than other patents issued without corporate assistance -Small firms tend to obtain greater value for UIL patents than patents generated by the large corporations -Small firms' UIL patents tend to reveal more generality than those of large corporations

Table 2.2 : University–Industry Linkage (Cont'd and end)

Title	University–Industry Collaboration	Results
Measuring impact of U–I mutual funding on the corporation's performance by number of patents, number of publications, and number of cross-institutional publications (Chai & Shih, 2016)	Jointly funding corporations by university and industry (shared budget)	-For SMEs and large projects, funded corporations issued more publications than unfunded firms - Young corporations and firms involved in large projects issue significantly more patents up to 4 years after corporation funding -The number of cross-institutional publications is significantly enhanced for corporations that obtained funding compared to unfunded companies (for three years after funding)

2.3.1 Co-invention and co-authorship network

Innovative activities occurring in different regions and economic growth are the main concerns of economic geography (Lee, 2015). Localized knowledge spillovers (LKSs) target the geographical proximity of different partners engaging in innovative activities in cluster(s), for instance: firms, inventors, and research facilities (Lee, 2015). Spatial concentration of different actors located in clusters can improve the knowledge exchange and diminish general costs through increasing the number of researchers, mobility and personal collaboration opportunities (Lee, 2015). The social network in the high technologies such as biotechnology can span different geographical areas across the world, and it is not bound to the local region (Coe & Bunnell, 2003; Gertler & Levitte, 2005; Lee, 2015). Among the collaboration networks, co-invention is associated with patents generated by more than one inventor (Cantner & Graf, 2006;

Ejermo & Karlsson, 2006; Lee, 2015). There are different kinds of participation including co-invention, co-authorship, strategic alliances and also informal and personal relationship of different actors (Sun, 2016).

To analyze social network collaboration, the multidisciplinary technique of social network analysis (SNA) has been developed by sociologists and then accomplished with the use of mathematics and statistics (Cantner & Graf, 2006). It is applied in the fields of sociology, marketing, computing and industrial engineering (Cantner & Graf, 2006). There is a wide range of studies that use SNA for their network analysis. For instance, Cowan and Jonard (2004) used SNA to measure the impact of network characteristics on performance through simulation. Jaffe, Trajtenberg, and Henderson (1993) compared the impact of social proximity and geographical proximity on knowledge spillovers. They found that social proximity significantly affects knowledge spillovers, to a greater degree than geographical proximity (Cantner & Graf, 2006). Sun (2016) used SNA to map the correlation of different partners in the patents co-assignship network. We explained in Section 4.3 the network measures used to analyze the co-invention and co-authorship network centrality in our study.

Walsh et al. (2016) identified different forms of co-invention activities including co-invention (with customers, suppliers, competitors), co-assignees (which concentrates on the share of intellectual property among different patentees), and any formal and informal collaboration (excluding co-invention and co-assignees) in the US. The authors demonstrated that approximately 23% of triadic patents (patents registered in Japan and the EPO and granted by the USPTO, year 2000–2003) reflect non-co-invention collaboration; 10% of such patents include collaboration with customers, 4% with universities, and 12% with suppliers. For the co-inventor network, collaboration is divided among suppliers (5%), customers (4%), competitors (1%), firms (2%), universities (2%) and government organizations (0.5%). Walsh et al.'s (2016) results show that in the US, it is rare to jointly generate patents with competitors' participation. Furthermore, their findings indicate that for the large firms, the extent of collaboration is 13% with suppliers (including co-invention, co-assignees, and formal and informal collaboration excluding co-invention and co-assignees); and 35% of those suppliers were partners for joint invention. Likewise, 11% of collaborations exist with customers (30% of those customers were partners for co-invention) and 4% with universities (in 40% of those partnerships, customers were engaged as co-inventors) (Walsh et al., 2016).

2.4 Research gap

In science-based industries, the product development process is based on a collaborative network of academic scientists and other public research institutes with industrial scholars (George et al., 2002; Oliver, 2004). Biotechnology and nanotechnology are science-based domains that drive other industries forward (Baba et al., 2009; Niosi & Reid, 2007; Oliver, 2004). Therefore, the university–industry linkage is crucial in the biotechnology and nanotechnology fields (Baba et al., 2009; Niosi & Reid, 2007; Oliver, 2004). In the biotechnology sector, collaborations between universities and other players, including firms and research facilities, are deemed essential for actors to compete and survive in this competitive area (Bowie, 1994; Oliver, 2004; Peters, Groenewegen, & Fiebelkorn, 1998). Various researchers highlight the strategic role of U–I alliances (Bowie, 1994; Liebeskind et al., 1996; Oliver & Julia Porter, 1997) and demonstrate that such linkage significantly increases the number of patents as an essential source of market value (Shaker, 1996). Patents are indeed an important requirement of the product commercialization process (Almeida, 1996; Grant & Baden-Fuller, 1995). Biotechnology is considered to be one of the few domains where the ideas and knowledge generated in universities and research labs can be transferred to firms quickly (Baba et al., 2009; Cohen et al., 2002). Many start-up biotechnology firms use intellectual property as one of their key assets to protect the rights over their idea generation (Arora & Merges, 2004; Gans, Hsu, & Stern, 2002; Giuri et al., 2007). This helps explain why only one third of patents generated by individual inventors have no collaborative ties with other partners (Wagner-Dobler, 2001). Conversely, the proportion of inventors in mutual networks issuing patents serves to highlight the prevalence of collaboration in the biotechnology and nanotechnology domains (Wagner-Dobler, 2001).

The impacts of U–I collaboration on scientific and technological production have been measured by several factors. Various researchers have examined the role of U–I collaboration on patent licensing, article publication, production performance, and R&D productivity (Branstetter & Nakamura, 2003; Hausman, Hall, & Griliches, 1984; Motohashi, 2005). Motohashi (2005) reveals that small start-up firms achieve a greater productivity from the collaborative network. Other studies assumed that networks of scientists and those of inventors have distinctive social structures, although in some aspects, their activities overlap (Murray, 2002; Partha & David, 1994).

Traditional bibliometric methods are often used to assess UILs (Henderson & Cockburn, 1994; Podolny & Stuart, 1995; Zucker, Darby, & Brewer, 1998) and also to measure how such ties affect overall performance, specifically where science-based technology is concerned (Henderson & Cockburn, 1994; Zucker et al., 1998). Murray (2002) identified three traditional university–industry collaborative networks: the citation of papers in patents; the publication of papers by firms and industrial scientists; and the co-publication of papers by academic scientists and industrial inventors. Murray (2002) proposed a novel concept dubbed "patent–paper pairs" to understand which aspects of science and technology are linked together, and simultaneously to identify which firms or scientists have a significant impact on science and technology. The patent–paper pairs concept is based on the premise that both scientists and inventors contribute to idea generation through publications and patenting. This methodology tries to identify which patents and papers are paired, linking science and technology (Ducor, 2000; Leopold, May, & Paaß, 2005; Murray, 2002). A number of authors have used an accurate content analysis to measure the similarity between patents and papers in order to identify such pairs (Lubango & Pouris, 2010; Murray, 2002; Podolny & Stuart, 1995). Patent–paper pairs are the patents and papers that are issued from the same project (Murray, 2002). Lubango and Pouris (2010) studied 70 patents from the USPTO, EPO, and WIPO and found 58 patents (82%) initiated by scientists from South African universities linked to articles. They surmised that authors have a propensity to generate patents and to publish articles at the same time. Magerman et al. (2011) studied the impact of patent–paper pairs on citation flows and demonstrated that there is no significant difference between the forward citations of patents belonging to patent–paper pairs and those of patents that are not associated to these pairs. However, their findings did reveal that publications linked to a patent received significantly more citations compared with publications without a patent counterpart.

With respect to prior literature studying UILs, there is still a lack of attention given to measuring the impact of patent–paper pairs on patent quality by considering different quality factors such as number of claims, patent forward citations and patent backward citations.

Furthermore, as discussed in Section 2.3, the licensing of academic patents by corporations is addressed as a channel to connect the universities and research facilities to the private sector. There is a large amount of research on patent ownership structure (Crespi, Geuna, Nomaler, & Verspagen, 2010; Henderson, Jaffe, & Trajtenberg, 1998a; Lissoni, Montobbio, & Seri, 2010; Motohashi & Muramatsu, 2012; Mowery & Ziedonis, 2002; Sampat, Mowery, & Ziedonis, 2003; Sterzi, 2013).

Kenney and Patton (2009) raised criticisms of the Bayh–Dole Act, stating that claiming university ownership of patents is a dysfunctional procedure, with information asymmetries and potentially inconsistent intentions between the inventors and universities. It is not economically efficient, as it causes a delay in licensing and prevents inventors from commercializing their inventions in a timely manner (Kenney & Patton, 2009). Thus, they proposed two substitute solutions for patent ownership. First, inventors would be free to decide whether the ownership of their patents would lie with either universities and corporations (Kenney & Patton, 2009). This approach encourages inventors' entrepreneurship, as they can choose between public and private patentees, considering the advantages and disadvantages of each option (Kenney & Patton, 2009). Second, the inventors would make all their inventions publically available through a strategic public domain, and the university administration would not be involved in licensing (Kenney & Patton, 2009). Kenney and Patton (2011) argue that university ownership is not crucial in Europe and Japan. The inventors build extra intermediaries between themselves and the competitive market by licensing their patents in the Technology Licensing Offices (TLOs) (located at universities) instead of with corporations (Kenney & Patton, 2009, 2011). Audretsch, Lehmann, and Warning (2005) and Thursby, Fuller, and Thursby (2009) reveal that U.S. professors assign a significant number of patents to corporations instead of universities, even as university employees.

There is an important debate in many countries regarding which institution can own the intellectual property rights. In Canada, different universities have different approaches to owning patents; for instance, the University of British Columbia owns the patents generated by its scientists, while at Simon Faster University patents are owned by the inventors (Rasmussen, 2008). The link between Intellectual Property and R&D grants and its impact on innovation performance is still disputed (Hanel, 2006). Several scholars have assessed the impact of public assignees (including government and university) on patent quality and then compared patents privately held by corporations (Bessen, 2008; Crespi et al., 2010; Lissoni et al., 2010; Mowery & Ziedonis, 2002; Popp, 2006; Popp et al., 2013; Sterzi, 2013). Most researchers assumed that patents assigned to the governments were related to more essential needs and would tend to be cited more (Popp, 2006; Popp et al., 2013).

Former research has not given adequate attention to measuring the impact of patent assignees across different institutions (including university, industry and government) on patent quality in the biotechnology domain in Canada. Therefore, we set out to measure patent quality associated with public assignees versus private assignees in this study, for patents generated by academic inventors residing in Canada. Moreover, we are going to examine the impact of various network structure on innovation performance.

CHAPTER 3 RESEARCH QUESTIONS AND HYPOTHESES

3.1 Patent ownership and patent quality

Prior to the Bayh–Dole Act, universities, profit or non-profit organizations, and public institutions were obligated to give the permission for their inventions to the government that funded their research (Grimaldi, Kenney, Siegel, & Wright, 2011). A significant change took place after 1980, giving the authority for the innovation ownership to universities and other non-profit organizations. Bayh–Dole deals with the ownership of patents granted through the federal government. Research facilities, universities, and other public institutions under the Bayh–Dole Act can decide about the ownership of patents. Hence, universities can hold the ownership right to their patents, instead of the government (Grimaldi et al., 2011; Henderson et al., 1998a; Sampat et al., 2003). This law supports patent commercialization in universities (Grimaldi et al., 2011; Henderson, Jaffe, & Trajtenberg, 1995, 1998).

The Bayh–Dole Act which changed patent ownership policy in the US does not exist in Canada; instead, each university has its own policy for making a decision regarding patent ownership (Atkinson-Grosjean, House, & Fischer, 2001; Hoye, 2006; Kenney & Patton, 2011). For instance, at Waterloo, inventors can own their patents (Kenney & Patton, 2011). In 1989 the Intellectual Property policy was reformed in Canada from the first-to-invent to first-to-file policy (Hanel, 2006). Furthermore, the duration of the patent grant was changed from 17 to 20 years (Hanel, 2006). In first-to-invent, when two persons claim the same patent, the USPTO evaluates the contribution of each inventor to determine who has the right to the patent. In first-to-file, the patent is granted to the first inventor who files the patent application. Hoye (2006) surveyed 37 Canadian universities and found there are four different intellectual property policies existing at universities in Canada: (1) the university reserves the right of first offer on IP conducted from its academic research, in any circumstance—this is called the "First Offer" policy; (2) inventors share the revenues resulting from their patents with the university, when inventors commercialize the patents; (3) inventors share the patents' revenues with the university when the university commercializes the patent; and (4) the university makes an agreement with inventors to consider different thresholds for various revenue levels, to decide the revenue distribution between university and inventor (Hoye, 2006).

With the "First Offer" policy, the university has the right to assess all the academic inventions that would be interesting for the inventors to commercialize, then the university owns and commercializes the innovation (Hoye, 2006). This policy occurs in the universities containing the TLOs. Among the 37 Canadian universities surveyed by Hoye (2006), 30 have TLOs, of which 13 reserve the First Offer right of university ownership, while the other 17 do not (Hoye, 2006). In this policy individual inventors can only own their patents if the university is not interested to commercialize the inventor's patents; still, however, there are some universities that control the patent licensing by individual inventors. For instance, at McGill University, inventors need the approval of the TLOs located at the university to commercialize their inventions (Hoye, 2006).

Many European countries along with Canada have used government tools to encourage innovation commercialization from universities (Rasmussen, 2008). Canada has a long history of state and provincial involvement to commercialize innovation (Atkinson-Grosjean et al., 2001; Rasmussen, 2008; Slaughter & Leslie, 1997). A survey of innovation commercialization procedures in Canada would be interesting in several aspects: (1) Canada has a decentralized education system which makes government intervention difficult (Slaughter & Leslie, 1997); (2) in Canada there are extensive federal programs that support innovation commercialization; (3) Canada has a large public research sector and a small domestic market, as European countries do (Rasmussen, 2008). Canadian universities spent CAD$36.4 million on Intellectual Property management in 2003, allotted to: external resources (25%), licensing revenues (36%), institutional grants (29%), and institutional allocations (10%) (Rasmussen, 2008).

The reform that occurred in 1989 in Canada, associated with the change in the Intellectual Property Rights policy to first-to-file, dramatically increased the number of patent applications issued by foreign and domestic inventors residing in Canada (Hanel, 2006). This reform significantly increased R&D grants specifically in the pharmaceutical industry. Canada is ranked third, after the US and Japan, for the number of patents arising from grants per dollar allotted (Hanel, 2006), as R&D grants have significantly increased the number of patents (Hanel, 2006; M. Trajtenberg, 2000). However, the increasing number of patents doesn't necessarily improve the innovation quality (Hanel, 2006). Rafiquzzaman and Mahmud's (2002) studies reveal the quality of Canadian patents has improved compared to other G-7 countries (United States, Canada, France, Germany, Italy, Japan, and the United Kingdom) except the US, when quality is measured by the number of patent citations.

Likewise, to assess the impact of patent ownership structure on innovation outcome in the US, Mowery and Ziedonis (2002) examined the impact of the Bayh–Dole Act on patent content at the Columbia U., U. of California, and Stanford University, both before and after 1980. Mowery and Ziedonis (2002) used forward citations following six-year windows as an index to measure the "importance" of patents. The forward citations show the influence of citing patents on subsequent patents. "Generality" is an index to show different technology classes associated with citing patents (Mowery & Ziedonis, 2002). Accordingly, a higher "generality" value shows the higher number of technology fields involved in citing patents (Mowery & Ziedonis, 2002).

The explorations of Mowery and Ziedonis (2002) demonstrate that there is no evidence of decline in the "importance" or "generality" of patents after 1980. However, the patents tend to be less significant and less general than those issued by highly experienced universities both before and after 1980, while being initially assigned to companies after the Bayh–Dole Act (Mowery & Ziedonis, 2002). The studies of these universities, which are among the top patent holders in the United States, illustrate that the number of biomedical patents increased both before and after 1980. Hence, the passage of Bayh–Dole did not bring significant contributions to this increasing number of biomedical patents. Accordingly, Mowery and Ziedonis (2002) reveal that patenting is more relevant to factors other rather than Bayh–Dole. They argue that patent quality is more likely linked to the history of inventors and patentees. They indicate that Bayh–Dole facilitates the entrance of inexperienced inventors to generate patents. However, their explorations illustrate that the impact of Bayh–Dole on patent content was modest. Moreover, they found that the "importance" and "generality" of the University of California (UC) and Stanford University patents did not decrease after the Bayh–Dole Act came into force. In contrast, Henderson et al. (1998a) determined that the importance and generality of university patents declined after the passage of Bayh–Dole. According to the Bayh–Dole Act literature, more attention has been paid to measuring inventors' experience in patenting predating Bayh–Dole (Henderson et al., 1998a; Mowery & Ziedonis, 2002). Mowery and Ziedonis (2002) compared patents issued by qualified universities after 1980 with patents assigned to companies less experienced in patenting, pre-1980. They proposed that the decline in post-1980 patents is more related to new, inexperienced academics or public institutions as patentees, rather than being related to Bayh–Dole. Their results thus show that the decline in post-1980 patent quality is more affected by the qualifications of new inventors than by changes made by the new ownership rights legislation. By contrast, Henderson et al. (1998a) conclude that the decline of academic patents is associated with the large number of patents issued by small firms after the passage of Bayh–Dole.

However, the number of patents developed by university scientists increased after the Bayh–Dole Act came into effect. The main purpose of Bayh–Dole is that the majority of valuable university patent technologies are unexploited (Motohashi & Muramatsu, 2012). Therefore, university ownership of intellectual property rights results in significant contributions to industry (Motohashi & Muramatsu, 2012). The process of patent commercialization at universities is facilitated through shifting patent ownership to the universities themselves and restructuring academic scientists' intellectual property rights. As a consequence, these scientists tend to develop more patents (Henderson et al., 1998, 1998a; Motohashi & Muramatsu, 2012; Sampat et al., 2003). Through granting licensing authority to the universities, the number of patents at universities and research facilities is increased, although the quality of patents held by universities is less known (Motohashi & Muramatsu, 2012).

Bessen (2008) stated that individual inventors in a low-technology paradigm might not obtain high patent value, however this does not mean that they issue low quality patents. Instead, it shows that small inventors might receive less value through issuing patents (Bessen, 2008). However, other inventors involved in small firms may generate very valuable patents, as well as those in large corporations (Bessen, 2008). In a high-technology market (Silicon Valley, for instance), small firms can offer their patents to the market and there is an opportunity for large firms with great financial assets to purchase their innovations (Bessen, 2008).

There is a huge difference in patent value between different categories of patentees (Bessen, 2008). Small and individual patentees, firms with less than 500 employees, and non-profit organizations obtain on average less than half the value compared with patents granted to large corporations (Bessen, 2008). However, this does not hold true for small and individual inventors in a high-technology market (Bessen, 2008). Small firms can be fit perfectly into the technology market, with high demand for acquisition of small firms' innovation outcomes by large technology-driven corporations (Bessen, 2008).

3.1.1 Government assignees versus private-sector assignees

Numerous scholars have investigated the links between patent ownership and patent quality (Crespi et al., 2010; Henderson et al., 1998a; Lissoni et al., 2010; Motohashi & Muramatsu, 2012; Mowery & Ziedonis, 2002; Sampat et al., 2003; Sterzi, 2013). Popp et al. (2013) assessed the impact of assignees' type on the patent citations at six energy technologies fields including: Hybrid, Nuclear, Solar, Wind, Efficiency, and Fuel Cell. Popp et al. (2013) defined different dummy variables to identify various assignees' institutions including U.S. government, industry, university, other research facilities and U.S. government child patents. Popp et al. (2013) defined two dummy variables according to the government assignees. First, a dummy variable for government assignees was set at 1, where patents were assigned to the U.S. government laboratories (Popp et al., 2013). Second, U.S. government child patents were also set at 1, where patents were privately held by a corporation but cited at least one patent that was assigned to the U.S. government (Popp et al., 2013). Popp et al.'s (2013) outcomes demonstrated that the results vary across different technology domains (fuel cell, solar energy and wind); government patents obtained higher quality. However, only 1.4% of patents in the wind sector were assigned to the government. For the remaining domains, the government assignees received fewer citations (Popp et al., 2013).

Likewise, Popp (2006) discovered that government patents are not cited more frequently in subsequent patents than other types of assignees. This result can be explained by the nature of the government projects. They have greater risk than other research projects but government has enough resources to take the risk; private companies cannot take such tremendous risks. The U.S. government patents obtained 22% less citations than private patentees (Popp et al., 2013). According to Popp's (2006) findings, the government patents tended to receive more citations after 1981 compared to patents issued before 1981. There can be two possible explanations: first, patents concentrated more on applied science before 1981, while later patents were linked to more basic knowledge and so tended to be cited more than before (Popp, 2006).

The second explanation involves the nature of government patents accomplished at laboratories, which seems to have changed over time (Popp, 2006). Particular policy actions took place in 1980 to shift patent ownership from the public to the private sector; these include the Stevenson–Wylder Technology Innovation Act of 1980, the Bayh–Dole Act of 1980, and the

Federal Technology Transfer Act of 1986 (Popp, 2006). The Technology Innovation Act launched a technology transfer office to engage all federal laboratories (Popp, 2006). The Federal Technology Transfer Act of 1986 deals with the collaborative R&D projects run with the cooperation of government laboratories and private corporations (Popp, 2006). Accordingly, the shift in the nature of government patents encouraged private corporations to cooperate with the government in patenting, causing the government patents to be cited more after 1981 (Popp, 2006). However, the government patents were still not cited as frequently as patents held by corporations (Popp, 2006; Popp et al., 2013). The above results show that as the nature of government patents changed over time, privately owned patents became more appropriate for the commercialization and marketing of innovations, and thus were cited more (Popp, 2006; Popp et al., 2013).

As we discussed above, the results may vary according to the domains and regions (Popp, 2006; Popp et al., 2013). With respect to the former studies, U.S. government child patents that were assigned to firms obtained greater quality in terms of patent citations than government patents (Popp, 2006; Popp et al., 2013). There is still a lack of attention given to measure the impact of government assignees on the quality of biotechnology patents issued by inventors residing in Canada. Therefore, in this section, we seek an answer to the question, *"Do public patents obtain more quality than patents that were privately assigned by the corporations?"* Therefore, this thesis proposes a hypothesis regarding the impact of government assignees on quality of patents generated by academic inventors.

Hypothesis 1: Patents generated by at least one academic inventor and exclusively owned by the government are of a lesser "quality" than those owned by industrial assignees.

In most of the literature reviewed in the previous and current chapters, scholars have used various indicators that they claim measure, or is a proxy for, "quality". A few scholars have warned that these proxies are just that, proxies, and do not measure quality per se. These indicators may measure impact, usage, generality or diversity of prior art or of future applications, etc. In this thesis, although we use the term "quality" as a general term, it is meant as implying impact, usage, diversity, etc. The next chapter will define the exact indicators that will be used for this purpose.

3.1.2 Academic assignees versus industrial assignees

Patent ownership depends on a variety of legislation and institutional factors. Certain countries have their own intellectual property strategy. Essentially, universities in those countries tend to own their inventions instead of companies. For instance, in the UK and the Netherlands, universities are able to manage their inventions in accordance with internal policies (Lissoni, 2012). Similarly, professors can keep the privilege of their inventions in Scandinavian countries and Germany (Lissoni, 2012). The status of these countries in regard to academic patenting is outstanding. Furthermore, certain universities may own the inventions of their scientists through internal intellectual property policies (Lissoni, 2012). Thus, professors have high control over their inventions and they tend to keep their own patent rights (Lissoni, 2012). Conversely, there is a lower proportion of academic ownership in certain other countries, where universities have less control over their assets (Lissoni, 2012).

Sterzi (2013) identified that there is still a lack of attention given to measuring the impact of patent ownership including university and firms on patent quality. Comparing the quality of patents owned by universities with the quality of company-owned patents during the period 1990–2001, Sterzi (2013) found that academic patents owned by firms show greater quality in the first year of patent application compared to those assigned to universities and other research facilities. However, this difference diminishes and then disappears over time, with an increase in citations of academic patents. This is due to the fact that patents acquired by companies mostly target direct commercial benefits in the short term, while those owned by universities and other public institutions tend to answer scientific questions that have an impact over longer periods (Czarnitzki, Hussinger, & Schneider, 2012; Sterzi, 2013). Firms' patents obtained 44% higher forward citations than academic patents in first three years after patent application date, however this rate diminished to 23% after six years (Sterzi, 2013).

Lissoni et al. (2010) and Crespi et al. (2010) also investigated whether there is a link between patent ownership and patent quality. Lissoni et al. (2010) assessed patent quality for five

European countries (Sweden, Italy, the Netherlands, France, and Denmark). They found that patents owned by industry are of a greater quality compared to patents owned by universities. Likewise, Crespi et al. (2010) measured the value of academic patents in six European countries (the Netherlands, Spain, France, Italy, the UK, and Germany). Crespi et al. (2010) were unable to find any evidence to identify a relationship between ownership and patent quality.

However, analyzing the patents owned by universities is not a fundamental indicator for university science and technology linkage (Meyer, 2003). Instead, patents owned by at least one academic inventor may be more essential to measure science–technology transfer (Meyer, 2003).

In previous studies, there is inadequate research to measure the quality of patents generated by academic inventors residing in Canada and owned across different institutions including universities and corporations. Therefore, we suggested the following hypothesis in this study to measure the impact of academic patents on patent quality:

Hypothesis 2: Patents generated by at least one academic inventor and assigned to universities and other academic research facilities are of a lesser "quality" than those owned by industrial assignees.

As discussed in Section 3.1, the Bayh–Dole Act deals with patents that receive public grants from the government but are accomplished by and assigned to the universities. We highlighted the impact of the Bayh–Dole Act on "importance" or "generality" of the patents in Section 3.1. In this study we set out to examine the so-called "quality" of patents assigned to the universities and other research facilities in cases where the inventor(s) received public funding from the government. We wanted to assess the impact of government grants on patent "quality" in those cases. We discuss in detail the impact of the Bayh–Dole Act on patent quality in Sections: 2.4, 3.1, 3.1.1, and 3.1.2.

Thus, we propose a hypothesis including government funding, academic assignees and patent quality, presented below:

Hypothesis 2A: Patents generated by at least one academic inventor and assigned to the university tend to rank higher in terms of "quality" when grants were received from the government.

3.1.3 Network collaboration characteristics and patent quality

There are various examinations assessing the influence of scholars' research collaboration network on patents generated by corporations (Gilding, 2008; Guan & Chen, 2012; Mariani, 2004; Tether, 2002). Furthermore, there are studies that measure the impact of different players' network position on their partners' performance, where the actors' knowledge flows in interactive networks (Bettencourt, Kaiser, & Kaur, 2009; Chen & Guan, 2010; Cowan & Jonard, 2004; Guan & Chen, 2012; Schilling & Phelps, 2007).

Previous studies investigated the impact of various actors' network structure, where their connectivity centers on the partners' innovation outcomes (Bettencourt et al., 2009; Chen & Guan, 2010; Cowan & Jonard, 2004; Guan & Chen, 2012; Schilling & Phelps, 2007). Guan and Chen (2012) assessed the influence of network position on patenting at the national level, including the countries playing crucial roles as knowledge creators. Schilling and Phelps (2007) examined the firms' network characteristics on industrial innovations.

Xiang, Cai, Lam, and Pei (2013) structured the new model to integrate the patent citation and co-invention network. They considered the patent citation as explicit, codified knowledge which is easily identified through the patent document. Co-inventors first engage in a long process of sharing non-codified knowledge; however, various face-to-face relationships between different partners is required to effectively shape the co-invention networks (Bresman, Birkinshaw, & Nobel, 2010; Szulanski, 1996; Uzzi, 1996; Xiang et al., 2013). The co-inventors network is associated with tacit knowledge, which is non-codified and more difficult to track. Various personal relationships are required to transfer such knowledge. Xiang et al. (2013) believed the patent citation doesn't show the whole picture of knowledge exchange; therefore they considered the network properties of co-inventors as a complementary entity to complete the whole picture of knowledge transfer. Incorporating both the patent citations and the co-invention networks comprehensively reflects the true extent of knowledge transfer between different partners, including explicit as well as tacit knowledge (Xiang et al., 2013). Various scholars have explored the network properties of knowledge transfer (He & Fallah, 2009; Marquetoux, Stevenson, Wilson, Ridler, & Heuer, 2016; Xiang et al., 2013). They reveal a clustering co-efficient as a measure of network cohesion; where information in the short path with high density can broadly diffuse faster (He & Fallah, 2009; Marquetoux et al., 2016; Xiang et al., 2013).

Betweenness centrality is measured according to the geodesic path in the network; it demonstrates how frequently the actors between all actor pairs are located in the network's shortest path (Gilsing, Cloodt, & Bertrand–Cloodt, 2016). Gilsing et al. (2016) investigate the impact of betweenness centrality on innovation performance. Actors that occupied a highly centralized network tend to obtain high reputation, power and innovation performance (Gilsing, Nooteboom, Vanhaverbeke, Duysters, & van den Oord, 2008). Essentially, betweenness centrality provides players faster access to strategic information, among other benefits, and facilitates the broad spread of information through the whole network (Gilsing et al., 2016). The central position allows actors to control the information flow as well as the information visibility in the network (Burt, 1995). Therefore the actors dealing with high betweenness centrality are situated in the crossroads of strategic information and tend to obtain better innovation performance (Gilsing et al., 2016). Hagedoorn and Cloodt (2003) used four indicators including R&D input, patent citations, number of patents, and generating new products to build a composite structure to measure innovation performance as the latent variable. Patent citation and prior art of patents were found as the most common proxy to measure patent quality (Hagedoorn & Cloodt, 2003). Therefore, in this section, we want to find out whether government patents or university patents obtain more or less citations when the inventors are highly centralized in the co-invention or co-authorship network. Previously, we discussed the impact of both government and academic assignees on patent quality. We suggested both government and university patents are likely to receive less citation than patents privately held by corporations. This study seeks to answer the following question: *Do co-invention and co-publication network characteristics have a significant influence on patent quality?* This research observes the influence of the scholars' clustering method and its correlated network positions of the university patents.

Accordingly, we proposed the following hypotheses including interactive variables of assignees (government and university) and co-invention and co-authorship network centrality:

Hypothesis 3A: Patents generated by at least one academic inventor and owned by the government are of a lesser quality than industrial assignees, even when the academic inventor(s) is highly centralized in the co-invention network.

Hypothesis 3B: Patents generated by at least one academic inventor and owned by the government are of a lesser quality than industrial assignees, although the academic inventor(s) is highly centralized in the co-publication network.

Hypothesis 4A: Patents generated by at least one academic inventor and assigned to universities and other academic research facilities are of a lesser quality than industrial assignees, although the academic inventor(s) is highly centralized in the co-invention network.

Hypothesis 4B: Patents generated by at least one academic inventor and assigned to universities and other academic research facilities are of a lesser quality than industrial assignees, even when the academic inventor(s) is highly centralized in the co-publication network.

3.2 Patent–paper pairs and patent quality

A number of scholars have explored various metrics to find a good proxy measures of innovation quality, as inspired by the scientometric literature and also as initiated by Manuel Trajtenberg (1990) (Jaffe, Trajtenberg, & Henderson, 1992; Narin, Hamilton, & Olivastro, 1997). There is ample evidence in the science–technology linkages literature expressing patent citations as a very good proxy for innovation performance, while various patent quality indicators are examined (B. H. Hall, Jaffe, & Trajtenberg, 2005; Harhoff et al., 1999). Bonaccorsi and Thoma (2007) selected multiple indicators used by B. H. Hall and Trajtenberg (2004), Henderson et al. (1998a), and Lanjouw and Schankerman (2004) to measure innovation productivity. The authors categorized the patent inventors in three groups. The first group is composed of patent inventors, where all inventors are also named as author(s) of scientific publication(s) in nano science and technology (NST). The second group consists of inventors who have no scientific publication in NST. The third group comprises patent inventors, where at least one of the inventors has published article(s) in the nanotechnology domain. Analyzing the impact of each inventor category on patent quality, Bonaccorsi and Thoma (2007) discovered the quality of patents solely generated by the inventors community to be lower than patent quality linked to the author–inventor network.

Haeussler and Sauermann (2013) presented evidence on the social impacts of authorship and inventorship on innovation performance. Scientists share their ideas through publications and can receive recognition from other researchers through citations of their scientific articles, and also through benefits such as increased salaries and consulting opportunities, as positive outcomes of their inclination to authorship (Haeussler & Sauermann, 2013; Merton & 1973). Inventorship is also rewarding, however; academic inventors can receive peer recognition in their professional network from patenting, in addition to the revenues they can generate by licensing their innovations and ideas (Dasgupta & David, 1987).

Murray and Stern (2007) studied the impact of intellectual property on knowledge diffusion, putting patent–paper pairs at the heart of their research strategy. They indicated that inventors tend to both publish articles and issue patents, and particularly that half of the publications in the field of nature biotechnology are linked to patents within five years of publication. Murray and Stern (2007) categorized the patent–paper pairs in two groups: pre-grant period with no formal Intellectual Property Right (IPR), and post-grant period including IPR associated to the time period during which articles are published. Their findings demonstrate that the citation rate of publications associated to patent–paper pairs declines after the patents are granted (see also Heisey and Adelman (2009) and Kang, Ryu, and Lee (2009).

Various scholars have suggested that IPR offers financial and social benefits for innovative activities (see for instance Hellmann (2007) and Kitch (1977), while others abide by the "anti-common" perspective, arguing that IPR has a negative impact on innovations. The debate between these two approaches points to the question of how IPR affects a researcher's inclination to generate more knowledge in future scientific activities. Some scholars take the approach that IPR is more akin to "privatizing" knowledge and thus prevents knowledge flows between researchers' ideas and their exploration (Argyres & Liebeskind, 1998; Heller & Eisenberg, 1998). Murray and Stern (2007) explored whether there is a difference in the citation rate of publications that are patented. According to their findings, as well as those of Heisey and Adelman (2009), intellectual property acquisition has a negative impact on knowledge application by subsequent scientists. Thus, the number of publication citations decreases after patents are granted.

Likewise, Magerman et al. (2015) used text mining to find patent–paper pairs. They explored the forward citation of publications belonging to such pairs and compared the citation rate with that of un-paired articles. They concluded that publications with a patent counterpart received more citations than scientific publications that were unconnected to patents. Furthermore, they found that patenting activities do not hinder research activities. Instead, involvement in patenting activities has a significantly positive impact on the research footprint of authors (Feldman, Kenney, & Lissoni, 2015; Magerman et al., 2015).

A survey of the literature on patent–paper pairs and the impact on innovation performance reveals that less attention has been directed to assessing the impact of such pairs on patent quality; different patent quality indicators have been chosen for measuring this impact. This paper therefore aims to answer the following question: *Do patent–paper pairs have a higher quality than other patents that are not linked to such publications?* With this debate in mind, the following hypothesis is therefore proposed:

Hypothesis 5: Patents invented by at least one inventor who has also authored a scientific article in a similar field within a short time frame are of a higher quality compared with patents that have been developed without close links to publications.

3.3 Patent–grant pair and patent quality

Kang and Park (2012) investigated the impact of government R&D support on biotechnology patents in Korea. They found that government funds positively affect firms' innovation, while financing holds a positive influence on domestic and international collaborations (Kang & Park, 2012). Kang and Park (2012) further concluded that inter-firm collaborations positively affect corporations' innovation. Moreover, Kang and Park (2012) reveal that government grants related to R&D projects have a positive influence on firms' patents. Government improves the innovation rate by supporting R&D projects.

Block and Keller (2009) investigated the top 100 published patents in R&D magazines for the period of the 1970s through 2006. Block and Keller (2009) discovered approximately 90 percent of the best-awarded innovations in the US received government grants. Accordingly they proposed that government funding is positively related to firms' innovation through the positive link of government granting and internal R&D resources (Block & Keller, 2009). Likewise, there is a positive association of government funds and external collaborations (Block & Keller, 2009). The external collaborations also positively influence patenting (Block & Keller, 2009). Consequently, government grants affect innovation directly as well as indirectly, through both internal and external R&D collaboration resources (Block & Keller, 2009).

De Jong and Freel's (2010) findings reveal that granting in R&D projects diminishes the geographical distance obstacles to finding a valuable partner located in a distant region. Several scholars have found that R&D resources positively affect corporations' innovation performance (Belussi, Sammarra, & Sedita, 2010; Freel, 2003; Kang & Park, 2012; Parthasarthy & Hammond, 2002; Romijn & Albaladejo, 2002). L. A. Hall and Bagchi-Sen's (2007) investigations imply that government funding definitely affects the R&D intensity in U.S. biotechnology corporations. Furthermore, firms' R&D intensity is positively correlated with innovation performance (L. A. Hall & Bagchi-Sen, 2002, 2007; Kang & Park, 2012). Scholars' investigations identify several funding sources that might affect the scientists' activities leading to patenting (Geuna, 2001; Geuna & Nesta, 2006; Goldfarb & Henrekson, 2003; Guerzoni, Taylor Aldridge, Audretsch, & Desai, 2014; Gulbrandsen & Smeby, 2005). Guerzoni et al. (2014) discovered that academic scientists are encouraged toward patent invention, when they obtain funding from their own academy. On the other hand, academic scholars have lower propensity to be issued patents (Guerzoni et al., 2014), when gaining financial support from non-academic institutions or corporations.

Gulbrandsen and Smeby's (2005) findings are not consistent with those of Guerzoni et al. (2014). Gulbrandsen and Smeby (2005) found that those scientists who obtain external funding collaborate more than those with no financial support from corporations. Moreover, Gulbrandsen and Smeby (2005) suggested that scholars with industrial funding can generate more patents and accomplish more commercial activities than those with no firms' funding.

There are no prior explorations that solely examine the correlation of financial support and commercial activities (Gulbrandsen & Smeby, 2005). Few scholars reveal that increasing the number of patents and boosting university entrepreneurship programs can increase the number of contracts (Geuna & Nesta, 2006). Gulbrandsen and Smeby (2005) findings emphasize that academic scientists who gain industrial funding gradually collaborate with other partners at universities, foreign research facilities, firms, and their colleagues at the same department. Furthermore, Gulbrandsen and Smeby (2005) results illustrate that collaboration and industrial funding are positively associated with patent invention and commercial output.

Guan and Yam (2015) examined the impact of public funding on innovation performance, measured by the number of patents as one of the indicators of innovation performance, in Beijing in the 1990s. Guan and Yam (2015) categorized the government funding in three categories: Direct Earmarks, Special Loans, and Tax Credits. Money that comes from the Direct Earmarks is assigned to equipment, renewal, procurement, and new product development for the projects engaging in high risk (Guan & Yam, 2015). This financial resource is assigned to high-priority projects in national technology development in China (Guan & Yam, 2015). China's government offers Special Loans to firms, which must be paid back, when the firms cannot obtain loans from the bank easily (Guan & Yam, 2015). Under the Tax Credits, companies can obtain tax exemptions or reductions over the three years after the corporation released its product(s) into the market (Guan & Yam, 2015). Their outcomes show all the government financial support is not related to the patents generated at either high-tech or general firms (Guan & Yam, 2015). Direct Earmarks is negatively related to the patents generated by the firms (Guan & Yam, 2015). These results show that the government funding system in China does not perform efficiently, and that the funding system in that country should be restructured to provide more market information on the funding process (Guan & Yam, 2015).

Therefore, this study seeks an answer to the following question: *"Do federally funded patents tend to obtain more citations?" We thus postulate that:*

Hypothesis 6: Patents generated by **at least one academic inventor** in Canada who <u>received</u> **<u>grants</u> from a government** in a **<u>similar field of patenting</u>** within **a short time frame** obtained significantly higher patent quality.

As we discussed in Section 3.1.3, we considered whether co-publication or co-invention network centralization has a significant effect on patent citations, as a patent quality indicator

(Xiang et al., 2013). Therefore, in this thesis, we measured whether the patents in patent–grant pairs obtain higher quality than patents without such a link, when the academic inventors occupy a highly centralized co-publication network.

Hypothesis 6A: Patents generated by at least one academic inventor who received **grants from a government** in a **similar field of patenting** within **a short time frame** are of a higher quality, even when the inventors are highly centralized in the co-publication network.

3.4 Star scientists and patent quality

A number of studies explore the impact of faculty prestige on scholars' involvement with industrial patents (Geuna & Nesta, 2006; Perkmann, King, & Pavelin, 2011; Siegel, Wright, & Lockett, 2007). Bercovitz and Feldman's (2011) findings indicate that "star scientists" bring significant value to joint team members. Zucker and Darby (1996) defined star scientists as the best partners of the biotechnology firms who had published at least forty genetic studies in *GenBank*[1] (Zucker & Darby, 1996, 2001; Zucker et al., 2002; Zucker et al., 1998). Furukawa and Goto (2006a, 2006b) likewise considered "core scientists" as industrial scholars who had published large numbers of scientific articles and obtained remarkably numerous paper citations. Baba et al.'s (2009) findings imply, in contrast with prior studies, that the most effective university–industry collaborations are associated with "Pasteur scientists" instead of star scientists. Pasteur scientists are those essential players in the university–industry knowledge transfer network who have published qualified articles as well as generating patents (Baba et al., 2009).

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[1] GenBank is a NIH genetic sequence database that covers the DNA DataBank of Japan, the European Molecular Biology Laboratory (EMBL), and GenBank at NCBI.

Hong and Su (2013) determined that social proximity and university prestige characterize the bridges among non-local scholars at universities and corporations who jointly develop new products. Collaboration with prestigious universities offers credibility for corporations in presenting product quality (Hong & Su, 2013). Various scholars indicate that firms tend to collaborate with top-tier rather than second-tier universities, regardless of the distance between them (J. D. Adams, 2005; Hong & Su, 2013; Laursen, Reichstein, & Salter, 2011).

Bercovitz and Feldman (2011) found that partners maintained interest in collaborating with star scientists regardless of the geographical distance, when the scientists' reputation is considered. These researchers also determined that the value of the scientists' reputation can compensate for the negative impact of coordination costs over a distance. However, Bercovitz and Feldman (2011) outcomes indicate there is no evidence to demonstrate that scientists' reputations encourage distant participation. They offer two possible explanations. First, because opportunities to work with star scientists are in high demand, there are ample numbers of local partners available to collaborate with them (Bercovitz & Feldman, 2011). It is not beneficial for the star scientists to suffer traveling expense and long-distance collaboration cost, when they can easily collaborate with local partners (Bercovitz & Feldman, 2011). Second, many star scientists cooperate with scholars at start-up companies that are located close to the universities (Bercovitz & Feldman, 2011).

Thus, this study aims to identify the relationship between academic star scientists and university involvement with firms. It seeks to the answer the following question: *Do more prestigious academic faculties raise the likelihood of academics to generate high-quality patents?*

Perkmann et al. (2011) suggested that the association of scientists' qualifications and university–industry linkage depends on the field, and that this relationship differs in various disciplines. They demonstrated that the faculty chair has a positive influence on corporation engagement in technology-oriented fields. Various scholars have discovered that the quality of both university and industrial firm increases the likelihood of university–industry linkage (Breschi, Lissoni, & Montobbio, 2007; Geuna & Nesta, 2006; Stephan, Gurmu, Sumell, & Black, 2007). Thus, in this study, we seek an answer to the following question: *Do star scientists positively affect the quality of an innovation outcome? Hence, the next hypothesis:*

Hypothesis 7: Patents generated by star scientists receive more numerous citations than patents issued without engaging prestigious scholars.

In this section we proposed hypotheses regarding the impact of patent–paper pairs, patent ownership, and patent–grant pairs on patent quality. The Bayh–Dole Act passed during the 1980s gives the authority for the universities to retain their intellectual property rights. There are debates over supporting public patent ownership versus favoring industrial assignees. Supporters of academic ownership say it encourages scholars' incentives at universities to generate new products and ideas, leading to economic growth (Sampat, 2006). Licensing is one of the channels by which universities can contribute to innovation commercialization (Sampat, 2006). However, the impact of public ownership is not so clear on other channels of knowledge transfer (Sampat, 2006). Licensing of academic patents by the corporations is considered as one of the significant channels of UILs. There is extensive literature that measures the impact of UILs on innovation performance.

In this research we are aware of the concerns regarding the use of patent citations or claims as proxies for patent "quality" (Alcacer & Gittelman, 2004; Jung & Lee, 2014). However, while the inventors filing the patent might not be aware of the examiners' backgrounds and qualifications, or the number of examiners, the presence of the prior art of the patents demonstrates the existence of the associated former knowledge in the patent (Jung & Lee, 2014). Some scholars have found that the aggregate citations are a meaningful proxy for the knowledge flows (Jaffe, Trajtenberg, & Fogarty, 2000; Jung & Lee, 2014); and Jung and Lee (2014) used patent citation as a reasonable proxy for the knowledge flows. We used forward citations, number of claims and Herfindahl index of both forward and backward citations to measure patent quality.

CHAPTER 4 DATA AND METHODOLOGY

4.1 Data and variables

Three data sources were applied in this exploration to find potential patent–paper pairs: the United States Patent and Trademark Office (USPTO) for patents[2] and Elsevier's Scopus for papers.[3] The Scopus database includes authors' names, their affiliations, publication date, title and abstract for each scientific article. The USPTO provides information on the inventors' names and their addresses, the assignees' names and their addresses, patent application and granting dates, the number of claims, etc. First, all the papers and patents in Canada in which at least one author or one inventor had an address or an affiliation in Canada were extracted. This exercise yielded a database of 563,684 scientists having published 180,719 articles, giving 1,013,450 lines representing article-scientist pairs, and a database of 14,082 inventors having generated 16,392 patents, giving 51,315 patent-inventor pairs. These two databases were merged using a roughly unique ID for each individual (i.e., identifying the individuals who had common names in both patents and papers[4]). From this merged database, we selected only the patents and articles belonging to scientists-inventors residing in the province of Quebec. The data sample for the patent–paper pairs research in this study was restricted to the patents generated by academic inventors residing in Quebec, because the very detailed funding data required for this study only exists in this province. This study hence covers the data belonging to 2,517 scientists and inventors residing in Quebec who were involved in patenting and in publishing activities during the period 1985 through 2005 in the biotechnology and nanotechnology domains. These individuals were involved in filing 1,110 patents over this period.

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[2] Canadian biotechnology and nanotechnology inventors generally patent in the US in addition, or in lieu of, patenting in Canada (Beaudry & Kananian, 2013). Furthermore, the Canadian Intellectual Property Office (CIPO) does not provide consistent addresses for inventors, which adds to the difficulty of disambiguating inventor's names.

[3] Scopus generally links authors with their affiliations, which greatly facilitates matching with the USPTO database and with disambiguation of names. Because of the large number of individuals to match for this research, this database was therefore favoured.

[4] Better precision is not necessary prior to the data mining similarity analysis.

As funding is crucial in patenting, the third database applied in this research is related to public grants and contracts. Thus, the *Quebec University Research Information System* (*Système d'Information sur la Recherche Universitaire*—SIRU), provided by the Quebec Ministry of Education, was used. This database contains information for the yearly amounts of contracts and grants obtained by Quebec academics. Out of the 372,967 records of SIRU, we selected the grants and contracts of the 2,203 Quebec scientists-inventors identified by the patent-paper selection exercise. Yearly public and private funding was calculated for each academic scientist residing in Quebec, as both grants and contracts were measured in this observation. In addition, for all 2,679 Canadian university scientists-inventors that collaborated with Quebec Academic-inventors, we extracted funding information from the Tri-Council Agencies (the Natural Science and Engineering Research Council – NSERC; the Canadian Institutes of Health Research – CIHR; and the Social Sciences and Humanities Research Council – SSHRC).

In this analysis, the information from the USPTO, SIRU and Scopus databases was grouped in two datasets. The first dataset contains 53,577 observations linked to biotechnology and nanotechnology inventors in Canada for the period 1996 to 2005. There were 10 rows, representing as many years, for each inventor, some of which are the academic-inventors described above, covering different information regarding the grants, contracts, article citation numbers, career age and tens of other variables through 1996 until 2005. This very detailed yearly information for each inventor, is then aggregated at the patent level (only for the relevant years – i.e. that of the patent application) according to the unique patent identification number, and comprises of 1,110 patents. Since there might be more than one inventor linking to each patent, the average of grants, contracts, and other indicators associated with inventors has been calculated for each unique patent. In other words, all the variables that were initially measured at the academic-inventor-year level and then grouped (averaged) at the patent level for all the academic inventors. On caveat of this method is that as we do not have the amount of funds provided to industrial scientists, only the public and private funds that transit via university accounts are considered in this study.

4.2 Dependent variables

Many scholars have used various patent indicators that they claim are good proxies for the "quality" of patents, including the number of patent backward citations, the number of forward citations, the number of claims, the number of IPC-subclasses, patent renewal times, and the number of patent applicants as dependent variables (Carpenter et al., 1980; Goetze, 2010; Hirschey & Richardson, 2004; Narin et al., 1987; Manuel Trajtenberg, 1990). For instance, the number of forward citations counts the number of times that patents have been cited in subsequent patents during the 5-year period after the patents were granted (Burke & Reitzig, 2007; Manuel Trajtenberg, 1990). The number of backward citations counts the number of patents referenced as citations in the patent document (Burke & Reitzig, 2007; Narin et al., 1987). Henderson et al. (1998a) used the Herfindahl index as a measure of patent concentration. Bonaccorsi and Thoma (2007) constructed a quality index built from different quality factors such as the number of forward citations, the number of backward citations, family size and the number of claims. Bonaccorsi and Thoma (2007) integrated 1 minus the Herfindahl index of backward citations as a component of their originality index. A higher value of originality index demonstrates patents are less concentrated, and hence more diversified (Henderson et al., 1998a).

The dependent variables of this investigation are therefore amongst the commonly used proxies for determining patent "quality". The following variables have been selected for this purpose in this study: the number of patent forward citations [$NbFCit5_t$], the number of claims [$NbClaims_t$], 1 minus the Herfindahl index of forward citations [$HerfIndexFCit5_t$], which is an index of the diversity of the patent classes of the pool of patents that cite a particular patent, and 1 minus the Herfindahl index of backward citations [$HerfIndexBWCit_t$], which is a measure of the diversity of the patent classes of the prior knowledge that a particular patent cites.

4.3 Independent variables

The variable *Grant3*$_t$ measures the average amount of grants raised by each academic inventor residing in Quebec over the 3 years prior to the patent application.[5] Similarly, *Contract3*$_t$ measures the amount of contract funding raised over the past 3 years, averaged among the Quebec academic inventors named on the patent document[6]. Payne and Siow (2003) found a small but positive impact of funding on the rate at which researchers have contributed patents. Separating grants from contracts, Beaudry and Kananian (2013) concluded that grants have little or no effect on the number of patent citations, finding an inverted U-shaped relationship with the number of claims. Thus, Beaudry and Kananian's (2013) outcomes suggest a substitution effect between grants and contracts. Contracts, however, have a positive impact on both the number of citations and the number of claims.

The scientists and inventors team itself may influence the quality of the resulting patent, as scientists and inventors tend to work in a group and do not generally work alone. Beaudry and Schiffauerova (2011) assessed the impact of the network characteristics of Canadian nanotechnology inventors on patent quality measured by the number of claims. The researchers discovered that more central individuals in terms of betweenness centrality (i.e., good intermediaries) produce a higher patent quality (Beaudry and Schiffauerova (2011). Conversely, J. C. Wang, Chiang, and Lin (2010) found that high brokerage has a negative impact on the patent renewal decision, where high brokerage is similar to the intermediary position and measured by betweenness centrality.

In these studies, the network vertices represent the scientists or inventors, and the edges between the vertices correspond to the collaborative links between scientists or inventors leading to articles or patents (Carrington, Scott, & Wasserman, 2005). The co-authorship and co-

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[5] We have no means by which to evaluate the amount of funding raised by out of Quebec inventors and invested by the assignees. This variable is a control for the capacity of the academic team to raise funds.

[6] All grants and contracts monetary values have been deflated using the consumer price index to consider constant dollar values.

invention networks of scientists and inventors were respectively mapped in this study by using the social network analysis software Pajek.

Certain intermediary nodes are indeed crucial for bridging between various clusters and sub-clusters to diffuse information, knowledge and financial resources between different players (Ebadi & Schiffauerova, 2015). Betweenness centrality is a measure that identifies such gatekeepers in the network (Ebadi & Schiffauerova, 2015). Betweenness centrality shows the frequency of the node located between pairs of other nodes, occupying the shortest path of a graph (Szczepański, Michalak, & Rahwan, 2016). Essentially, betweenness centrality is a way to measure control of flow, knowledge in our case, in the network (Ebadi & Schiffauerova, 2015; Freeman, 1978; Marquetoux et al., 2016; Szczepański et al., 2016). Technically, betweenness of node k is defined as the share of time that node i can reach to node j through node k on the shortest path between node i and node j (Borgatti, 2005; Ebadi & Schiffauerova, 2015). Betweeness centrality is calculated by a formula, presented below, where i and j occupy a network as non-adjacent nodes (Ebadi & Schiffauerova, 2015):

$$bc_k = \sum_{i \neq k \neq j} \frac{\sigma_{ij}(k)}{\sigma_{ij}} \qquad \text{Equation 4.1}$$

A high value of betweenness centrality for node k characterizes the essential control of node k in diffusing the flow between two other non-adjacent nodes, represented by node i and j (Ebadi & Schiffauerova, 2015; Wasserman & Faust, 1994).

A clustering coefficient identifies the probability that node i and j are connected to node k, when node i and j are directly connected to each other (Marquetoux et al., 2016). The clustering coefficient shows the cliquishness of the network (Ebadi & Schiffauerova, 2015; Marquetoux et al., 2016; Watts & Strogatz, 1998). Scholars with a high clustering coefficient tend to tightly cluster to increase their connectivity; as a result, knowledge can transfer rapidly among players (Ebadi & Schiffauerova, 2015). The clustering coefficient specifies the triangle of actors who build a cluster, and it is calculated by the local clustering coefficient (Ebadi & Schiffauerova, 2015).The local clustering coefficient of a node i is measured by the number of two adjacent nodes that connect to node i to build a cluster as triangle nodes, divided by the number of all three nodes that are connected together in the cluster (Watts & Strogatz, 1998), as presented below:

$$lcc_i = \frac{number\ of\ tri\ angles\ connected\ to\ node\ i}{number\ of\ triples\ centered\ on\ node\ i}$$

Thus, the overall clustering coefficient is calculated by the average of local clustering coefficients divided by the number of nodes representing vertices in the network of players, as demonstrated by the formula:

$$cc = \left[\sum_{i=1}^{n} lcc_i\right] / n \qquad \text{Equation 4.2}$$

In this study, to characterize the researchers' positions within three-year[7] interactive networks, a number of indicators were constructed: betweenness centrality (*BtwCentArt3*$_t$) and cliquishness attributes (*CliqnessArt3*$_t$), of individual scientists both belonging to the co-publication network, averaged over all inventors of a particular patent. Furthermore, the co-invention network was characterized by a third and a fourth variables: Betweenness centrality (*BtwCentPat3*$_t$) measures the importance of an inventor as an intermediary in the co-invention[8] network (Freeman, 1978), averaged over all academic inventors of a given patent; Cliquishness represents the likelihood that the direct neighbours of researchers are also connected to each other (Nooy, Mrvar, & Batagelj, 2011) in the co-invention network (*CliqnessPat3*$_t$), averaged over all researchers of a given patent.

The literature generally finds individuals who are most productive in terms of technological outputs generally produce most papers (Balconi & Laboranti, 2006; Calderini, Franzoni, & Vezzulli, 2007; Meyer, 2006; Van Looy, Ranga, Callaert, Debackere, & Zimmermann, 2004). The intrinsic individual quality is probably what drives this high production and constitutes a latent variable in this analysis. It is therefore important to measure this quality. The average

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[7] The time window for building the networks differs from one study to another, when collaboration history is reviewed. Schilling and Phelps (2007) used 3-year windows to map the firm collaboration network. In contrast, Gulati and Gargiulo (1999) estimated 5-year windows. Thus, different combinations of 3- and 5-year subnetworks were calculated in this study to build the network metrics, and the 3-year subnetworks were chosen as the most that yielded the most consistent result.

[8] The average betweenness centrality of scientists in the co-invention network is also calculated; but as this variable never showed any significance in the results, it was eliminated from the models.

number of article citations obtained by academic inventors in the past 3 years is calculated as a first proxy of "scientific quality" in this analysis (*$ArtCit3_t$*) as quality on the science side may drive quality on the technology side. A second proxy for individual quality is associated with the type/reputation of the research chair held by academic inventors in their careers. According to this measurement, the variable (*$MaxChair_t$*) is defined as an ordinal variable, taking the value 0 if an academic inventor never held a chair, the value 1 for an industrial chair, the value 2 for an NSERC or CIHR chair and the value 3 for a Canada research chair.

Furthermore, the "career" age (*Age_t*) of a scientist is included as a proxy for real age, as the impact of the scientist's age on patent quality is estimated. Career age corresponds to the average age during the whole period in which an inventor appears in the database from raising funds, publishing articles or patenting. This control variable expresses the fact representing older scientists maybe more creative (Cole & Cole, 1973; Kyvik & Olsen, 2008; Merton & 1973). Conversely, particular researchers believe scholars may make their most important discoveries before the age of 40 (C. W. Adams, 1946; Gieryn, 1981; Stern, 1978; Zuckerman, 1977).

4.3.1 Patent–paper pairs methodology

Several researchers have employed various methodologies to construct patent–paper pairs. Murray and Stern (2007) tried to match the articles and papers published in *Nature Biotechnology Journal* by asking experts to find the connection between the matched articles and papers. Ziedonis (2012) used an "Inventor-based matching" algorithm to extract the patent–paper pairs. Ziedonis's (2012) algorithm is structured around the names of inventors who participated in both patenting and publishing. Two assumptions were necessary for this methodology: first, inventors who contributed to publications were considered as the link between science and technology; second, the patent application year was close to the publication date, within 2 years either side of the patent application date (Ziedonis, 2012). While Murray and Stern (2007) limited their patent–paper pairs to one patent linked to one publication, Ziedonis (2012) matched a number of common publications to a single given patent.

A number of researchers used text-mining tools to find inventors who were also named as authors in a similar domain (Lissoni, Montobbio, & Zirulia, 2013). Lissoni and Montobbio

(2006) selected the potential patent–paper pairs as those for which at least one inventor published scientific articles during the period [t - 2, t + 2], where t corresponds to the patent's application date. In one of their methods (they compared five), Lissoni and Montobbio (2006) calculated the cosine similarity between the patent and paper documents to measure content similarity. Lissoni and Montobbio (2006) identified the top 10% of potential patent–paper pairs as the actual patent–paper pairs, with similarity measures ranging from 0.145 to 0.75. Ducor (2000), however, discovered that authors were not always matched with the inventors who published (Haeussler & Sauermann, 2013).

A similar methodology to Magerman et al. (2011, 2015) was used in this study. In Magerman et al.'s (2011, 2015) methodology, content similarity was measured to analyze the similarity of titles and abstracts of patents and papers, where at least one inventor was listed as an author of the publication. All the words of these documents were first indexed, and then evident stop words were removed. The vector space was created based on a document-by-term matrix generated from the patent and paper documents (Magerman et al., 2011, 2015; Salton, Wong, & Yang, 1975). The patent and article documents occupied the rows of the matrix, and particular distinctive terms extracted from the documents were added as the columns (Magerman et al., 2011, 2015). Then, a Term Frequency and Inverse Document Frequency (TF-IDF) method was used as a classic data mining technique (Magerman et al., 2011, 2015). Term Frequency and Inverse Document Frequency (TF-IDF) was used to find the term frequencies of the words in the documents, in order to measure the similarities between the patent and paper documents (Magerman et al., 2011, 2015).

In our research, the potential patent–paper pairs were first identified by selecting the patents originated by the authors-inventors network. According to our examination, 22,688 potential biotechnology patent–paper pairs were therefore extracted, with at least one of the inventors publishing at least one article in the period [t - 2, t + 2], where t corresponds to the patent application date. Moreover, 20,003 patent–paper pairs were discovered as potential nanotechnology patent–publication pairs originating in Canada. The text mining software Rapidminer was used to calculate the cosine similarity between the paired patent and paper documents. In this test, the similarity measures ranged from 0 to 0.78 for biotechnology, and from 0 to 0.53 for nanotechnology (theoretically, similarity measures range from 0 to 1). As with the methodology of Lissoni and Montobbio (2006), patent–paper pairs were selected from the top

10 percentile of the similarity in our observation. This roughly corresponds to a similarity measure of 0.30 for both biotechnology and nanotechnology samples. A dummy variable (*dPPP*) was created, taking the value 1 if the patent had a paper counterpart (i.e., the patents and papers are similar enough according to the top 10 percentile measure) and 0 otherwise. Then, this threshold was examined to see whether it yielded significant results in the regression models. Accordingly, 249 actual nanotechnology patent–paper pairs and also 376 biotechnology patent–paper pairs[9,10] were discovered in Canada, while the 0.30 threshold was used to measure the similarity. Because of the poor performance of this dummy variable in our regressions, and that regarding the threshold selected, we reverted to using the original measure of similarity in our regressions (*Similarity*). Results using the dummy variable *dPPP*, will therefore not be reported in this thesis.

4.3.2 Patent–grant pairs methodology

A review of the literature reveals a lack of attention to the topic of patent–grant pairs. To research this linkage, we measured the similarity of grants titles (from the Tri-Council Agency database) and patent titles (extracted from the USPTO database) using Rapidminer. First, we found the inventors (associated with our patent sample) who received grants from the federal government. Then, to increase our selection accuracy we applied the condition below to narrow the time window, in order to find the linkage between a patent and its relevant grants:

$$[\text{Year}_{\text{patent application}}-2] <= \text{Year}_{\text{grant}} <= [\text{Year}_{\text{patent application}}]$$

The potential patent–grant pairs were therefore selected where public grants were assigned to inventors during a maximum of two years preceding the patent application year, and no further than the patent application year. Then, to improve the selection process, we assessed the similarity of the field associated with both patents and grants. We deleted the potential patent–

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[9] These patent–paper pairs were all checked individually to ensure that no two individuals with the same name were mistakenly associated in patent–paper pairs.

[10] Note that the nanobiotechnology field overlaps both biotechnology and nanotechnology; hence the total number of patent–paper pairs (PPP) found is less than the sum of both numbers of PPP.

grant pairs where inventors received grants in the biotechnology domain and generated patents in nanotechnology, or vice versa. We also kept the instances of inventors who received grants in either nanotechnology or biotechnology and generated patents in the combined field of nanobiotechnology which intersects both fields.

In our sample, there were 1,110 patents, which were associated with 4,131 patent–scientist pairs. We merged our patent–scientist pairs table (including those 4,131 records) with the Tri-Council Agencies database including 202,586 records, yielding 10,768 lines. Therefore, we applied the above-mentioned procedure to find potential patent–grant pairs, yielding 1,456 lines. Then, we measured the content similarity of titles of patents and grants belonging to potential patent–grant pairs that were extracted so far. Finally, we aggregated our data according to the patent identification and calculated the maximum and minimum similarity measure for each patent. As a result, we had a sample covering 1,110 observations including the maximum and minimum similarity, which arose from the patents and grants for each unified patent. Finally, we checked the significance of the similarity variable in our analysis model to find the threshold of the similarity between patents and grants. Various similarity values were tested, ranging from 0.05 to 0.5. Finally, the threshold similarity of 0.1 was selected as a limit of the similarity. In this research, we generated a dummy variable associated with the patent–grant pairs. It equals 1 when the patent is part of a patent–grant pair, otherwise 0. Accordingly, 41 patent–grant pairs were identified in this research. In our measurement models, we used patent–grant pairs as a dummy variable and not as a similarity variable.

4.4 Model specification

4.4.1 Impact of patent–paper pairs on patent quality

To analyze the impact of the patent–paper similarity [*Similarity*] variable on patent quality, several methods have been applied in this research. We used the Wu-Hausman test to find whether there is endogeneity in our model. The number of forward citations ($NbFCit5_t$), the number of claims ($NbClaims_t$) (both transformed by taking the natural logarithm) 1 minus the Herfindahl index of backward citations ($HerfIndexBWCit_t$) and 1 minus the Herfindahl index of forward citations ($HerfIndexFCit5_t$) were measured as the dependent variables. According to the results, our model (including the patent–paper similarity attribute) does potentially suffer from endogeneity problems, when the number of claims (*NbClaims*$_t$) and 1 minus the Herfindahl index of forward citations (*HerfIndexFCit5*$_t$) are examined as the dependent variables (*HerfIndexBWCit*$_t$ and *HerfIndexFCit5*$_t$ are both normal continuous variables; therefore we didn't apply logarithms for both Herfindahl variables).

There are several possible explanations for this endogeneity. First, unobserved heterogeneity may plague the analysis because of poor data quality. Accordingly, an effort was made to clean the data to accurately match the name of scientists and inventors in this research. This step was performed manually and as such is not immune from human errors. Second, the number of patent citations was assumed to be linked to the total average of contracts received by academic inventors (*Contract3*$_t$). However, the contracts are also probably related to the amount of grants raised (Grant3$_t$) (Beaudry & Schiffauerova, 2011), which is one of the explanatory variables in this test. Thus, the contracts were observed as an endogenous variable in this examination.

To correct for potential endogeneity, the two-stage least-squares (IVRegress 2SLS) regressions were estimated. The average amount of contracts (in constant CAD$) raised over three years *(Contract3*$_t$*)* is highly correlated with particular variables, which are treated as instruments. Three instrumental variables are used to estimate the average amount of contracts: the average amount of past contracts received in the same university (*Contract3U*$_{t-2}$), the average amount of grants for equipment and infrastructure obtained by inventors (*GrantEI3*$_{t-1}$), and the number of innovation loops (*Loop*$_t$). The average amount of past contracts received in the same university (*Contract3U*$_{t-2}$) shows that universities that traditionally collaborate a great deal with industry are probably closer to the so-called third mission of universities. The average amount of grants for equipment and infrastructure raised by academic-inventors (*GrantEI3*$_{t-1}$) is related to the sharing of important biotechnology and nanotechnology infrastructure that is often encouraged to ensure the survival of these laboratories. The number of innovation loops (*Loop*$_t$), as suggested by Beaudry and Kananian (2013), measures the number of times academic inventors received funds from companies for research purposes, when these firms simultaneously own these patents. Thus, researchers having closer links with industry are likely to attract more contracts.

In this analysis, various lag structures were estimated for the instrumental variables. A two-year lag was selected for universities' past contracts (*Contract3U*$_{t-2}$). Likewise, for the equipment and infrastructure grants (*GrantEI3*$_{t-1}$), a one-year lag yields the most consistent results. Moreover, we used the Sargan test to verify whether our instrumental variables were valid, the tests confirms that our instrumental variables are valid. Please refer to Table E.1–Table E.2. We used the IVRegress 2SLS procedure to account for potential endogeneity (these results are summarized in Table E.1, Table E.2, Table 6.3, and Table 6.5).

Equation 4.3 below presents the instrumental variable model where the average of contracts (*Contract3*$_t$) is the endogenous variable, and where the instrumental variables include universities' past contracts (*Contract3U*$_{t-2}$), equipment and infrastructure grants (*GrantEI3*$_{t-1}$), and number of innovation loops (*Loop*$_t$). This is the first stage of the 2SLS regression. The second stage of the model estimates the number of forward citations [*NbFCit5*$_t$], the number of claims [*NbClaims*$_t$], 1 minus the Herfindahl index of forward citations [*HerfIndexFCit5*$_t$] and 1 minus the Herfindahl index of backward citations [*HerfIndexBWCit*$_t$] (see Equation 4.4).

$$\text{Contract3}_t = f(\text{Contract3U}_{t\text{-}2}, \text{GrantEI3}_t, \text{Loop}_t, 2^{nd}\,stage) \qquad \text{Equation 4.3}$$

$$\left\{\begin{array}{l}\text{NbFCit5}_t\\ \text{NbClaims}_t\\ \text{HerfIndexFCit5}_t\\ \text{HerfIndexBWCit}_t\end{array}\right\} = f\left(\begin{array}{l}\text{Contract3}_t, \text{Grant3}_t\\ \text{Age}_t, \text{MaxChair}_t,\ \text{ArtCit3}_t\\ \text{BtwCentArt3}_t, \text{BtwCentPat3}_t\\ \text{CliqnessArt3}_t, \text{CliqnessPat3}_t\\ \text{Similarity}_t, \text{dPGP}_t, \text{dGovAssignee}_t, \text{dAcAssignee}_t, \text{dNanoEx}\end{array}\right) \qquad \text{Equation 4.4}$$

Understandably, not all models will exhibit endogeneity problems, and as such, only Equation 4.4 will be estimated, i.e. without the first stage equation). The Wu-Hausman test results imply there is no endogeneity for number of forward citations (*NbFCit5*$_t$) and 1 minus the Herfindahl index backward citations (*HerfIndexBWCit*$_t$) (refer to appendix Table E.1–Table E.2).

As robustness checks, we also estimated models on the number of citations and claims (as opposed to the natural logarithm of these two measures) using Poisson regressions. A Poisson model is demonstrated below in Equation 4.5, where y represents the dependent variable and x the independent variable:

$y = \beta_0 + \beta x + \varepsilon$ where β is the coefficient and ε is a residual Equation 4.5

$$P(Y_i = y_i) = \exp\lambda(x_i).\left[\frac{\lambda(x_i)}{y_i!}\right]$$ Equation 4.6

$$E(y_i \mid x_i) = \lambda_i = e^{x_i\beta}$$
$$E(y_i \mid x_i) = Var[y_i \mid x_i] = \lambda_i$$ Equation 4.7
$$\lambda_i = Exp(\beta x_i + \varepsilon)$$

Our models suffered from over-dispersion and we couldn't use the Poisson model in our analysis. We therefore had to estimate negative binomial regressions which do not impose that the mean is equal to the variance as it is the case in Poisson regressions. The negative binomial regression (nbreg) is demonstrated below:

$$y_i = \beta_0 + \beta x_i + \varepsilon$$
$$E(y_i \mid x_i) = Var[y_i \mid x_i] = \lambda_i$$ Equation 4.8
$$Var[y_i \mid x_i] = E(y_i \mid x_i)(1 + \alpha[E(y_i \mid x_i)])$$

If α = 0 then the Poisson models is the appropriate model; otherwise, if $\alpha \neq 0$ then there is over-dispersion, and negative binomial regression (nbreg) is the correct model. Beta as the regression coefficient is a measure of how strongly each predictor variable influences the dependent variable.

Finally, all the variables have been transformed by Z Score grand mean centered to normalize the variables and hence minimize multicollinearity problems when using interactive variables (Z = x – μ / σ, μ = mean and σ = standard deviation) to measure impact of patent–paper similarity on patent quality. The corresponding results are shown in Table 6.2 (*NbFCit5*$_t$), Table 6.3 (*NbClaims*$_t$), Table 6.4 (*HerfIndexBWCit*$_t$), and Table 6.5 (*HerfIndexFCit5*$_t$).

4.4.2 Impact of public assignees versus industrial assignees on patent quality

To compare the quality of patents assigned to the public sector with patents privately held by corporations, several models were used in this study. Whether to use the Tobit model or the Ordinary Least Square (OLS) method was addressed as a primary question in the analysis. Since there is a significant number of 0 values, the Tobit model (left censored) was chosen as the more appropriate model to analyze the natural logarithm of the number of forward citations [$NbFCit5_t$], 1 minus the Herfindahl index of forward citations [$HerfIndexFCit5_t$], and 1 minus the Herfindahl index of backward citations [$HerfIndexBWCit_t$]. The Tobit model is the econometrics model initially proposed by Tobin (1958) to demonstrate the relationship between a non-negative dependent variable (y_i) and independent variables (x_i). Finally, the Tobit regression model was used for the natural logarithm of number of claims [$NbClaims_t$].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + ... + \beta_m X_m \qquad \text{Equation 4.9}$$

$$\begin{matrix} y_{it} = y_{it}^* & \text{if} & y_{it}^* > 0 \\ y_{it} = 0 & & y_{it}^* \leq 0 \end{matrix} \qquad \text{Equation 4.10}$$

Where μ is a normal distribution with Means=0 and Variance=σ^2 :

$$y_{it}^* = \beta x_{it} + \mu_{it} \qquad \text{Equation 4.11}$$

y* represents a latent model, x demonstrates the independent variables, and y is a linear combination of independent variables ($X_1, X_2, ..., X_m$).

To measure the impact of patent ownership structure on $NbFCit5_t$, $NbClaims_t$, $HerfIndexBWCit_t$, and $HerfIndexFCit5_t$, Equation 4.4 was used. We used the square root of the clustering coefficient of the co-publication network (all averaged) to normalize this variable. Moreover, the natural logarithm of betweenness centrality of both co-publication and co-invention network is measured in the final model in order to normalize centrality variables. We tested the square effect of each variable to examine both the linear and non-linear effect of the variables (quadratic effect). Therefore, we added the square variables when there was a significant effect. Finally, we added the interactive variables to measure the impact of academic or government assignees on patent quality, when inventors were situated in a highly centralized co-invention and co-authorship network. As a next step, we tested whether there is endogeneity in our model or not. Once again, the IVRegress 2SLS method was the most appropriate model for the analysis. To analyze the endogeneity, IVRegress was used along with the Wu-Hausman and Sargan tests. Results are shown in Table F.1–Table F.4 in the appendix. The Wu-Hausman test's results illustrate that there is no endogeneity for the number of forward citations [$NbFCit5_t$], the number of claims [$NbClaims_t$], or 1 minus the Herfindahl index of forward citations [$HerfIndexFCit5_t$] and 1 minus the number of Herfindahl index of backward citations [$HerfIndexBWCit_t$]. The results are identified in Table F.1 (number of forward citations [$NbFCit5_t$]), Table F.2 (number of claims [$NbClaims_t$]), Table F.3 (Herfindahl index of backward citations [$HerfIndexBWCit_t$]), and Table F.4 (Herfindahl index of forward citations [$HerfIndexFCit5_t$]) in the appendix. For both the Wu-Hausman and Sargan tests we investigated two potential endogenous variables: the average dollar amount of contracts ($Contract3_t$) and of grants ($Grant3_t$) as an endogenous variables.

We selected two groups of variables to measure the two different models for endogeneity in our analysis. First, we considered the average value of contracts ($Contract3_t$) as an endogenous variable, and $Contract3U_{t-2}$, $GrantEI3_{t-1}$, and *Loop* as instrumental variables, as discussed in the previous section 4.4.1. Second, instead of average value of Contract ($Contract3_t$), we assumed the average value of grants that inventors received in a given year ($Grant3_t$) as an endogenous variable. The average value of former grants that the same university obtained ($Grant3U_{t-1}$), and the average value of grants for equipment and infrastructure received by inventors ($GrantEI3_{t-2}$) were treated as instrumental variables. According to the Sargan test results, our instrumental variables were valid in both models. However, the Wu-Hausman test results demonstrate that endogeneity is not apparent or not appropriately measured in the second approach, where the average value of grants that inventors received ($Grant3_t$) was assumed as an endogenous variable.

Then, we measured the robustness of our model. The number of forward citations ($NbFCit5_t$) and number of claims ($NbClaims_t$) are both count measures. Moreover, in our observations, there were a significant number of forward citations ($NbFCit5_t$) assigned to 0 (543 observations out of 1110). Therefore, the Zero-inflated negative binomial (Zinb) method was assumed to be an appropriate measurement for the forward citations ($NbFCit5_t$) (as a dependent variable), where there is an excess of zeros in the dependent variable. We compared the Zinb test versus the standard negative binomial method to find which technique was most appropriate for the number of forward citations (*NbFCit5*$_t$). The Vuong test systematically rejected the standard negative binomial method for forward citations (*NbFCit5*$_t$). Accordingly, the Zinb method was chosen as the correct method to analyze the number of forward citations (*NbFCit5*$_t$). The Zinb test results are shown in Table B.1–Table B.3 of the appendix. The Zero-inflated negative binomial (Zinb) model is present below:

$y_i = 0$ with probability of q_i

$$y_i = P(Y_i = y_i) = \exp\lambda(x_i).\left[\frac{\lambda(x_i)}{y_i!}\right] \text{ with probability of } (1-q_i) \qquad \text{Equation 4.12}$$

Where λ respects the equations below for binomial negative:

$$\begin{aligned} P(Y_i = y_i) &= (1-q_i)BN(y_i) && \text{if } y_i > 0 \\ P(Y_i = y_i) &= q_i + (1-q_i)BN(y_i) && \phantom{\text{if }} y_i = 0 \end{aligned} \qquad \text{Equation 4.13}$$

Once again, as our model suffered from over-dispersion, so the Zero-inflated Poisson model (Zip) was not applicable to the number of forward citations (*NbFCit5*$_t$) or to the number of claims (*NbClaims*$_t$).

The Herfindahl index of forward citations (*HerfIndexFCit5*$_t$) and backward citations (*HerfIndexBWCit*$_t$) were continuous dependent variables for which there was no "found" endogeneity, and therefore standard OLS regression models were selected for them.

Similarly to the previous section, the final model used Tobit for the (*NbFCit5*$_t$) variable, since 48% of the total of forward citations (*NbFCit5*$_t$) sample (543 out of 1110 patent observations) equals 0, as results are shown in Table 6.8. To determine whether public assignees are involved in fewer multidisciplinary domains compared to industrial assignees, we used the Herfindahl index indicator—either the Herfindahl index of backward citations (*HerfIndexBWCit*$_t$), results are determined in Table 6.10, or the Herfindahl index of forward citations (*HerfIndexFCit5*$_t$) variables, results are implied in Table 6.11.

4.4.3 Impact of patent–grant pairs on patent quality

To measure impact of patent–grant pairs on *$NbFCit5_t$, $NbClaims_t$, $HerfIndexBWCit_t$,* and *$HerfIndexFCit5_t$*, Equation 4.4 was used.

To assess the impact of the dummy variable associated with patent–grant pairs on patent quality, we first tested for endogeneity and robustness. The Wu-Hausman test outcomes reveal that endogeneity is not present in our model, when (*$Grant3_t$*) was examined as the endogenous variable. Therefore, considering the significant number of zeros, we used Tobit for *$NbFCit5_t$*, *$HerfIndexBWCit_t$*, and *$HerfIndexFCit5_t$*. We used the natural logarithm of *$NbFCit5_t$* to normalize this variable. *$HerfIndexBWCit_t$* and *$HerfIndexFCit5_t$* were multiplied by 100. We used OLS regressions for the natural logarithm of *$NbClaims_t$* as there is always at least one claim for the patent and there was no 0 assigned to this variable. The corresponding results are presented in Table 6.15 (*$NbFCit5_t$*), Table 6.16 (*$NbClaims_t$*), Table 6.17 (*$HerfIndexBWCit_t$*), and Table 6.18 (*$HerfIndexFCit5_t$*).

Previous researchers have attempted to investigate the factors bridging science and technology. Among these factors, grants and contracts, joint invention and authorship, and specific features of individual scholars (e.g., reputation and career age) have been highlighted. In advanced biotechnology and nanotechnology, scholars deeply and broadly engage in U–I collaborations (Lee, 2016). Scientists and firms are not bound by their collaboration networks in local areas but have expanded their partnership areas to distant universities, corporations, and individuals to provide better opportunities, tapping the skills and knowledge of their distant partners (Lee, 2016). Past literature shows an increasing trend for joint invention and publication activities among scientists at firms and universities (Lee, 2016; Wuchty, Jones, & Uzzi, 2007). Teams are more productive in accumulating knowledge and encouraging better innovation performance at universities and corporations (Singh & Fleming, 2009). Scholars located in the center of the collaborative network have access to strategic information and can control and widely distribute information flow in the network.

CHAPTER 5 DESCRIPTIVE STATISTICS

Before presenting the results, the descriptive statistics of variables are briefly presented in Table 5.1. Moreover, the correlation matrix is provided in Table K.1–Table K.3 in the appendix. The examination of these descriptive statistics should give us insight and the anticipated results presented in the sixth chapter of this thesis.

Table 5.1 : Descriptive statistics

Variable	Nb Obs	Mean	Std. Dev.	Min	Max
Dependent variables					
$NbFCit5_t$	1110	1.4649	2.7838	0	42
$NbClaims_t$	1110	18.4153	16.1117	1	151
$HerfIndexFCit5_t$	1110	0.8213	0.2602	0	1
$HerfIndexBWCit_t$	1110	0.7253	0.2978	0	0.9872
Independent variables					
$Grant3_t$ [a]	1110	316,827.7	1,021,492	0	8,170,096
Age_t [a]	1110	12.7511	4.2974	1	21
$MaxChair_t$ [b]	1110	0.5162	0.8689	0	3
$ArtCit3_t$ [a]	1110	17.1270	41.2803	0	712
$BtwCentArt3_t$ [a]	1110	4.801	10.318	0	76.6230
$CliqnessArt3_t$ [a]	1110	22.6845	14.3057	0	117.8727
$BtwCentPat3_t$ [a]	1110	299.814	880.071	0	6466.6890
$CliqnessPat3_t$ [a]	1110	5,583.617	3764.399	0	10,000
dNanoEx	1110	0.1640	0.3704	0	1
$dGovAssignee_t$ [d]	1110	0.0315	0.1748	0	1
$dAcAssignee_t$ [d]	1110	0.1604	0.3671	0	1
dPGP	1110	0.0369	0.1887	0	1
$Similarity_t$	1110	0.1494	0.1458	0	0.7773
Endogenous variables					
$Contract3_t$ [a, c]	1110	240,149.2	1,078,342	0	10,600,000
Instrumental variables					
$Contract3U_{t-2}$ [a, c]	1110	22,564.86	26,837.2	0	95,158.06
$GrantEI3_{t-1}$ [a, c]	1110	17,570.03	130,513.9	0	2,561,704
Loop [e]	1110	0.2252	0.4179	0	1

Notes: (a) All the variables have been averaged over all academic inventors that contributed to a given patent; (b) Only this variable uses the maximum value of all academic inventors (*MaxChair*); (c) Only endogeneity exist in the model including patent–paper similarity, there is no endogeneity for the model associated to patent–grant pairs and also the model to measure the impact of patent ownership structure on patent quality; (d) These variables are calculated according to the exclusive government assignees (*dGovAssignee*$_t$) and exclusive academic assignees (*dAcAssignee*$_t$); (e) This variable is the independent variable for the model to assess the impact of patent ownership structure on patent quality and it is the instrumental variable for the model including patent–paper similarity.

5.1 Patent–paper pairs

Figure 5.1 illustrates the total number of patents and the number of those belonging to patent–paper pairs in the fields of biotechnology and nanotechnology, over the period examined in the regression analysis. This graph shows a highly volatile evolution of the number of patents over the years, while 20% of these patents were linked to patent–paper pairs (demonstrated in Figure 5.1).

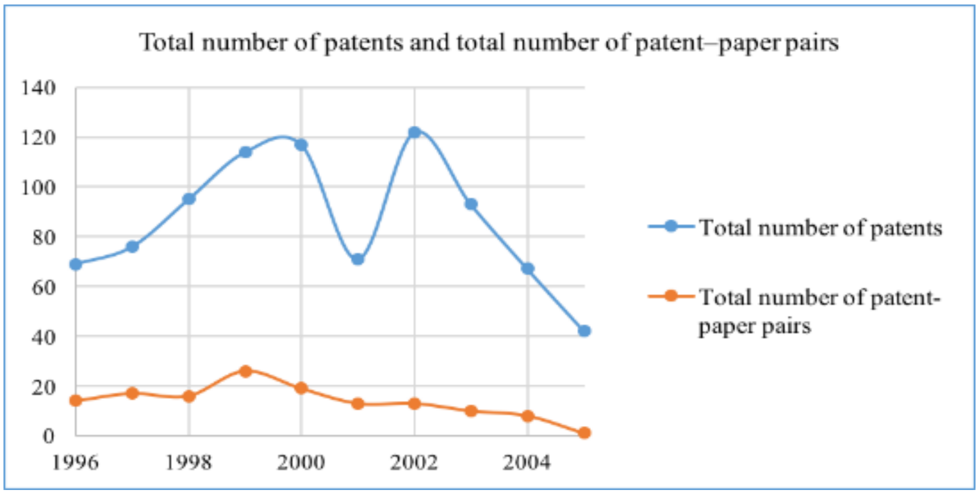

Figure 5.1 : Total number of patents generated by academic inventors in Canada and total of patent–paper pairs for biotechnology and nanotechnology in Quebec.

Figure 5.2 shows that patents that were part of patent–paper pairs were generally less cited 5 years after their official grant year, suggesting that their quality is less than those that do not have such links. This graph supports our results presented in Table 6.2, which shows the negative impact of patent–paper pairs on patent citation. Figure 5.2 shows the decreasing trend of patent–paper pairs over time. The difference between the number of citations of patents belonging to patent–paper pairs and citation of patents not linked to publications also decreases until finally the numbers converge in 2005 ($NbFCit5_t^{PPP}$ - $NbFCit5_t^{Non\text{-}PPP}$ = 0.0157, t = 2005). This graph shows that if we increase our time window beyond 2005, there will likely be no significant difference between patents belonging to patent–paper pairs and patents without such a link, as stated in the discussion of future research in Chapter 7.

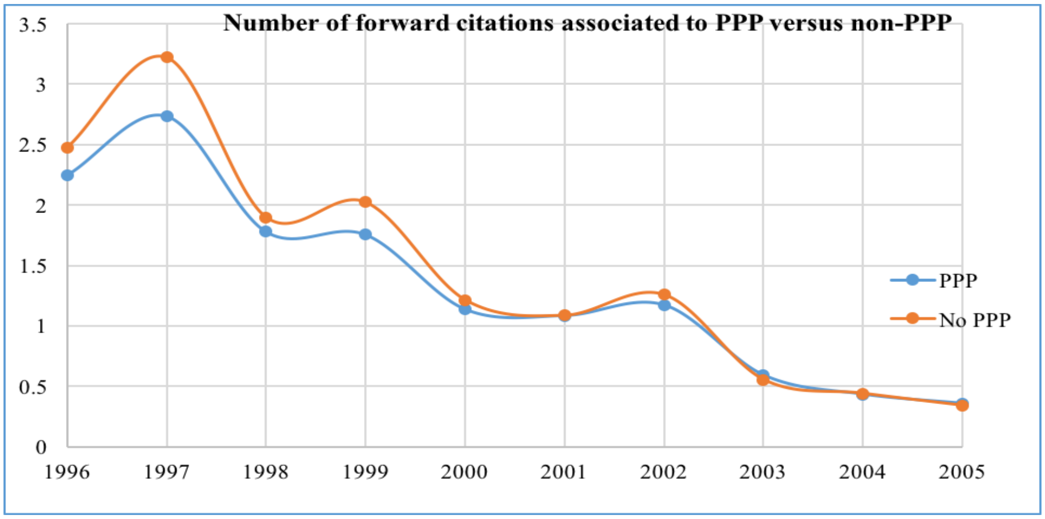

Figure 5.2 : Total number of citations after 5 years per patent, for patents that are part of a patent–paper pair or not, in the combined fields of biotechnology and nanotechnology in Quebec.

According to our results indicated in Table 6.3, patent–paper pairs should have a negative impact on number of claims. However, as is shown in Figure 5.3, this difference is very slight. As we discussed above, if we observe results over a longer period, the difference might tend to be not significant beyond 2005.

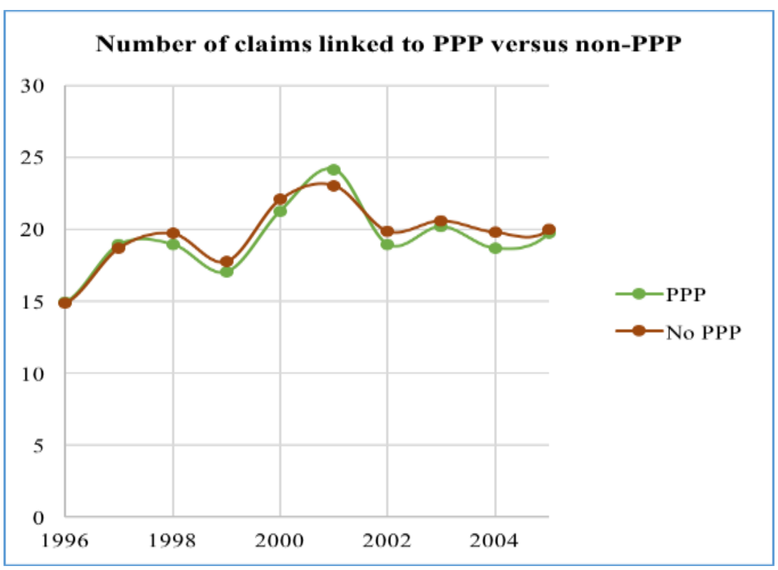

Figure 5.3 : Total number of claims per patent, for patents that are part of a patent–paper pair or not, in the combined fields of biotechnology and nanotechnology in Quebec.

5.2 Publics assignees versus industrial assignees

Approximately 30% of patents in the study were assigned to academic institutions (shown in Figure 5.4). In this study, we observed academic assignees, government assignees, and industrial assignees.

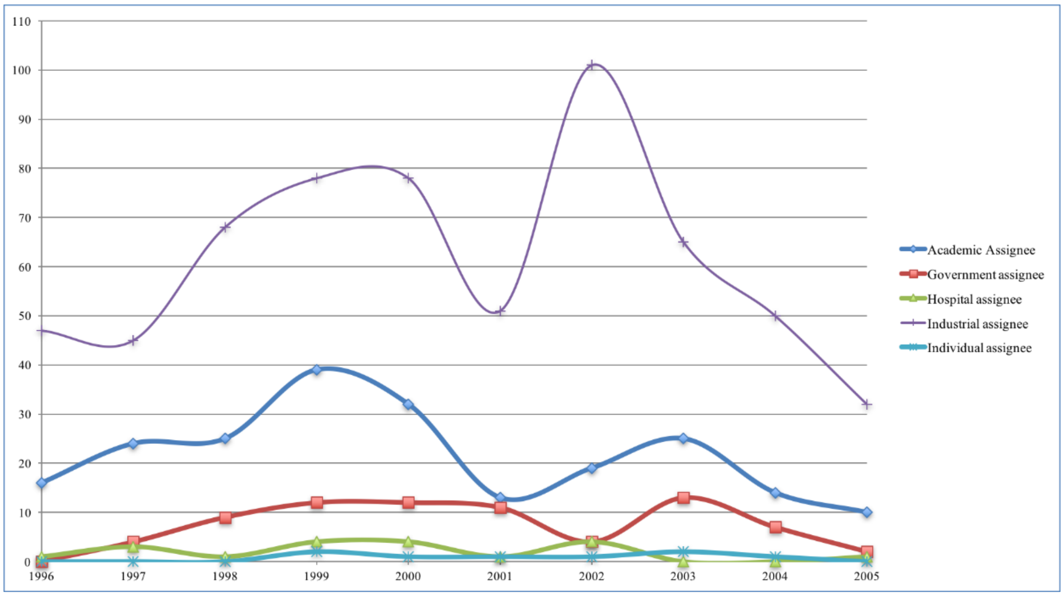

Figure 5.4 : Total number of patents by type of assignee (academic, government, industrial, hospital and individual assignee) in biotechnology and nanotechnology in Canada.

As represented in Figure 5.5, patents assigned to universities and other research facilities received fewer citations than patents assigned to non-academic patentees. This graph supports our results presented in Table 6.8; that is, a negative impact of academic assignees on patent forward citations. Likewise, the government patentees tended to receive fewer citations than non-government patentees, as presented in Figure 5.7. Thus, patents assigned to public patentees received less citations than patents assigned to the non-public patentees. Our results presented in Table 6.8–Table 6.9 substantiate the graphs in Figure 5.5–Figure 5.8.

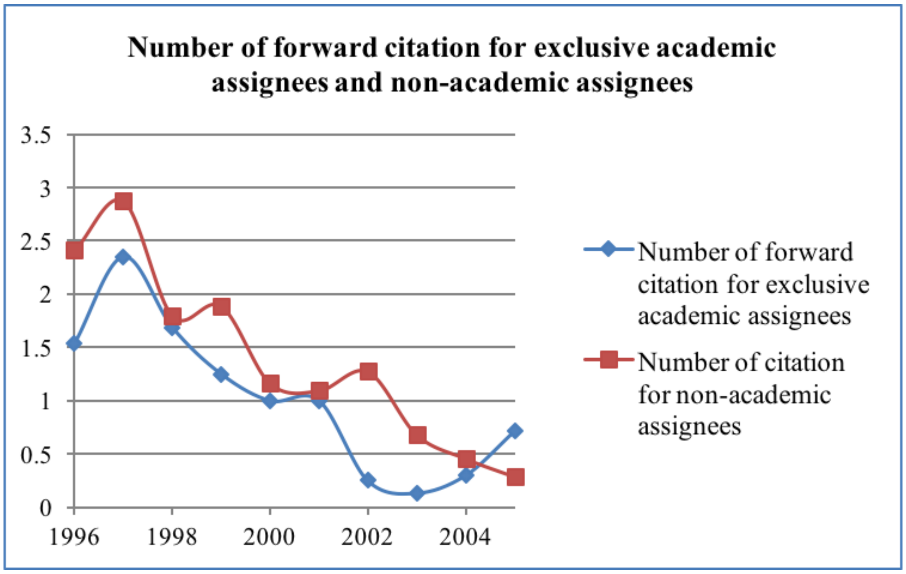

Figure 5.5 : Total number of citations per patent for type of assignee (academic-assignee and non-academic assignee) in biotechnology and nanotechnology in Canada.

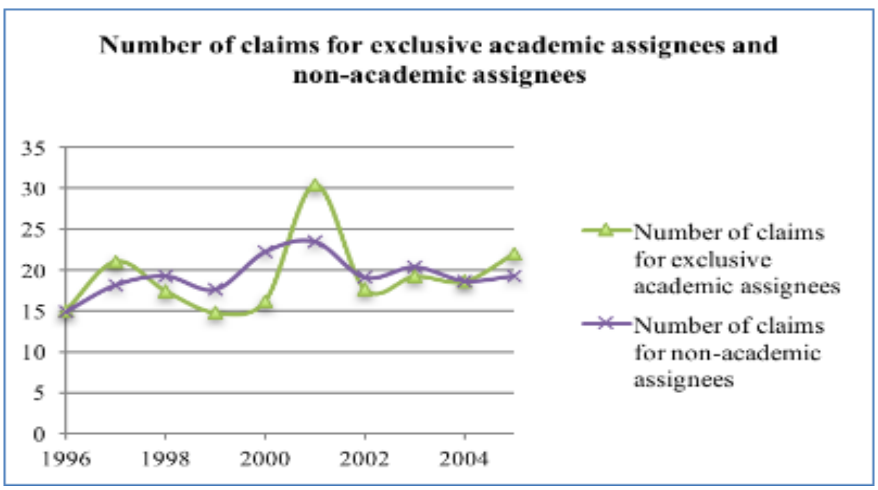

Figure 5.6 : Total number of claims per patent for type of assignee (academic-assignee and non-academic assignee) in biotechnology and nanotechnology in Canada.

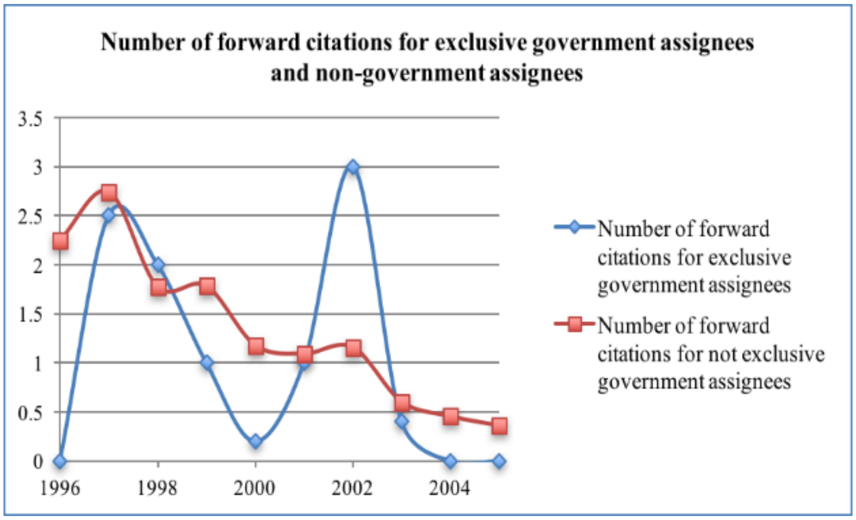

Figure 5.7 : Total number of citations per patent for type of assignee (government-assignee and non-government assignee) in biotechnology and nanotechnology in Canada.

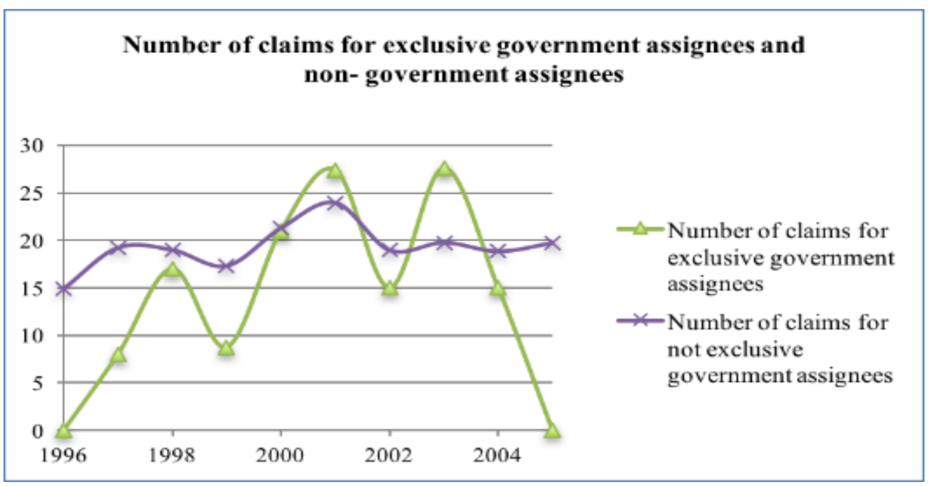

Figure 5.8 : Total number of claims per patent for type of assignee (government-assignee and non-government assignee) in biotechnology and nanotechnology in Canada.

As Figure 5.9 reveals, patents privately assigned to industry obtained more forward citations than those assigned to public patentees. We expected this result, as we compared the patent citations associated with public patentees (including university and government) with patents assigned to industrial assignees (refer to Table 6.8).

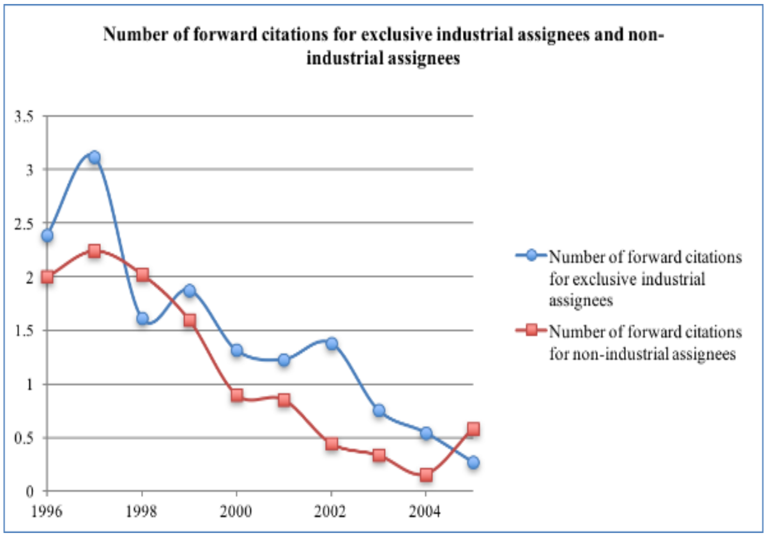

Figure 5.9 : Total number of citations per patent for industrial and non-industrial assignees in biotechnology and nanotechnology in Canada.

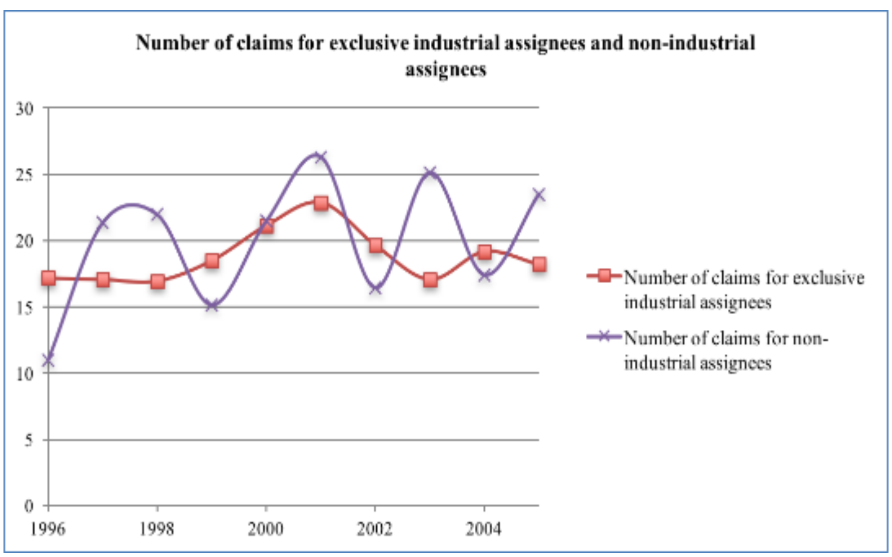

Figure 5.10 : Total number of claims per patent for industrial and non-industrial assignees in biotechnology and nanotechnology in Canada.

5.3 Patent–grant pairs

As implied in Figure 5.11, patent–grant pairs negatively affect patent citations. That is, patents that are part of patent–grant pairs obtain fewer citations than patents without such a link, as indicated in Table 6.15.

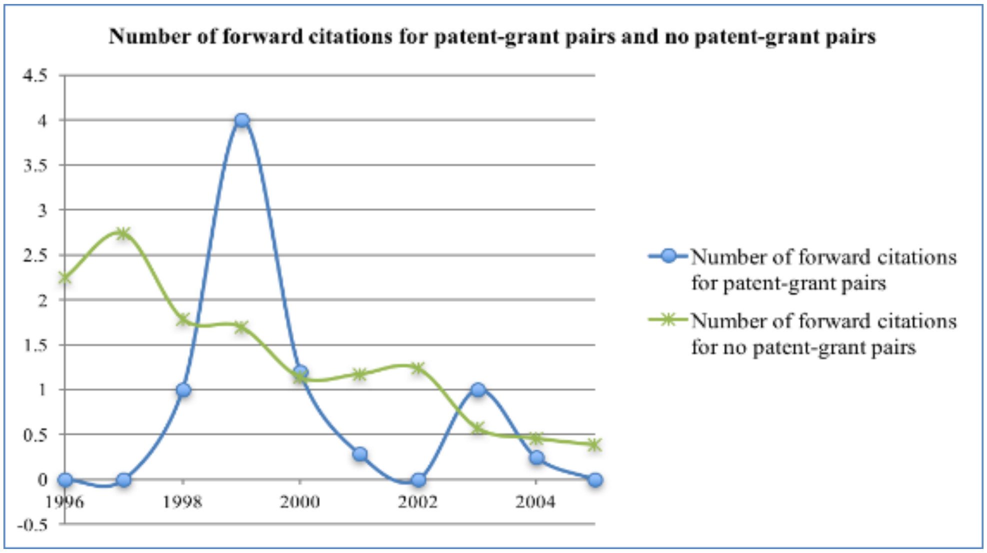

Figure 5.11 : Total number of forward citations for patent–grant pairs and non-patent–grant pairs.

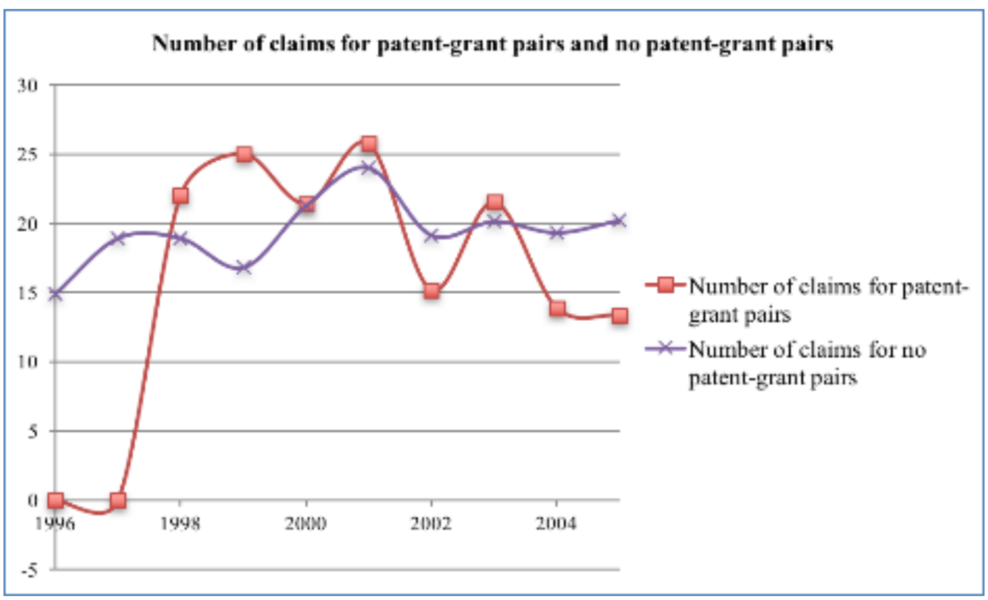

Figure 5.12 : Total number of claims for patent–grant pairs and non-patent–grant pairs.

As Figure 5.13 determines the average amount of public funding (operating costs and infrastructure grants) and private funding (contracts) in constant Canadian dollars obtained per academic inventor. Beaudry and Allaoui (2012) discovered a slightly higher proportion of grants compared to contracts. This sample eliminates scientists that do not patent, and that may not have as close a link with industry as their academic inventor colleagues.

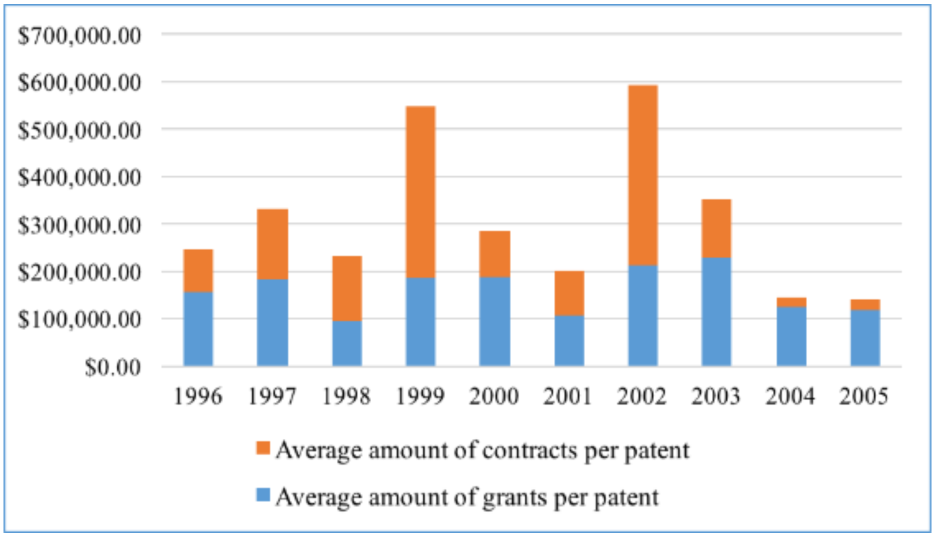

Figure 5.13 : Average amount (for each patent) of contracts and grants (in constant Canadian dollars) which academic inventors received in Quebec for the combined fields of biotechnology and nanotechnology.

Gress (2010) analyzed the USPTO patent citation trend for the period 1963–2002, measuring patent originality by the number of forward citations, and patent generality by the number of backward citations. A patent backward citation is generated once when a patent is issued, while patent forward citations are continuously being added over time (Gress, 2010). Another difference between generating patent forward citations and backward citations is associated with the citation procedure. Backward citations are generated when a patent was filed, while for forward citations, we have the whole dataset and therefore are able to measure the number of patent citations in subsequent patents going back to the year that a focal patent was granted.

Gress (2010) calculated the ratio of patent forward citations to backward citations in different domains. According to Gress's (2010) research, the ratio of forward citations to backward citations radically decreased for specific domains including Mechanical, Chemical, Electrical, Drugs and medical, Computers and communications. The computer and software domain slowly expanded its influence until reaching a peak in 1999; then its ratio suddenly decreased to the situation pre-1975. Gress (2010) implies that this descent can be explained by the increasing accuracy of either citing or classifying the patents.

Our descriptive data shows a negative trend for the forward citations of patents associated with patent–paper pairs, either public and private assignees, and patent–grant pairs. Therefore, we examined the ratio of forward citations to backward citations for patents generated by academic inventors (residing in Canada) in the biotechnology and nanotechnology domains, with graphs presented in Figures 5.14–5.16.

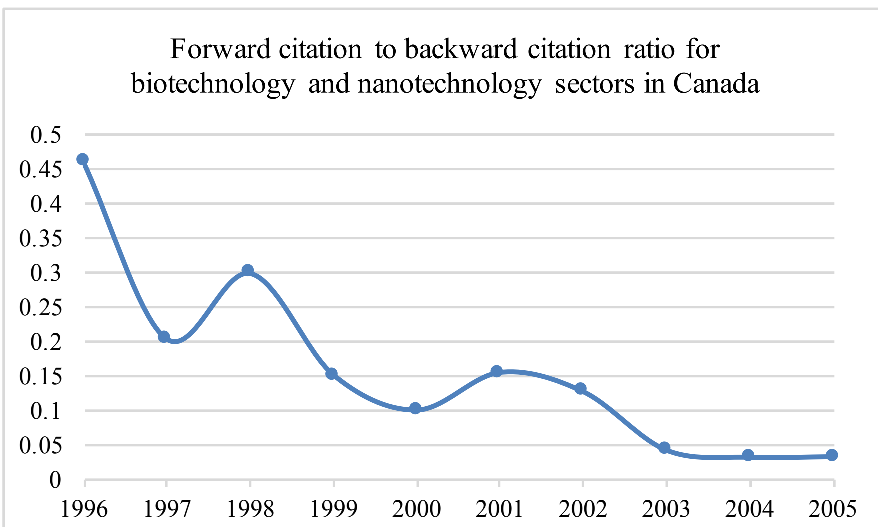

Figure 5.14 : Forward citation to backward citation ratio in nanotechnology and biotechnology in Canada.

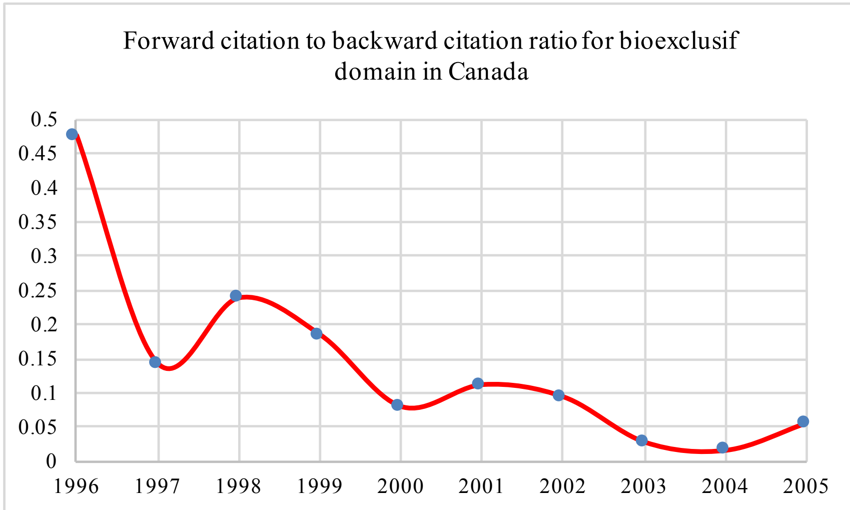

Figure 5.15 : Forward citation to backward citation ratio in bioexclusif domain in Canada

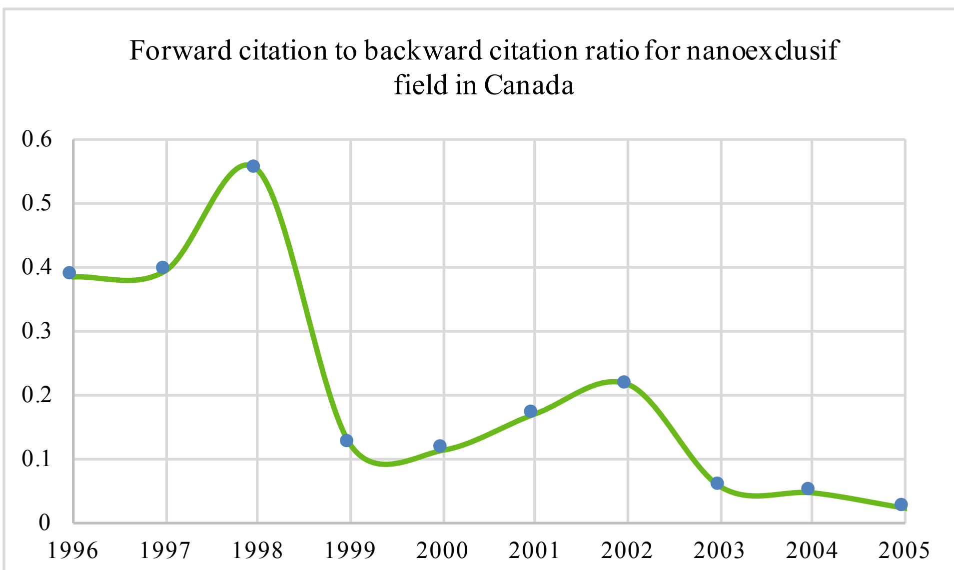

Figure 5.16 : Forward citation to backward citation ratio for nanoexclusif in Canada

Our results reveal a negative trend of the ratio of forward citations to backward citations. It seems patents tend to summarize former knowledge as the prior art of the patents instead of offering novel ideas. According to Gress's (2010) studies, the negative trend of this ratio demonstrates that patents are becoming more general (generality measured by backward citations) instead of more original (originality measured by the forward citations). There are several potential explanations for the negative trend of forward citations in biotechnology and nanotechnology. The first explanation is mentioned above—increasing generality of patents instead of the originality. Further, the negative trend of forward citations might be related to the proximity of corporations. Gittleman's (2007) findings show that geographical proximity among biotechnology firms leads the patents (generated by the corporations) to be highly cited in subsequent patents. However, the collaboration of the distant partners mostly leads to the papers that are cited in the patents (Gittelman, 2007). Therefore, there are several other potential explanations that can be investigated.

It is not essentially accurate to conclude that the novelty of the patents in biotechnology and nanotechnology in Canada decreased because of the negative trend of the forward citations as the originality measure, and this question can be studied in further research. It would be interesting to find out whether the negative forward citation trend is more related to the novelty of the patents (measured by forward citations as the originality factor), or, indeed whether it is more associated with a change in patenting policy.

CHAPTER 6 RESULTS

This section presents the results for the impact of patent–grant pairs, patent–paper pairs and academic and government assignees on patent "quality" as measured by the number of forward citations (*NbFCit5*$_t$), the number of claims (*NbClaims*$_t$), 1 minus the Herfindahl index of forward citations (*HerfIndexFCit5*$_t$) and 1 minus the Herfindahl index of backward citations (*HerfIndexBWCit*$_t$).

6.1 Impact of patent–paper pairs on patent quality

The results of evaluating impact of patent–paper pairs on patent quality are presented in Table 6.2–Table 6.5. Table 6.1 presents a summary of the analysis models applied in this study to measure the impact of patent–paper pairs on patent quality.

Table 6.1 : Summary of measurement models used to examine the impact of patent and paper similarity (associated to patent–paper pairs) [Similarity$_t$] on patent quality

	Endogeneity test	Analysis models
Number of forward citations	2SLS regression (ivregress) [*NbFCit5*$_t$]	Regression (regress) [*NbFCit5*$_t$]
Number of claims	2SLS regression (ivregress) [*NbClaims*$_t$]	2SLS regression (ivregress) [*NbClaims*$_t$]: There is endogeneity First regression: Regress [Contract3$_t$] [a]
Herfindahl index of forward citations	2SLS regression (ivregress) [*HerfIndexFCit5*$_t$]	2SLS regression (ivregress) [*HerfIndexFCit5*$_t$]: There is endogeneity First regression: Regress [Contract3$_t$] [a]
Herfindahl index of backward citations	2SLS regression (ivregress) [*HerfIndexBWCit*$_t$]	Regression (regress) [*HerfIndexBWCit*$_t$]

As mentioned in the fourth chapter, we used the Sargan test to measure whether our instrumental variables were valid or not. Then, we applied the Wu-Hausman test to assess whether we could reject H0 that the variables that are exogenous. Our findings show that our instrumental variables are valid (indicated in Table 6.3 and Table 6.5) and that according to the Wu-Hausman test, we can reject H0 for the number of number of claims [$NbClaims_t$] and Herfindahl index of forward citations [$HerfIndexFCit5_t$], implying that we can reject the H0 that there are exogenous variables in these models. Therefore, the results demonstrate endogeneity for the number of claims [$NbClaims_t$] and 1 minus the Herfindahl index of forward citations [$HerfIndexFCit5_t$], when the average value of contracts ($Contract3_t$) is considered as the endogenous variable (indicated in Table 6.3 and Table 6.5). Accordingly, [Contract3_t] is an endogenous variable, instrumented by [$\text{Contract3U}_{t\text{-}2}$], [$\text{GrantEI3}_{t\text{-}1}$], and [Loop]. Endogeneity results of forward citations and Herfindahl index of backward citations (as the dependent variables) are presented in Table E.1 and Table E.2 in the appendix. Our results show there is no endogeneity for forward citations and Herfindahl index of backward citations, while average value of contracts ($Contract3_t$) is measured as the endogenous variable.

Our results show there is a negative impact of patent–paper pairs [$Similarity_t$] on patent quality, as presented in Table 6.2–Table 6.5. Therefore, we reject Hypothesis 5 regarding number of forward citations and number of claims. We cannot accept Hypothesis 5 considering Herfindahl index of forward and backward citations, since they are not significant.

Our results demonstrate that patents generated by a highly centralized co-publication network [$BtwCentArt3_t$] positively affect the number of forward citations, but have a negative effect when the patent is assigned to the university [$dAcAssignee_t \times BtwCentArt3_t$]. The impact of a patent that is located in a highly centralized co-invention network on the number of forward citations is not significant, but it is positive when the patent is linked to the publications [$Similarity_t \times BtwCentPat3_t$]. Our outcomes reveal that the patent–paper pair has a negative impact on patent forward citation, but when the inventors are situated in a highly centralized co-invention network, the results change to be positive, as shown in Table 6.2. Regarding the number of claims, inventors located in a highly centralized co-invention network tend to obtain a higher number of claims, but when the centrality is further boosted the number of claims diminishes, as presented in Table 6.3.

Table 6.2 : Impact of patent and paper similarity (associated with patent–paper pairs) on the number of forward citations [$NbFCit5_t$] – Regression results

Variables	**FC (1)**	**FC (2)**
[$Contract3_t$] [a]	0.0321	0.0331
	(0.0255)	(0.0253)
[$Grant3_t$] [a]	-0.0426	-0.0075
	(0.0302)	(0.0280)
[Age_t] [a]	-0.1754***	-0.1773***
	(0.0221)	(0.0220)
$[Age_t{}^a]^2$	-0.0640***	-0.0647***
	(0.0158)	(0.0157)
[$MaxChair_t$] [a]	0.0218	0.0035
	(0.0237)	(0.0209)
[$ArtCit3_t$] [a]	-0.0443*	-0.0471*
	(0.0244)	(0.0245)
[$BtwCentArt3_t$] [a]	0.0711***	0.0495**
	(0.0262)	(0.0244)
[$BtwCentPat3_t$] [a]	-0.0251	0.0039
	(0.0364)	(0.0348)
$[(BtwCentPat3_t)^a]^2$	-0.0418	-0.0440*
	(0.0261)	(0.0265)
$dAcAssignee_t$	-0.1046*	-0.1341**
	(0.0613)	(0.0543)
dNanoEx	0.3340***	0.3280***
	(0.0569)	(0.0572)
$Similarity_t$ [a]	-0.0429**	-0.0448**
	(0.0218)	(0.0222)
$dAcAssignee_t$ × [$Grant3_t$] [a]	0.1130*	
	(0.0607)	
$dAcAssignee_t$ × $MaxChair_t$ [a]	-0.0895*	
	(0.0496)	
$dAcAssignee_t$ × [$BtwCentArt3_t$] [a]	-0.1023*	
	(0.0543)	
$dAcAssignee_t$ × [$BtwCentPat3_t$] [a]	0.1359*	
	(0.0719)	
$Similarity_t$ × [$Grant3_t$] [a]		0.0492*
		(0.0270)
$Similarity_t$ [a] × [$MaxChair_t$] [a]		-0.0056
		(0.0232)
$Similarity_t$ [a] × [$BtwCentArt3_t$] [a]		-0.0013
		(0.0228)
$Similarity_t$ [a] × [$BtwCentPat3_t$] [a]		0.0418*
		(0.0246)
Constant	0.6957***	0.6920***
	(0.0392)	(0.0397)
Nb observations	1083	1083
Log Likelihood	-1081.4	-1084.23
R^2	0.12197	0.11738
R^2 Adjusted	0.10879	0.10413
P value	0.0000	0.0000

Notes: [(a)] All the variables have been calculated by Z Score (Z) = x – μ / σ, μ=mean and σ = standard deviation. Moreover, ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses.

Table 6.3 : Impact of patent and paper similarity (associated with patent–paper pairs) on the number of claims [*NbClaims$_t$*] – IV Regression Two-stage least squares (2SLS) results

Variables	**CL (1)**	**CL (2)**
[Contract3$_t$] [a]	-0.2352***	-0.2427***
	(0.0904)	(0.0864)
[Grant3$_t$] [a]	0.1464**	0.1184**
	(0.0582)	(0.0528)
[Age$_t$] [a]	0.0669**	0.0694**
	(0.0275)	(0.0275)
$[\text{Age}_t{}^a]^2$	-0.0149	-0.0105
	(0.0200)	(0.0197)
[MaxChair$_t$] [a]	0.0124	0.0086
	(0.0296)	(0.0263)
[ArtCit3$_t$] [a]	-0.0206	-0.0191
	(0.0314)	(0.0312)
[BtwCentArt3$_t$] [a]	-0.0811**	-0.0668**
	(0.0327)	(0.0301)
[BtwCentPat3$_t$] [a]	0.1586***	0.1492***
	(0.0484)	(0.0457)
$[(\text{BtwCentPat3}_t)^a]^2$	-0.1514***	-0.1453***
	(0.0363)	(0.0361)
dAcAssignee$_t$	0.0353	-0.0172
	(0.0770)	(0.0684)
dNanoEx	0.3410***	0.3400***
	(0.0716)	(0.0717)
Similarity$_t$ [a]	-0.0608**	-0.0695**
	(0.0271)	(0.0275)
dAcAssignee$_t$ × [Grant3$_t$] [a]	-0.1784**	
	(0.0772)	
dAcAssignee$_t$ × MaxChair$_t$ [a]	0.0118	
	(0.0619)	
dAcAssignee$_t$ × [BtwCentArt3$_t$] [a]	0.0638	
	(0.0705)	
dAcAssignee$_t$ × [BtwCentPat3$_t$] [a]	0.0048	
	(0.0894)	
Similarity$_t$ × [Grant3$_t$] [a]		0.0288
		(0.0334)
Similarity$_t$ [a] × [MaxChair$_t$] [a]		-0.0623**
		(0.0287)
Similarity$_t$ [a] × [BtwCentArt3$_t$] [a]		0.0172
		(0.0285)
Similarity$_t$ [a] × [BtwCentPat3$_t$] [a]		-0.0452
		(0.0305)
Constant	2.7034***	2.6902***
	(0.0550)	(0.0545)
Nb Observations	1083	1083
Chi Square	98.5088	101.7190
R^2	0.0487	0.0483
R^2 Adjusted	0.0345	0.0340
Wu-Hausman	0.0202	0.0121
Sargan	0.1646	0.2773

Notes: [(a)] All the variables have been calculated by Z Score (Z) = x – μ / σ, μ=mean and σ = standard deviation. Moreover, ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses.

Table 6.4 : Impact of patent and paper similarity (associated with patent–paper pairs) on the Herfindahl index of backward citations [*HerfIndexBWCit*$_t$] – Regression results

Variable	HBC (1)	HBC (2)
[Contract3$_t$] ^{a}	0.0156*	0.0184**
	(0.0083)	(0.0082)
[Grant3$_t$] ^{a}	-0.0195**	-0.0153*
	(0.0096)	(0.0090)
[Age$_t$] ^{a}	0.0178**	0.0170**
	(0.0071)	(0.0071)
[Age$_t$ ^{a}]^2	0.0080	0.0093*
	(0.0051)	(0.0051)
[MaxChair$_t$] ^{a}	0.0063	0.0013
	(0.0077)	(0.0068)
[ArtCit3$_t$] ^{a}	0.0050	0.0041
	(0.0079)	(0.0079)
[BtwCentArt3$_t$] ^{a}	0.0176**	0.0077
	(0.0084)	(0.0079)
[BtwCentPat3$_t$] ^{a}	0.0040	0.0144
	(0.0117)	(0.0112)
[BtwCentPat3$_t$]^2	-0.0102	-0.0162*
	(0.0084)	(0.0086)
dAcAssignee$_t$	0.0080	-0.0010
	(0.0195)	(0.0177)
dNanoEx	-0.0062	-0.0069
	(0.0181)	(0.0182)
Similarity$_t$ ^{a}	-0.0035	-0.0030
	(0.0072)	(0.0073)
dAcAssignee$_t$ × [(Grant3$_t$) ^{a}]	0.0161	
	(0.0198)	
dAcAssignee$_t$ × MaxChair$_t$ ^{a}	-0.0271*	
	(0.0163)	
dAcAssignee$_t$ × [(BtwCentArt3$_t$) ^{a}]	-0.0576***	
	(0.0180)	
dAcAssignee$_t$ × [(BtwCentPat3$_t$) ^{a}]	0.0486**	
	(0.0227)	
Similarity$_t$ × Grant3$_t$		-0.0006
		(0.0086)
Similarity$_t$ ^{a} × [MaxChair$_t$] ^{a}		-0.0009
		(0.0075)
Similarity$_t$ ^{a} × [(BtwCentArt3$_t$) ^{a}]		-0.0106
		(0.0075)
Similarity$_t$ ^{a} × [(BtwCentPat3$_t$) ^{a}]		0.0202**
		(0.0079)
Constant	0.7971***	0.8003***
	(0.0127)	(0.0128)
Nb observations	986	986
Log Likelihood	174.679	172.31
R^2	0.0350	0.0303
R^2 Adjusted	0.0190	0.0143
P value	0.0043	0.0177

Notes: [(a)] All the variables have been calculated by Z Score (Z) = x – μ / σ, μ=mean and σ = standard deviation. Moreover, ***, **, * show significance at the 1%, 5%, and 10% levels.

Table 6.5 : Impact of patent and paper similarity (associated with patent–paper pairs) on the Herfindahl index of forward citations [*HerfIndexFCit5$_t$*] – IV Regression Two-stage least squares (2SLS) results

Variables	**HFC (1)**	**HFC (2)**
[Contract3$_t$] [a]	-0.0690**	-0.0682**
	(0.0293)	(0.0279)
[Grant3$_t$] [a]	0.0220	0.0158
	(0.0189)	(0.0171)
[Age$_t$][a]	0.0151*	0.0163*
	(0.0089)	(0.0089)
[Age$_t$ ^{a}]^2	0.0013	0.0032
	(0.0065)	(0.0064)
[MaxChair$_t$] [a]	0.0127	0.0116
	(0.0096)	(0.0085)
[ArtCit3$_t$] [a]	0.0111	0.0128
	(0.0102)	(0.0101)
[BtwCentArt3$_t$] [a]	-0.0016	-0.0034
	(0.0106)	(0.0097)
[BtwCentPat3$_t$] [a]	0.0209	0.0185
	(0.0157)	(0.0147)
[(BtwCentPat3$_t$)^a]^2	-0.0159	-0.0191
	(0.0118)	(0.0116)
dAcAssignee$_t$	-0.0008	-0.0010
	(0.0250)	(0.0221)
dNanoEx	-0.0411*	-0.0411*
	(0.0232)	(0.0231)
Similarity$_t$ [a]	0.0063	0.0083
	(0.0088)	(0.0089)
dAcAssignee$_t$ × [Grant3$_t$] [a]	-0.0232	
	(0.0250)	
dAcAssignee$_t$ × [MaxChair$_t$][a]	-0.0008	
	(0.0201)	
dAcAssignee$_t$ × [BtwCentArt3$_t$] [a]	-0.0056	
	(0.0229)	
dAcAssignee$_t$ × [BtwCentPat3$_t$] [a]	-0.0091	
	(0.0290)	
Similarity$_t$ × [Grant3$_t$] [a]		-0.0088
		(0.0108)
Similarity$_t$ [a] × [MaxChair$_t$] [a]		-0.0248***
		(0.0093)
Similarity$_t$ [a] × [BtwCentArt3$_t$] [a]		0.0098
		(0.0092)
Similarity$_t$ [a] × [BtwCentPat3$_t$] [a]		0.0017
		(0.0098)
Constant	0.8388***	0.8387***
	(0.0178)	(0.0176)
Nb Observations	1083	1083
Chi Square	17.4014	28.5234
P value	0.3601	0.0274
Wu-Hausman	0.0088	0.0062
Sargan	0.6142	0.7087

Notes: [(a)] All the variables have been calculated by Z Score (Z) = x – μ / σ, μ=mean and σ = standard deviation. Moreover, ***, **, * show significance at the 1%, 5%, and 10% levels.

Table 6.6 : Summary of results for the impact of patent–paper pairs similarity

	Forward citations [$NbFCit5_t$]	Herfindahl index of forward citations [$HerfIndexFCit5_t$]	Number of claims [$NbClaims_t$]	Herfindahl index of backward citations [$HerfIndexBWCit_t$]
$Similarity_t$ [a]	**Significant and negative** (--)	Not significant	**Significant and negative** (--)	Not significant

Notes: a) All the variables have been calculated by Z Score (Z) = x – μ / σ, μ=mean and σ = standard deviation. Futhermore, +++, ++, + as well as ---, --, - show significance at the 1%, 5%, and 10% levels, respectively, in different directions (positive or negative), for instance: -0.8190 *** (indicated by ---), -2.1959 * (identified by -), and 28.1833 *** (determined by +++).

Our results demonstrate that inventors occupying a highly centralized co-publication network positively affect technological breadth, measured by the Herfindahl index of patent backward citations. This finding reveals that inventors who are located in a highly centralized co-publication network tend to engage in more technology domains. However, when a university owns the patent, the results of the highly centralized co-publication network on the technology concentrations are negative. A highly centralized co-invention network positively acts on technological breadth while interacting either with academic assignees [$dAcAssignee_t$ × $BtwCentPat3_t$] or patent–publication pairs [$Similarity_t$ × $BtwCentPat3_t$], though without interacting with other variables it does not have a significant effect.

6.2 Impact of patent ownership structure on patent quality

All results associated with the impact of patent ownership structure are presented in Table 6.8–Table 6.11. Furthermore, we measured the robustness of our model as well as tested for potential endogeneity. Results are shown in the appendix F in Table F.1–Table F.4 for the endogeneity tests and in Table B.1–Table B.7 for the robustness checks. Our results demonstrate that although our instrumental variables are valid (see Sargan test results in Table F.1–Table F.4), potential endogeneity does not seem to be present in our model when the average amount of grants ($Grant3_t$) is measured as an endogenous variable (see the Wu-Hausman test in Table F.1–Table F.4). The summary of measurement models used in this analysis is shown in Table 6.7 below to assess the impact of patent ownership structure on patent quality.

Table 6.7 : Summary of measurement models applied (in this study) to assess the impact of public assignees versus industrial assignees on patent quality

	Endogeneity Test	Robustness Test	Final models
Number of forward citations	2SLS regression (ivregress) [$NbFCit5_t$]	Zero-inflated binomial regression (zinb) ($NbFCit5_t$)	Tobit regression (tobit) [$NbFCit5_t$]
Number of claims	2SLS regression (ivregress) [$NbClaims_t$]	Negative binomial regression (nbreg) ($NbClaims_t$)	Regression (regress) [$NbClaims_t$]
Herfindahl index of forward citations	2SLS regression (ivregress) [$HerfIndexFCit5_t$]	Regression (regress) [$HerfIndexFCit5_t$]	Tobit regression (tobit) [$HerfIndexFCit5_t$]
Herfindahl index of backward citations	2SLS regression (ivregress) [$HerfIndexBWCit_t$]	Regression (regress) [$HerfIndexBWCit_t$]	Tobit regression (tobit) [$HerfIndexBWCit_t$]

The results to assess the impact of patent ownership structure on patent quality are summarized in Table 6.13 below. We generated the dummy variable [$dAcAssignee_t$] to define exclusive academic assignees, as well as the [$dGovAssignee_t$] variable to determine exclusive government assignees in our analysis. The industrial assignee is considered as the omitted variable in this study, therefore in our model we compared the impact of public assignees (including universities and government) with that of industrial assignees, on patent quality. As our findings demonstrate, the patents publicly held by academic assignees and government obtained fewer citations than those privately assigned. Furthermore, our outcomes reveal the public patentees were involved in less diversified technology domains than industrial patentees were. Therefore, we validate Hypotheses 1 and 2 in terms of negative impact of public patentees on patent forward citations and Herfindahl index of backward citations. We cannot accept Hypotheses 1 and 2 regarding number of claims and Herfindahl index of forward citations, as these results are not significant.

Our results show that the average of grants [$Grant3_t$] has a negative impact on technological breadth (Herfindahl index of backward citations); however, the increasing amount of grants that academic inventors received caused the Herfindahl index of backward citations to increase. Career age of academic inventors [Age_t] positively affects the patent forward citations; nevertheless, career age negatively affects patent forward citations to a high degree. Conversely, career age has a negative impact on technological concentration; but academic inventors with high career age obtain greater technological breadth. Academic inventors situated in highly centralized co-publication networks [$BtwCentArt3_t$] obtain less technological breadth, although by increasing betweenness centrality, they engage in more technology domains. Inventors who occupy highly clustering coefficients [$CliqnessPat3_t$] in co-invention network receive more claims, though by increasing the clustering coefficient, they obtain fewer claims.

Our results suggest that patents generated by inventors in a highly centralized co-publication network and owned by a university [$dAcAssignee_t \times BtwCentArt3_t$] have a positive impact on the number of claims, while [*BtwCentArt3t*] is not significant without interacting with other variables, as demonstrated in Table 6.9. Moreover, our outcomes imply that both scientists' career age and academic ownership have a negative impact on technological breadth; however, when these variables are multiplied as interactive variables, the results are positive. When the career age is highly boosted, the patents generated by inventors with high career age and owned by the university have a non-significant effect on technological breadth, as shown in Table 6.10.

Similar to the results we obtained regarding the impact of patent–publication pairs on patent quality, patents situated in a highly centralized co-publication network have a negative impact on technological breadth as measured by the Herfindahl index of backward citations, when interacting with academic assignees. Likewise, patents that are owned by the university and issued by inventors positioned in a highly centralized co-publication network have a negative impact on technological breadth, even when co-publication centrality is boosted. Conversely, patents that are situated in a highly centralized co-invention network are associated with higher technology concentration when interacting with university ownership, as demonstrated in Table 6.10.

Table 6.8 : Impact of academic assignees and government assignees on the number of forward citations [NbFCit5$_t$] – Tobit results

Variables	**FC (3)**	**FC (4)**	**FC (5)**	**FC (6)**	**FC (7)**
Grant3$_t$	0.0039	0.0042	0.0047	0.0046	0.0037
	(0.0080)	(0.0080)	(0.0082)	(0.0080)	(0.0080)
Age$_t$	0.2770***	0.2800***	0.2797***	0.2857***	0.2798***
	(0.0391)	(0.0389)	(0.0389)	(0.0392)	(0.0388)
[Age$_t$]^2	-0.0136***	-0.0138***	-0.0138***	-0.0140***	-0.0138***
	(0.0017)	(0.0016)	(0.0016)	(0.0017)	(0.0016)
MaxChair$_t$	0.0248	0.0214	0.0213	0.0202	0.0203
	(0.0449)	(0.0448)	(0.0448)	(0.0447)	(0.0447)
ArtCit3$_t$	-0.0699**	-0.0656**	-0.0658**	-0.0651**	-0.0645**
	(0.0288)	(0.0287)	(0.0288)	(0.0287)	(0.0287)
BtwCentArt3$_t$	0.0803*	0.0776	0.0769	0.0750	0.0825*
	(0.0476)	(0.0474)	(0.0475)	(0.0474)	(0.0476)
CliqnessArt3$_t$	-0.1557*	-0.1509*	-0.1480*	-0.1588*	-0.1478*
	(0.0831)	(0.0829)	(0.0836)	(0.0829)	(0.0829)
[CliqnessArt3$_t$]^2	0.0167**	0.0162**	0.0159**	0.0170**	0.0161**
	(0.0073)	(0.0073)	(0.0073)	(0.0073)	(0.0073)
BtwCentPat3$_t$	-0.0234	-0.0326*	-0.0320*	-0.0330*	-0.0335*
	(0.0183)	(0.0185)	(0.0186)	(0.0185)	(0.0185)
CliqnessPat3$_t$	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loop	-0.0777	-0.0583	-0.0600	-0.0605	-0.0564
	(0.0959)	(0.0977)	(0.0978)	(0.0975)	(0.0976)
dNanoEx	0.5375***	0.5390***	0.5387***	0.5494***	0.5415***
	(0.1024)	(0.1019)	(0.1019)	(0.1020)	(0.1018)
dGovAssignee$_t$		-0.4503**	-0.3659	2.7605	-0.2087
		(0.2247)	(0.3820)	(2.0556)	(0.3334)
dAcAssignee$_t$		-0.2158*	-0.2161*	-0.2118*	-0.2164*
		(0.1111)	(0.1111)	(0.1109)	(0.1110)
dGovAssignee$_t$ × Grant3$_t$			-0.0111		
			(0.0408)		
dGovAssignee$_t$ × Age$_t$				-0.5010	
				(0.3570)	
dGovAssignee$_t$ × [Age$_t$]^2				0.0179	
				(0.0147)	
dGovAssignee$_t$ × BtwCentArt3$_t$					-0.2294
					(0.2374)
Constant	-0.7954***	-0.7435***	-0.7485***	-0.7708***	-0.7530***
	(0.2761)	(0.2751)	(0.2757)	(0.2760)	(0.2750)
Constant (Sigma)	1.1320***	1.1263***	1.1263***	1.1244***	1.1256***
	(0.379)	(0.0377)	(0.0377)	(0.0376)	(0.0376)
Nb observations	1110	1110	1110	1110	1110
Chi Square	135.78	143.07	143.15	145.97	144.02
Pseudo R^2	0.0515	0.0542	0.0543	0.0553	0.0546
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table 6.9 : Impact of academic assignees and government assignees on the number of claims [$NbClaims_t$] – Regression results

Variables	**CL (3)**	**CL (4)**	**CL (5)**	**CL (6)**
$Grant3_t$	0.0021	0.0009	0.0041	0.0038
	(0.0052)	(0.0052)	(0.0056)	(0.0057)
Age_t	0.0119**	0.0130**	0.0133**	0.0123*
	(0.0061)	(0.0060)	(0.0066)	(0.0067)
$MaxChair_t$	-0.0019	-0.0037	-0.0004	-0.0006
	(0.0292)	(0.0292)	(0.0293)	(0.0293)
$ArtCit3_t$	-0.0370**	-0.0362*	-0.0378**	-0.0371**
	(0.0186)	(0.0186)	(0.0186)	(0.0187)
$BtwCentArt3_t$	-0.0377	-0.0201	-0.0398	-0.0355
	(0.0325)	(0.0309)	(0.0326)	(0.0330)
$CliqnessArt3_t$	-0.0372**	-0.0352**	-0.0369**	-0.0362**
	(0.0177)	(0.0178)	(0.0178)	(0.0179)
$BtwCentPat3_t$	-0.0180	-0.0219	-0.0174	-0.0175
	(0.0135)	(0.0136)	(0.0138)	(0.0139)
$CliqnessPat3_t$	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$[CliqnessPat3_t]^2$	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loop	-0.0610	-0.0626	-0.0573	-0.0539
	(0.0635)	(0.0638)	(0.0639)	(0.0641)
dNanoEx	0.4014***	0.3966***	0.3977***	0.3972***
	(0.0670)	(0.0671)	(0.0671)	(0.0673)
$dGovAssignee_t$	-0.0110	-0.0164	-0.0115	-0.0789
	(0.1415)	(0.1417)	(0.1416)	(0.5990)
$dAcAssignee_t$	-0.1926*	-0.0913	0.0811	0.0661
	(0.1020)	(0.0797)	(0.2337)	(0.2345)
$dGovAssignee_t \times Grant3_t$				-0.0205
				(0.0282)
$dGovAssignee_t \times Age_t$				0.0185
				(0.0425)
$dGovAssignee_t \times BtwCentArt3_t$				-0.1044
				(0.1537)
$dGovAssignee_t \times BtwCentPat3_t$				0.1751
				(0.1548)
$dAcAssignee_t \times Grant3_t$			-0.0193	-0.0189
			(0.0148)	(0.0149)
$dAcAssignee_t \times Age_t$			-0.0116	-0.0107
			(0.0159)	(0.0160)
$dAcAssignee_t \times BtwCentArt3_t$	0.1230*		0.1452**	0.1411*
	(0.0714)		(0.0736)	(0.0739)
$dAcAssignee_t \times BtwCentPat3_t$		0.0286	0.0264	0.0289
		(0.0414)	(0.0424)	(0.0425)
Constant	2.5315***	2.4987***	2.5003***	2.5067***
	(0.1301)	(0.1286)	(0.1349)	(0.1360)
Nb observations	1110	1110	1110	1110
Log Likelihood	-1333.14	-1334.40	-1331.78	-1330.30
R^2	0.0804	0.0783	0.0827	0.0851
R^2 Adjusted	0.0687	0.0665	0.0684	0.0674
P value	0.0000	0.0000	0.0000	0.0000

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

Table 6.10 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [HerfIndexBWCit$_t$] – Tobit results

Variables	HBC (3)	HBC (4)	HBC (5)	HBC (6)
Grant3$_t$	-3.5835***	-4.0213***	-4.1213***	-3.9320***
	(0.8930)	(0.8809)	(0.9198)	(0.9436)
[Grant3$_t$]^2	0.2913***	0.3276***	0.3333***	0.3168***
	(0.0723)	(0.0709)	(0.0744)	(0.0767)
Age$_t$	-2.4630***	-2.3854***	-3.1368***	-3.0260***
	(0.8743)	(0.8710)	(0.9469)	(0.9524)
[Age$_t$]^2	0.1560***	0.1482***	0.1742***	0.1707***
	(0.0373)	(0.0372)	(0.0403)	(0.0406)
MaxChair$_t$	-1.4641	-1.7369	-1.6456	-1.7210
	(1.1762)	(1.1659)	(1.1638)	(1.1648)
ArtCit3$_t$	1.1789	0.9448	0.9968	1.0385
	(0.7376)	(0.7362)	(0.7338)	(0.7357)
BtwCentArt3$_t$	-19.3000***	-15.1000***	-15.1000***	-14.8000***
	(5.0120)	(4.5945)	(4.5974)	(4.6214)
[BtwCentArt3$_t$]^2	3.3418***	2.4069***	2.5053***	2.5115***
	(0.9533)	(0.8669)	(0.8693)	(0.8733)
CliqnessArt3$_t$	0.3740	0.5006	0.4969	0.5355
	(0.7123)	(0.7121)	(0.7100)	(0.7128)
BtwCentPat3$_t$	0.9332*	0.5825	0.5581	0.4888
	(0.4812)	(0.4922)	(0.4954)	(0.5018)
CliqnessPat3$_t$	0.0012***	0.0012***	0.0011***	0.0011***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	1.8986	2.7843	2.2537	2.2075
	(2.5088)	(2.5089)	(2.5122)	(2.5124)
dNanoEx	4.2932	4.0600	3.9541	4.1029
	(2.6672)	(2.6592)	(2.6510)	(2.6630)
dGovAssignee$_t$	-15.9000***	-16.7000***	-16.6000***	41.9676
	(5.6721)	(5.6604)	(5.6294)	(54.9805)
dAcAssignee$_t$	-3.0103	-10.9000***	-40.7000***	-39.7000***
	(4.0612)	(3.1551)	(13.3118)	(13.3060)
dGovAssignee$_t$ ×				-1.4342
Grant3$_t$				(5.3341)
dGovAssignee$_t$ ×				0.0676
[Grant3$_t$]^2				(0.4357)
dGovAssignee$_t$ × Age$_t$				-6.3567
				(9.3957)
dGovAssignee$_t$ ×				0.1902
[Age$_t$]^2				(0.3775)
dGovAssignee$_t$ ×				14.2206
BtwCentArt3$_t$				(41.3865)
dGovAssignee$_t$ ×				-4.7572
[BtwCentArt3$_t$]^2				(8.8873)
dGovAssignee$_t$ ×				5.3655
BtwCentPat3$_t$				(6.4303)
dAcAssignee$_t$ ×			4.4057	4.2226
Grant3$_t$			(2.9462)	(2.9490)
dAcAssignee$_t$ ×			-0.3459	-0.3293
[Grant3$_t$]^2			(0.2361)	(0.2364)
dAcAssignee$_t$ × Age$_t$			4.4044*	4.2923*
			(2.3324)	(2.3323)

Table 6.10 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [HerfIndexBWCit$_t$] – Tobit results (Cont'd and end)

Variables	**HBC (3)**	**HBC (4)**	**HBC (5)**	**HBC (6)**
dAcAssignee$_t$ ×			-0.1256	-0.1220
[Age$_t$]^2			(0.1015)	(0.1015)
dAcAssignee$_t$ ×	14.6620		-5.4047*	-5.8158*
BtwCentArt3$_t$	(11.6808)		(3.0493)	(3.0678)
dAcAssignee$_t$ ×	-3.6725*			
[BtwCentArt3$_t$]^2	(2.2062)			
dAcAssignee$_t$ ×		4.9531***	4.4546***	4.5128***
BtwCentPat3$_t$		(1.6185)	(1.6500)	(1.6497)
Constant	67.1451***	68.6378***	73.6572***	72.5337***
	(6.1761)	(6.0907)	(6.5620)	(6.5913)
Constant (Sigma)	31.7717***	31.7001***	31.5222***	31.4730***
	(0.7538)	(0.7521)	(0.7477)	(0.7466)
Nb observations	1110	1110	1110	1110
Chi Square	124.85	129.23	141.88	145.71
Pseudo R^2	0.0125	0.0129	0.0142	0.0146
P value	0.0000	0.0000	0.0000	0.0000

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

Our results show that both government assignees and the betweenness centrality of the co-invention network have a non-significant effect on the number of Herfindahl index forward citations. However, patents generated by academic inventors in a highly centralized co-invention network and owned by the government contribute to a higher Herfindahl index of forward citations [*dGovAssignee$_t$* × *BtwCentPat3$_t$*], as demonstrated in Table 6.11.

Table 6.11 : Impact of academic assignees and government assignees on the Herfindahl index of forward citations [HerfIndexFCit5$_t$] – Tobit results

Variables	**HFC (3)**	**HFC (4)**	**HFC (5)**	**HFC (6)**
Grant3$_t$	-0.2792	-0.2794	-0.2959	-0.3822
	(0.2535)	(0.2544)	(0.2705)	(0.2767)
Age$_t$	-6.9125***	-6.9137***	-7.4708***	-7.1349***
	(1.2185)	(1.2169)	(1.3515)	(1.3499)
[Age$_t$]^2	0.3344***	0.3344***	0.3511***	0.3318***
	(0.0515)	(0.0516)	(0.0568)	(0.0567)
MaxChair$_t$	0.6352	0.6353	0.6641	0.8310
	(1.4049)	(1.4049)	(1.4060)	(1.3980)
ArtCit3$_t$	5.9378**	5.9339**	5.8178**	5.3950**
	(2.3228)	(2.3324)	(2.3352)	(2.3263)
[ArtCit3$_t$]^2	-1.1408**	-1.1405**	-1.1142*	-1.0112*
	(0.5657)	(0.5667)	(0.5681)	(0.5655)
BtwCentArt3$_t$	-0.3917	-0.4006	-0.3776	-0.3792
	(1.5484)	(1.4885)	(1.5568)	(1.5625)
CliqnessArt3$_t$	-1.1490	-1.1480	-1.1591	-1.2072
	(0.8480)	(0.8507)	(0.8518)	(0.8500)
BtwCentPat3$_t$	0.7224	0.7204	0.7421	0.6001
	(0.5846)	(0.5990)	(0.6076)	(0.6103)
CliqnessPat3$_t$	0.0003	0.0003	0.0003	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Loop	-4.2984	-4.2880	-4.1883	-3.8730
	(3.0528)	(3.0678)	(3.0840)	(3.0662)
dNanoEx	-6.9714**	-6.9721**	-6.9275**	-7.2082**
	(3.2447)	(3.2459)	(3.2482)	(3.2392)
dGovAssignee$_t$	-2.9347	-2.9374	-2.8446	43.8251
	(6.8528)	(6.8558)	(6.8506)	(71.0542)
dAcAssignee$_t$	2.5975	2.4746	-17.5000	-17.6000
	(4.9149)	(3.8314)	(17.0338)	(16.9270)
dGovAssignee$_t$ × Grant3$_t$				0.0622
				(1.3830)
dGovAssignee$_t$ × Age$_t$				-15.9000
				(12.6867)
dGovAssignee$_t$ × [Age$_t$]^2				0.7704
				(0.5420)
dGovAssignee$_t$ × BtwCentArt3$_t$				11.7813
				(7.4346)
dGovAssignee$_t$ × BtwCentPat3$_t$				26.3748**
				(12.5475)
dAcAssignee$_t$ × Grant3$_t$			0.1974	0.2751
			(0.7562)	(0.7536)
dAcAssignee$_t$ × Age$_t$			2.6291	2.2809
			(3.1468)	(3.1263)
dAcAssignee$_t$ × [Age$_t$]^2			-0.0703	-0.0511
			(0.1365)	(0.1356)
dAcAssignee$_t$ × BtwCentArt3$_t$	-0.0841		-1.3988	-1.3352
	(3.4311)		(3.5635)	(3.5497)
dAcAssignee$_t$ × BtwCentPat3$_t$		0.0466	-0.4194	-0.2170
		(2.0972)	(2.1298)	(2.1178)
Constant	122.0000***	122.0000***	127.0000***	127.0000***
	(8.1727)	(8.0984)	(8.9235)	(8.9115)
Constant (Sigma)	36.4351***	36.4352***	36.4056***	36.1490***
	(1.0454)	(1.0454)	(1.0445)	(1.0366)

Table 6.11 : Impact of academic assignees and government assignees on the Herfindahl index of forward citations [HerfIndexFCit5$_t$] – Tobit results (Cont'd and end)

Variables	**HFC (3)**	**HFC (4)**	**HFC (5)**	**HFC (6)**
Nb observations	1110	1110	1110	1110
Chi Square	77.3436	77.3435	79.5135	93.0638
Pseudo R^2	0.0101	0.0101	0.0104	0.0122
P value	0.0000	0.0000	0.0000	0.0000

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

Below in Table 6.12, the linear and non-linear effects (quadratic effect) of variables are presented. We tested the quadratic effect of the independent variables and excluded the squared variables, when there was a non-significant effect of the (squared) variables. This helped us to have a better estimation and it decreased the probability of multicollinearity.

Table 6.12 : Linear and non-linear effect (quadratic effect) of variables to measure impact of public assignees on patent quality

	FC WO/Sq	FC W/Sq	CL WO/Sq	CL W/Sq	HBC WO/Sq	HBC W/Sq	HFC WO/Sq	HFC W/Sq
Grant3$_t$					NS	**---**		
(Grant3$_t$)^2						**+++**		
Age$_t$	---	**+++**			+++	**---/--**	+++/++/+	**---**
(Age$_t$)^2		**---**				**+++**		**+++**
ArtCit3$_t$							++/+	**++**
(ArtCit3$_t$)^2								**-**
BtwCentArt3$_t$					NS	**---**		
(BtwCentArt3$_t$)^2						**+++/++**		
CliqnessArt3$_t$	++/+	**NS**						
(CliqnessArt3$_t$)^2		**++/+**						
CliqnessPat3$_t$			NS	**++/+**				
(CliqnessPat3$_t$)^2				**--/-**				

Notes: WO/Sq (without squared variable) shows the impact of a variable without squared variables (linear impact), while W/Sq (with squared variable) demonstrates a quadratic effect. Selected models are bold and underlined. Furthermore, +++, ++, + as well as ---, --, - show significance at the 1%, 5%, and 10% levels, respectively, in different directions (positive or negative), for instance: -0.8190 *** (indicated by ---), -2.1959 * (identified by -), and 28.1833 *** (determined by +++).

We tested whether patents funded by government and assigned to the universities were of a higher quality, as proposed in Hypothesis 2A. Our results imply that university patents funded by government are more diversified; however, number of claims and patent citation variables are not significant. Therefore, we validate Hypothesis 2A in terms of Herfindahl index of backward citations, but we cannot approve Hypothesis 2A for number of forward citations, number of claims and Herfindahl index of forward citations.

Moreover, our findings reveal the government patents that were surrounded by inventors in a highly centralized co-invention network [$dGovAssignee_t \times BtwCentPat3_t$] (defined in Hypothesis 3A) tended to likely engage in more differentiated fields. Therefore, we reject Hypothesis 3A in terms of Herfindahl index of forward citations, while we cannot accept the hypothesis for number of claims, Herfindahl index of backward citations and number of forward citations.

We cannot accept Hypothesis 3B including the negative impact on quality of government patents generated by inventors occupying nodes in a highly central co-publication network [$dGovAssignee_t \times BtwCentArt3_t$]. Thus, we reject Hypothesis 3B for four patent quality indicators including number of claims, number of forward citations, and Herfindahl index of both backward and forward citations.

Furthermore, academic inventors established in a highly centralized co-invention network [$dAcAssignee_t \times BtwCentPat3_t$] (determined in Hypothesis 4A) were involved in diversified technological domains, when the patents were publicly assigned by universities. Therefore, we reject Hypothesis 4A considering number of Herfindahl index backward citations. We cannot accept Hypothesis 4A for number of claims, number of forward citations and Herfindahl index of forward citations. Our findings demonstrate that patents generated by inventors that occupy a highly centralized position in the co-publication network ($BtwCentArt3_t$) were less diversified, measured by 1 minus the Herfindahl index of backward citations as the technology breadth (HBC). The impact of the co-publication clustering coefficient is not significant on patent forward citations; however highly central co-publication clusters tend to receive more citations in subsequent patents. Our findings show patents generated by inventors occupied in a highly centralized co-publication network [$dAcAssignee_t \times BtwCentArt3_t$] (indicated in Hypothesis 4B) were associated with a greater number of claims, when these patents were publicly assigned to the universities, but, they were less diversified. Thus, we approve Hypothesis 4B in terms of number of Herfindahl index backward citations. However, we reject Hypothesis 4B considering number of claims. We cannot accept Hypothesis 4B for number of forward citations and Herfindahl index of forward citations.

Table 6.13 : Summary of results on impact of academic assignees and government assignees on patent quality

	Forward citations [$NbFCit5_t$]	Herfindahl index of forward citations [$HerfIndexFCit5_t$]	Number of claims [$NbClaims_t$]	Herfindahl index of backward citations [$HerfIndexBWCit_t$]
$dAcAssignee_t$	**Significant and negative** (--/-)	Not significant	Not significant	**Significant and negative** (---/--)
$dGovAssignee_t$	**Significant and negative** (--/-)	Not significant	Not significant	**Significant and negative** (---/--)
$dAcAssignee_t \times Grant3_t$	Not significant	Not significant	Not significant	**Significant and positive** (+), not significant in the model without claims
$dGovAssignee_t \times BtwCentArt3_t$	Not significant	Not significant	Not significant	Not significant
$dAcAssignee_t \times BtwCentArt3_t$	Not significant	Not significant	**Significant and positive** (+/++)	**Significant and negative** (-/--)
$dGovAssignee_t \times BtwCentPat3_t$	Not significant	**Significant and positive** (+/++)	Not significant	Not significant
$dAcAssignee_t \times BtwCentPat3_t$	Not significant	Not significant	Not significant	**Significant and positive** (+++/++)

Notes: +++, ++, + as well as ---, --, - show significance at the 1%, 5%, and 10% levels, respectively, in different directions (positive or negative), for instance: -0.8190 *** (indicated by ---), -2.1959 * (identified by -), and 28.1833 *** (determined by +++).

6.3 Impact of patent–grant pairs on patent quality

All of the results linked to patent–grant pairs are shown throughout Table 6.15–Table 6.18 in this section. Moreover, the results associated with endogeneity testing are shown in Table G.1–Table G.4 in the appendix, and robustness results are indicated in Table C.1–Table C.2 (in the appendix). Our results demonstrate the patents belonging to patent–grant pairs obtain fewer forward citations than patents that are not linked to such pairs. The [dPGP] variable is significant and negative, as shown in Table 6.15. However, patents linked to patent–grant pairs obtain a higher Herfindal index of forward citations [HerfIndexFCit5t] (indicated in Table 6.18), as they are more diversified and engaged in technology fields across multiple disciplines.

Our findings show our instrumental variables are valid (since if the *p*-value associated with the Sargan test is not significant then the instrumental variables are valid); see the Sargan test results in Table G.1–Table G.4. We defined four dependent variables, including: number of forward citations [$NbFCit5_t$], number of claims [$NbClaims_t$], Herfindahl index of forward citations [$HerfIndexFCit5_t$], and Herfindahl index of backward citations [$HerfIndexBWCit_t$]. According to the *p*-value associated with the Wu-Hausman test, we cannot reject H0 (defined above) for all four dependent variables, taking into consideration that the *p-v*alue is not significant (< 0.05). Thus, we cannot reject the H0. The results show the average of grants variable ($Grant3_t$) is exogenous and the endogeneity doesn't exist for the number of forward citations [$NbFCit5_t$], number of claims [$NbClaims_t$], Herfindahl index of forward citations [$HerfIndexFCit5_t$], and Herfindahl index of backward citations [$HerfIndexBWCit_t$]. We measured whether the variable is endogenous or exogenous. The summary of measurement models used in this analysis is shown in Table 6.14 below.

Table 6.14 : Summary of measurement models used (in this research) to investigate the impact of patent–grant pairs on patent quality

	Endogeneity test	Robustness test	Final models
Number of forward citations	2SLS regression (ivregress) [$NbFCit5_t$]	Zero-inflated binomial regression (zinb) [$NbFCit5_t$]	Tobit regression (tobit) [$NbFCit5_t$]
Number of claims	2SLS regression (ivregress) [$NbClaims_t$]	Negative binomial regression (nbreg) ($NbClaims_t$)	Regression (regress) [$NbClaims_t$]
Herfindahl index of forward citations	2SLS regression (ivregress) [$HerfIndexFCit5_t$]	Regression (regress) [$HerfIndexFCit5_t$]	Tobit regression (tobit) [$HerfIndexFCit5_t$]
Herfindahl index of backward citations	2SLS regression (ivregress) [$HerfIndexBWCit_t$]	Regression (regress) [$HerfIndexBWCit_t$]	Tobit regression (tobit) [$HerfIndexBWCit_t$]

Our results demonstrate that patent–grant pairs appear in fewer forward citations than patents without such a link, as presented in Table 6.15. However, they receive a greater Herfindahl index of forward citations, as shown in Table 6.18.

Moreover, as a complementary result, our outcomes reveal that while inventors receive more publication citations, they receive fewer patent citations in subsequent patents, as shown in Table 6.15.

Table 6.15 : Impact of patent–grant pairs on the number of forward citations [$NbFCit5_t$] – Tobit regression results

Variables	**FC (8)**	**FC (9)**	**FC (10)**	**FC (11)**	**FC (12)**
$Grant3_t$	0.0034	0.0034	0.0046	0.0033	0.0045
	(0.0079)	(0.0078)	(0.0079)	(0.0078)	(0.0079)
Age_t	0.2761***	0.2678***	0.2654***	0.2676***	0.2651***
	(0.0389)	(0.0390)	(0.0391)	(0.0390)	(0.0392)
$[Age_t]^2$	-0.0137***	-0.0132***	-0.0131***	-0.0132***	-0.0131***
	(0.0016)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
$MaxChair_t$	0.0235	0.0295	0.0316	0.0294	0.0315
	(0.0448)	(0.0447)	(0.0447)	(0.0447)	(0.0447)
$ArtCit3_t$	-0.0657**	-0.0667**	-0.0671**	-0.0666**	-0.0668**
	(0.0287)	(0.0286)	(0.0286)	(0.0287)	(0.0287)
$BtwCentArt3_t$	0.0834*	0.0818*	0.0823*	0.0823*	0.0830*
	(0.0470)	(0.0468)	(0.0468)	(0.0471)	(0.0471)
$CliqnessArt3_t$	-0.1470*	-0.1344	-0.1357*	-0.1347	-0.1361*
	(0.0825)	(0.0821)	(0.0821)	(0.0822)	(0.0821)
$[CliqnessArt3_t]^2$	0.0156**	0.0147**	0.0145**	0.0147**	0.0145**
	(0.0072)	(0.0072)	(0.0072)	(0.0072)	(0.0072)
$BtwCentPat3_t$	-0.0294	-0.0332*	-0.0312*	-0.0333*	-0.0312*
	(0.0184)	(0.0184)	(0.0184)	(0.0184)	(0.0184)
$CliqnessPat3_t$	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$dAcAssignee_t$	-0.2246**	-0.2008**	-0.2065**	-0.2009**	-0.2067**
	(0.0929)	(0.0929)	(0.0930)	(0.0929)	(0.0930)
dNanoEx	0.5372***	0.5704***	0.5642***	0.5699***	0.5635***
	(0.1020)	(0.1022)	(0.1023)	(0.1023)	(0.1024)
$dPGP_t$		-0.8190***	-2.1959*	-0.7896**	-2.1897*
		(0.2467)	(1.1836)	(0.3609)	(1.1845)
$dPGP_t \times CliqnessArt3_t$			0.4069		0.4111
			(0.2804)		(0.2825)
$dPGP_t \times [CliqnessArt3_t]^2$			-0.0017		-0.0017
			(0.0014)		(0.0015)
$dPGP_t \times BtwCentArt3_t$				-0.02938	-0.03475
				(0.26404)	(0.28133)
Constant	-0.7296***	-0.7007**	-0.6915**	-0.6999**	-0.6902**
	(0.2756)	0.2755	0.2765	0.2756	0.2767
Sigma	1.1281***	1.1223***	1.1214***	1.1223***	1.1213***
	0.03774	0.03751	0.03748	0.03751	0.03748
Statistics					
Nb observations	1110	1110	1110	1110	1110
Chi Square	140.986***	152.998***	155.499***	153.01***	155.514***
Pseudo R^2	0.0534	0.0580	0.0589	0.0580	0.0589

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

Table 6.16 : Impact of patent–grant pairs on the number of claims [$NbClaims_t$] – OLS regression results

Variables	**CL (7)**	**CL (8)**	**CL (9)**	**CL (10)**	**CL (11)**
$Grant3_t$	-0.0002	-0.0002	-0.0002	-0.0001	-0.0001
	(0.0051)	(0.0051)	(0.0052)	(0.0052)	(0.0052)
Age_t	0.0134**	0.0133**	0.0131**	0.0133**	0.0132**
	(0.0060)	(0.0060)	(0.0060)	(0.0060)	(0.0060)
$MaxChair_t$	-0.0038	-0.0040	-0.0040	-0.0037	-0.0037
	(0.0292)	(0.0292)	(0.0293)	(0.0292)	(0.0293)
$ArtCit3_t$	-0.0385**	-0.0385**	-0.0386**	-0.0395**	-0.0395**
	(0.0185)	(0.0185)	(0.0185)	(0.0186)	(0.0186)
$BtwCentArt3_t$	-0.0160	-0.0159	-0.0157	-0.0189	-0.0185
	(0.0308)	(0.0308)	(0.0308)	(0.0310)	(0.0311)
$CliqnessArt3_t$	-0.0348**	-0.0348**	-0.0359**	-0.0345*	-0.0351*
	(0.0177)	(0.0177)	(0.0179)	(0.0177)	(0.0179)
$BtwCentPat3_t$	-0.0184	-0.0182	-0.0178	-0.0177	-0.0175
	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0135)
$CliqnessPat3_t$	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$[CliqnessPat3_t]^2$	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$dAcAssignee_t$	-0.0210	-0.0221	-0.0226	-0.0217	-0.0221
	(0.0591)	(0.0593)	(0.0594)	(0.0594)	(0.0594)
dNanoEx	0.4024***	0.4007***	0.4000***	0.4016***	0.4011***
	(0.0670)	(0.0673)	(0.0674)	(0.0674)	(0.0674)
$dPGP_t$		0.0329	-0.2362	-0.0921	-0.2362
		(0.1310)	(0.5859)	(0.2008)	(0.5860)
$dPGP_t \times CliqnessArt3_t$			0.0619		0.0357
			(0.1314)		(0.1364)
$dPGP_t \times BtwCentArt3_t$				0.1211	0.1104
				(0.1474)	(0.1530)
Constant	2.4744***	2.4746***	2.4806***	2.4756***	2.4790***
	(0.1288)	(0.1289)	(0.1295)	(0.1289)	(0.1296)
Nb observations	1110	1110	1110	1110	1110
Log Likelihood	-1335.86	-1335.83	-1335.72	-1335.49	-1335.45
R^2	0.0759	0.0759	0.0761	0.0765	0.0766
R^2 Adjusted	0.0666	0.0658	0.0652	0.0656	0.0648
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table 6.17 : Impact of patent–grant pairs on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results

Variables	**HBC (7)**	**HBC (8)**	**HBC (9)**	**HBC (10)**	**HBC (11)**
$Grant3_t$	-3.7775***	-3.7752***	-3.7722***	-3.8250***	-3.8204***
	(0.8847)	(0.8847)	(0.8855)	(0.8878)	(0.8879)
$[Grant3_t]^2$	0.3135***	0.3132***	0.3129***	0.3180***	0.3176***
	(0.0715)	(0.0715)	(0.0716)	(0.0718)	(0.0718)
Age_t	-2.5374***	-2.5056***	-2.4986***	-2.4823***	-2.4539***
	(0.8745)	(0.8784)	(0.8830)	(0.8801)	(0.8868)
$[Age_t]^2$	0.1587***	0.1571***	0.1569***	0.1559***	0.1548***
	(0.0374)	(0.0376)	(0.0377)	(0.0377)	(0.0379)
$MaxChair_t$	-1.5190	-1.5304	-1.5307	-1.5078	-1.5083
	(1.1754)	(1.1757)	(1.1757)	(1.1760)	(1.1760)
$ArtCit3_t$	1.1454	1.1448	1.1456	1.1072	1.1061
	(0.7382)	(0.7382)	(0.7382)	(0.7398)	(0.7397)
$BtwCentArt3_t$	-17.1000***	-17.1000***	-17.1000***	-17.4000***	-17.4000***
	(4.6043)	(4.6065)	(4.6065)	(4.6157)	(4.6160)
$[BtwCentArt3_t]^2$	2.7635***	2.7756***	2.7756***	2.7929***	2.7939***
	(0.8665)	(0.8670)	(0.8670)	(0.8671)	(0.8671)
$CliqnessArt3_t$	0.2715	0.2658	0.2721	0.2791	0.3021
	(0.7164)	(0.7165)	(0.7210)	(0.7165)	(0.7219)
$BtwCentPat3_t$	1.1265**	1.1366**	1.1339**	1.1564**	1.1477**
	(0.4795)	(0.4803)	(0.4815)	(0.4810)	(0.4821)
$CliqnessPat3_t$	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$dAcAssignee_t$	-3.3943	-3.4647	-3.4632	-3.4377	-3.4300
	(2.3738)	(2.3810)	(2.3810)	(2.3805)	(2.3806)
dNanoEx	4.2352	4.1470	4.1525	4.2434	4.2663
	(2.6810)	(2.6909)	(2.6918)	(2.6940)	(2.6953)
$dPGP_t$		1.9835	3.7538	-2.4546	3.2635
		(5.2264)	(23.2695)	(7.9829)	(23.3498)
$dPGP_t \times CliqnessArt3_t$			-0.4066		-1.4134
			(5.2080)		(5.4236)
$dPGP_t \times BtwCentArt3_t$				6.7336	7.0148
				(9.9655)	(10.0234)
$dPGP_t \times [BtwCentArt3_t]^2$				-0.0525	-0.0494
				(0.1660)	(0.1664)
Constant	67.5917***	67.4395***	67.3774***	67.4019***	67.1738***
	(6.1616)	(6.1745)	(6.2254)	(6.1762)	(6.2379)
Constant (Sigma)	32.0067***	32.0054***	32.0052***	31.9959***	31.9947***
	(0.7595)	(0.7595)	(0.7595)	(0.7592)	(0.7592)
Nb observations	1110	1110	1110	1110	1110
Chi Square	108.963	109.107	109.113	109.716	109.784
Pseudo R^2	0.0109	0.0109	0.0109	0.0110	0.0110
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table 6.18 : Impact of patent–grant pairs on the Herfindahl index of forward citations [*HerfIndexFCit5$_t$*] – Tobit results

Variables	HFC (7)	HFC (8)	HFC (9)	HFC (10)	HFC (11)
$Grant3_t$	-0.3369	-0.3430	-0.3430	-0.3458	-0.3458
	(0.2479)	(0.2473)	(0.2473)	(0.2472)	(0.2472)
Age_t	-7.0573 ***	-6.7590 ***	-6.7410 ***	-6.8228 ***	-6.8171 ***
	(1.2130)	(1.2189)	(1.2213)	(1.2192)	(1.2221)
$[Age_t]^2$	0.3392 ***	0.3230 ***	0.3224 ***	0.3261 ***	0.3259 ***
	(0.0514)	(0.0517)	(0.0517)	(0.0517)	(0.0518)
$MaxChair_t$	0.6353	0.4584	0.4528	0.4290	0.4280
	(1.4046)	(1.4028)	(1.4031)	(1.4021)	(1.4022)
$ArtCit3_t$	5.4109 **	5.9396 **	5.9238 **	5.8975 **	5.8945 **
	(2.3012)	(2.3093)	(2.3100)	(2.3050)	(2.3055)
$[ArtCit3_t]^2$	-1.0414 *	-1.1765 **	-1.1717 **	-1.1507 **	-1.1500 **
	(0.5622)	(0.5653)	(0.5656)	(0.5643)	(0.5644)
$BtwCentArt3_t$	-0.2447	-0.1608	-0.1747	-0.0074	-0.0128
	(1.4794)	(1.4745)	(1.4751)	(1.4804)	(1.4825)
$CliqnessArt3_t$	-1.0484	-1.1493	-1.1239	-1.1700	-1.1639
	(0.8478)	(0.8450)	(0.8491)	(0.8446)	(0.8494)
$BtwCentPat3_t$	0.8149	0.9440	0.9347	0.9344	0.9324
	(0.5795)	(0.5786)	(0.5794)	(0.5783)	(0.5791)
$CliqnessPat3_t$	0.0004	0.0004	0.0004	0.0004	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$dAcAssignee_t$	2.7620	1.8908	1.9252	1.8708	1.8795
	(2.8782)	(2.8826)	(2.8852)	(2.8804)	(2.8834)
dNanoEx	-6.9269 **	-8.0948 **	-8.0662 **	-8.2388 **	-8.2312 **
	(3.2444)	(3.2550)	(3.2568)	(3.2563)	(3.2584)
$dPGP_t$		28.1833 ***	38.6921	37.2859 ***	39.5847
		(7.7279)	(35.6108)	(11.6503)	(35.6158)
$dPGP_t$ ×			-2.3444		-0.5404
CliqnessArt3t			(7.7340)		(7.9059)
$dPGP_t$ ×				-8.7258	-8.6017
$BtwCentArt3_t$				(8.1139)	(8.3186)
Constant	122 ***	120 ***	120 ***	121 ***	121 ***
	(8.1185)	(8.1396)	(8.1633)	(8.1293)	(8.1573)
Constant	36.4698	36.3184	36.3188	36.2921	36.2926
(Sigma)	1.0463 ***	1.0410 ***	1.0410 ***	1.0402 ***	1.0402 ***
Nb observations	1110	1110	1110	1110	1110
Chi Square	75.9482	90.3957	90.4881	91.533	91.5376
Pseudo R^2	0.0099	0.0118	0.0118	0.0120	0.0120
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

We analyzed the linear and non-linear effect of variables presented in Table 6.19 below:

Table 6.19 : Linear and non-linear effect (quadratic effect) of variables to measure impact of patent–grant pairs on patent quality

	FC WO/Sq	FC W/Sq	CL WO/Sq	CL W/Sq	HBC WO/Sq	HBC W/Sq	HFC WO/Sq	HFC W/Sq
$Grant3_t$					NS	**---**		
$(Grant3_t)^2$						**+++**		
Age_t	---	**+++**			+++	**---**	+/++	**---**
$(Age_t)^2$		**---**				**+++**		**+++**
$ArtCit3_t$							++/+	**++**
$(ArtCit3_t)^2$								**--/-**
$BtwCentArt3_t$					NS	**---**		
$(BtwCentArt3_t)^2$						**+++**		
$CliqnessArt3_t$	+	**NS**						
$(CliqnessArt3_t)^2$		**+**						
$CliqnessPat3_t$			NS	**++/+**				
$(CliqnessPat3_t)^2$				**-**				

Notes: WO/Sq (without square variable) shows the impact of a variable without squared variables (linear impact), while W/Sq (with squared variable) demonstrates a quadratic effect. Selected models are bold and underlined. Furthermore, +++, ++, + as well as ---, --, - show significance at the 1%, 5%, and 10% levels, respectively, in different directions (positive or negative), for instance: -0.8190 *** (indicated by ---), -2.1959 * (identified by -), and 28.1833 *** (determined by +++).

According to our results, we reject Hypothesis 6 in terms of number of forward citations, since the patents linked to patent–grant pairs [$dPGP_t$] receive fewer citations than other patents without such a link. However, we accept Hypothesis 6 when considering the Herfindahl index of forward citations [$HerfIndexFCit5_t$], as the patents receive more citations and are more diversified. We can't accept Hypothesis 6 when considering number of claims ($NbClaims_t$) and Herfindahl index of backward citations [$HerfIndexBWCit_t$], since the results are not significant. Furthermore, we couldn't find any significant effect of patent–grant pairs [$dPGP_t$] on patent quality when dealing with inventors who occupied in highly clustering coefficient co-publication networks [$dPGP_t \times CliqnessArt3_t$] as well as high co-publication network centrality [$dPGP_t \times BtwCentArt3_t$].

Accordingly, we cannot accept Hypothesis 6A proposing that there is a relationship between the two measured phenomena including patent quality as the dependent variable and patent–grant pairs dealing with inventors who occupied nodes in the highly centralized co-publication network as the independent variables. In Table 6.20, the results are summarized.

Table 6.20 : Summary of results for patent–grant pairs

Variables	**Forward citations [*NbFCit5$_t$*]**	**Herfindahl index of forward citations [*HerfIndexFCit5$_t$*]**	**Number of claims [*NbClaims$_t$*]**	**Herfindahl index of backward citations [*HerfIndexBWCit$_t$*]**
Patent–grant pairs [*dPGP*$_t$]	**Significant and negative** (---/--/-)	**Significant and positive** (+++)	Not significant	Not significant
PGP_t × $CliqnessArt3_t$	Not significant	Not significant	Not significant	Not significant
$dPGP_t$ × $BtwCentArt3_t$	Not significant	Not significant	Not significant	Not significant

Notes: +++, ++, + as well as ---, --, - show significance at the 1%, 5%, and 10% levels, respectively, in different directions (positive or negative); for instance: -0.8190 *** (indicated by ---), -2.1959 * (identified by -), and 28.1833 *** (determined by +++).

A key question in this research on patent quality concerns what the number of citations, the number of claims or the Herfindahl index actually measures. Is it really the patent "quality," as is often claimed in the literature? Patent citations measure the "use" of the patent as prior art cited in other patents, which implies how other technologies build upon a specific patent. Likewise, claims in a patent define the extent or the scope of the protection granted by the patent. The Herfindahl index, as a third element of this analysis, measures the diversification of technologies that patents engage. This research discovered a negative impact of the patent–paper pairs on patent quality, including the number of forward citations and number of claims. Prior studies have concluded there is no significant impact of patents that have paper counterparts on patent citation flows (Magerman et al., 2011). Moreover, this study corroborates former findings and further suggests that patents owned by universities yield a smaller number of citations in the technology world (Lissoni et al., 2010; Sterzi, 2013). The proximity between academic science and applied technology is generally crucial for knowledge transfer. However, the two fields do not seem to hold equal importance when it comes to having an impact in the technology world.

This exploration found that academic inventors holding a prestigious chair negatively impact the number of citations of the patents to which they contribute.

Collaboration networks among inventors are crucial to their innovation activities and their scientific performance, as inventors rarely work unaccompanied and isolated. Prior research have found that patents prevent competitors from capturing the market, while occupying better brokerage positions (Blind et al. 2009). To have a whole picture of knowledge transfer including explicit and tacit knowledge, both patent citation and measuring the network properties of the co-invention and co-authorship networks are required. Inventors that engage in the short path with a high degree of centrality and clustering can broadly and rapidly spread the information between different partners (Xiang et al., 2013). Our results reveal that better brokerage positions will only go so far to improve patent quality. Network positions that are too central and intermediary are eventually associated with declining quality.

Considering the impact of government assignees on patent citations, our study is consistent with Popp et al. (2013) and Popp (2006). The academic and government assignees obtain fewer citations than patents held by private-sector assignees. Furthermore, our findings show that patents assigned to government or universities and other research facilities engage in less diversified technology domains than patents that are privately held by corporations. Finally, our outcomes showed that patents belonging to patent–grant pairs obtained fewer patent forward citations, but are more diversified and engaged in multidisciplinary technology sectors, compared to patents not paired with grants.

It seems the nature of government patents has changed over time (Popp, 2006). As argued by Kenney and Patton (2009, 2011) in assessing the Bayh–Dole Act, university ownership of patents may actually impede innovation commercialization in a competitive market. Furthermore, several scholars have examined the impact of university, government and corporation patentees on patent quality (Bessen, 2008; Crespi et al., 2010; Lissoni et al., 2010; Mowery & Ziedonis, 2002; Popp, 2006; Popp et al., 2013; Sterzi, 2013). Past researchers have supposed that patents assigned to government laboratories would concentrate on essential needs and would be more likely to be cited than patents held by private corporations (Popp, 2006; Popp et al., 2013). However, the results of the present research show that government patents tend to obtain fewer citations than privately assigned patents. This conclusion is consistent with previous studies including Popp (2006) and Popp et al. (2013) which demonstrated the positive contribution of private assignees on patent citations in the energy sector.

CHAPTER 7 CONCLUSION AND RECOMMENDATIONS

A number of scholars have used patent data to analyze R&D outcomes, measuring firms' technological position in the competitive market, patent quality and value (Petruzzelli et al., 2015; Reitzig & Puranam, 2009). The first question that we should answer is, what is patent quality? Significant numbers of studies have investigated key indicators to measure patent quality. Duch-Brown and Costa-Campi (2015) state that patent citations reveal the intrinsic quality of the patents. Briggs (2015) present patent citation as the extensively common proxy of patent quality. With respect to former scholars, the forward citation and also the prior art of the patent have been used as the common measure of patent quality, showing the importance of the patents in knowledge spillovers (Briggs, 2015; Hagedoorn & Cloodt, 2003; Harhoff et al., 1999). Hagedoorn and Cloodt (2003) imply there is a positive association between a patent's importance and its number of citations in subsequent patents.

The difference in patent quality and value is blurred. Singh (2008) interchangeably used patent quality and value in his research. Prior works have attempted to measure patent value and influence in subsequent technology development, rather than the number of patents (Singh, 2008). Some authors found that the number of patent citations is positively associated with the direct indicators that measure patent value, including market value (B. H. Hall et al., 2005), renewal rate (Harhoff et al., 1999), and expert value evaluation (Albert, Avery, Narin, & McAllister, 1991). Singh (2008) defined patent quality as the number of patent forward citations. Singh (2008) tested technological breadth as the variable to assess patent quality. Technological breadth was calculated by 1 minus the Herfindahl index of cited patents in a focal patent (patent backward citations) as the measure of patent concentration. Singh's (2008) studies reveal that patents that are more diversified (higher number of Herfindahl index of backward citations) are of a greater quality than patents involved in fewer technology domains.

Petruzzelli et al. (2015) used technological breadth as the indicator to measure innovation influence measured by the number of forward citations. Conversely, according to Petruzzelli et al.'s (2015) research, being involved in various technology domains doesn't affect the patent citation in the biotechnology domain. However, it negatively affects the patent influence in subsequent innovation (measured by the number of citations) in non-biotechnology domains. Petruzzelli et al. (2015) reveal that patent importance and influence varies according to the domain. A possible explanation of the negative impact of high technology breadth on patent citations would be the complexity of the integration of various technology fields (Koput, 1997), low technology absorptive capacity (Cohen & Levinthal, 1990; Petruzzelli et al., 2015). However, Petruzzelli et al.'s (2015) research shows that high value of patent scope is linked to a greater number of forward citations non-biotechnology domain.

In this research, we used the number of patent forward citations, the number of claims and 1 minus the Herfindahl index of both forward and backward citations as proxies for patent quality indicators. We measured the impact of patent–paper pairs, patent ownership structure, and patent–grant pairs on patent quality, finding a negative impact on patent citations. With the passage of the Bayh–Dole Act, universities became involved in patenting and licensing their innovations, and they undertook enormous effort to set up their internal process for the Technology Transfer Office (TTO) to commercialize their innovations (Sampat, 2006). After the Bayh–Dole Act, universities have the right to decide what to patent and how to patent, giving universities the opportunity to license their patents for their own beneficial interest rather than for the public interest (Sampat, 2006).

Some scholars consider the Bayh–Dole Act as "possibly the most inspired piece of legislation to be enacted in America over the past half-century," suggesting that "more than anything, this single policy measure helped to reverse America's precipitous slide into industrial irrelevance" (Sampat, 2006).

While the Bayh–Dole Act has unquestionably facilitated university innovation transfer and commercialization in some cases, this is not true for all cases (Sampat, 2006). The importance of patents and commercialization of patents was not well recognized during the passage of the Bayh–Dole Act and afterward (Sampat, 2006). Neils Reimers, the manager of the Cohen-Boyer licensing program, stated: "Whether we licensed it or not, commercialisation of recombinant DNA was going forward.… A non-exclusive licensing program, at its heart, is really a tax… but it's always nice to say 'technology transfer'" (Reimers, 1998; Sampat, 2006).

Likewise, regarding the ownership of the patents by the public sector (including the government) instead of private contractors, there are serious debates between supporters and opponents of private patent ownership (Sampat, 2006). Vannevar Bush (as the "Director of the Wartime Office of Scientific Research and Development") stated that giving the authority to private contractors to retain their rights to license patents would encourage the corporations to significantly engage in producing new products and to commercialize the innovations from government-funded projects (Sampat, 2006). Conversely, opponents of private patent ownership have argued that the government gives the economic power to the large corporations at the expense of the small firms, by offering the opportunity for the corporations to own the innovations (Sampat, 2006).

Over the past quarter of the twentieth century, the corporations' role in defining the projects for the universities has enormously increased. In the wake of the Bayh–Dole Act, universities can decide how to act to license their innovations (Sampat, 2006). By monitoring how the universities make decisions on licensing, and how universities consider the public interest rather than self-interest when making such decisions, the public ownership system can be amended (Sampat, 2006).

Like every research, this study has some limitations. First, only the number of forward citations and Herfindahl index of backward and forward citations, and the number of claims were used to measure the patent quality in this research, since only these four indicators were accessible in the data for testing. There are, however, more indicators that could be used to measure patent quality, including the number of IPC-subclasses, patent renewals, patent families, and number of applicants (Goetze, 2010; Schettino et al., 2013; Seol et al., 2011). The methodology of the present research is consistent with previous studies. However, in order to truly measure patent quality, more complex indicators could be applied in further research.

The second limitation is associated with the scope of the data. The data used in this observation merely covers biotechnology and nanotechnology patents originating in Canada and cannot be generalized to other disciplines or to other geographical regions.

In terms of patent ownership structure, transferring technology to the private sector seems to be advisable, as the government and academic patents in this study tended to receive fewer citations. According to the results of Popp (2006) and Popp et al. (2013), U.S. government child patents, however, frequently obtained more citations than government parent patents. Frequently when a government child patent was assigned to the private sector, it cited at least one other patent that was assigned to the government. In light of such findings, it would be interesting to measure the citations of Canadian government child patents in future research. Researchers could measure the quality of patents that are privately held by corporations but that cite at least one patent assigned to the government. Accordingly, they could integrate the government contribution (generated from government laboratories) in privately held patents, to apply the added value by government to the commercialization of patents owned by the corporations.

Based on this study, where the citations of government patents in Canada were examined, two dummy variables can be defined for further research. One dummy variable can be set at 1, where the patent is assigned to the government in Canada, as defined in this research. A second variable, for the Canadian government child patents, can also be set at 1, for patents held by a private-sector assignee and citing at least one patent that is assigned to the government in Canada.

Patent citation in Canada across institutions including university, government and corporations was examined in this research. The citation of prior art might be different, however, across different countries. Therefore, inference of patent quality according to the prior art of the patents could be complicated (Alcácer, Gittelman, & Sampat, 2009). Nevertheless, evaluation of patent citations across different regions and nations could be applied in future research. Briggs's (2015) outcomes demonstrated that patents assigned to multiple countries obtain more forward citations than patents issued in a single country. Briggs's (2015) research also showed that patent co-owners in different geographical locations increase patent quality. Accordingly, the impact of joint assignees on patent quality could be studied.

In some cases the examiners and patent applicants add the prior art to patent citations. Accordingly, the proportion of examiners and patents applicants significantly affects the patent's number of backward citations. A higher proportion of patent applicants are linked to a higher number of patent examiners' citations. Therefore, the impact of the number of patent examiners on patent prior art citations can be investigated in future research.

The number of examiners varies across different technology domains. In the communication and electronics fields there is a large number of examiners (Alcácer et al., 2009). Moreover, the prior art of citations is related to the technology domain, region, examiner's experience, and relative proportion of examiners and patent applicants. All of these factors could be considered and addressed in further research to measure the quality and value of the patents associated with patent citations' prior art (Alcácer et al., 2009).

Measurement of the Herfindahl index of the inventors' geographical distribution can be addressed in a future study to investigate the impact of the inventors' cross-regional distribution network on patent quality in Canada. In this research we examined the impact of network clustering coefficient and betweenness centrality associated with the co-invention and co-authorship network on patent quality.

Regarding the patent–paper pairs, we found a negative impact of patent–paper pairs on the number of patent citations. However, according to Magerman et al. (2015), publications that are linked to patents receive significantly higher citations than papers without such a link. This result shows that patenting doesn't threaten scientific activity. The impact of patent–paper pairs on patent quality in other high-technology domains could be further investigated. Moreover, measurement can be done at the individual and corporation level to determine if there is any difference in the results. That is, the research can compare patent–paper pairs engaging individual scholars with those involving scientists in public and private institutions. According to our descriptive data, there is a decreasing trend of patents belonging to patent–paper pairs. Figure 5.3 shows a decreasing difference between citations of patents in patents–paper pairs and patents not linked to publications, with the two numbers converging by the year 2005. Likewise, as shown in Figure 5.4 in regard to number of claims, the difference between patent–paper pairs and patents without such a link tends to be not significant. Thus, increasing the research time window beyond 2005 may show that the difference in number of citations and number of claims will change further over a longer period, becoming even less significant.

Further research is clearly required to disentangle the role of academic inventors in the technology world, in regard to their position within the scientific and technological networks. What benefits accrue from university patents and from patents to which academics contribute? Again the researcher must ask, what is patent quality? What indicators are relevant at the individual patent level? This investigation has shown that all indicators are not interchangeable; they imply very different concepts used as proxies for quality, for lack of better indicators. The results obtained are highly dependent on the proxy type used to measure a particular concept. Empirical researchers therefore must tread with care in the realm of patent quality indicators. To quote Hagedoorn and Cloodt (2003, pp. 1365-1366), given "the variety in constructs, measurements, samples, databases, industries and country settings and inconsistency in definitions, it is of no surprise that there appears to be hardly any clear understanding of the concept and measurement of innovative performance." This research has taken due account of such concerns in assessing the impact of academic and government patent ownership, and of patent–paper pairs and patent–grant pairs, on patent quality, and finding the impacts negative. The results point clearly to the conclusion that academic and government patent ownership, as well as contributions by academic inventors, lack positive impact on patent quality.

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APPENDIX A – VARIABLES DESCRIPTION

Table A.1 : Description of Variables

Dependent Variables	***Description of Variables***
$NbClaims_t$	Log of number of claims in the patent document. We generated the natural logarithm of number of claims *ln ($NbClaims_t$)*.
$NbFCit5_t$	Log of number of forward citations in citing patents, during the 5 years following the granting year *ln ($NbFCit5_t$ +1)*. We generated the natural logarithm of number of forward citations with left censored.
$HerfIndexFCit5_t$	Herfindal index of forward citations This is a measure to demonstrate the technological concentration of the patent. High value of the *$HerfIndexFCit5_t$* variable demonstrates that the patent involves a variety of technologies. We multiplied by 100 to normalize this variable *($HerfIndexFCit5_t \times 100$)*.
$HerfIndexBWCit_t$	Herfindal index of backward citations This is a measure to demonstrate the technological concentration of the patent as the technological breadth. High value of the *$HerfIndexBWCit_t$* variable demonstrates that patent involves in varieties of technologies. We multiplied by 100 to normalize this variable *($HerfIndexBWCit_t \times 100$)*.
Independent Variables	
Age_t	Average “career” age of the academic inventors of the patent. This variable has been averaged over all academic inventors who contributed to a given patent.
$BtwCentPat3_t$	Average value amongst the academic inventors of the patent of the 3-year **co-invention** (patents) individual network betweenness centrality. We used the natural logarithm of betweenness centrality *ln* (*$BtwCentPat3_t$* $\times 10^4$ +1). This variable has been averaged over all academic inventors who contributed to a given patent.

Table A.1 : Description of Variables (Cont'd)

Dependent Variables	***Variables description***
CliqnessPat3$_t$	Average value amongst the academic inventors of the patent of the 3-year **co-invention** (patents) individual network clustering coefficient (cliquishness) (*CliqnessPat3*$_t$ × 10^4).
CliqnessArt3$_t$	Average value amongst the academic inventors of the patent of the 3-year **co-publication** (articles) individual network clustering coefficient (cliquishness). We used the square root of the clustering coefficient of the co-publication network (all averaged) to normalize this variable *Sqrt (CliqnessArt3*$_t$).
BtwCentArt3$_t$	Average value amongst the academic inventors of the patent of the 3-year **co-publication** (articles) individual network betweenness centrality. This variable has been averaged over all academic inventors who contributed to a given patent. We used the natural logarithm of betweenness centrality *ln (BtwCentArt3*$_t$ × 10^4 *+1)*.
Grant3$_t$	Average value amongst the academic inventors of the patent of the amount of grants received by the academic inventors of the patent over the three years prior to the patent application. This variable has been averaged over all academic inventors who contributed to a given patent. We used the logarithm of *ln (Grant3*$_t$ *+1)*.
ArtCit3$_t$	Average value amongst the academic inventors of the patent of the number of article citations received by their publications. This variable has been averaged over all academic inventors who contributed to a given patent *ln (ArtCit3*$_t$ *+1)*.
dAcAssignee$_t$	Dummy variable taking the value 1 if the assignee of the patent is an academic institution
dGovAssignee$_t$	Dummy variable taking the value 1 if the assignee of the patent is an government
dNanoEx	Dummy variable taking the value 1 if the domain of the patent is exclusively nanotechnology (i.e. excluding nanobiotechnology)
Similarity$_t$	Similarity between patents and papers

Table A.1 : Description of Variables (Cont'd and end)

Dependent Variables	***Variables description***
$dPGP_t$	Dummy variables set equals 1 when the patent is linked to the grants (similar content) within a short time frame (maximum 2 years) before patent application date.
$MaxChair_t$	Maximum value amongst the academic inventors of the patent of the ordinal variable representing the "best" chair occupied by an academic (0 = no chair, 1 = industrial chair, 2 = NSERC or CIHR chair, 3 = Canada Research Chair).
Endogenous variables	
$Contract3_t$	Average value amongst the academic inventors of the patent of the amount of contracts received by the academic inventors of the patent over the three years prior to the patent application. This variable has been averaged over all academic inventors who contributed to a given patent. We used the natural logarithm of average of contract received by the academic inventors of the patent $ln\ (Contract3_t + 1)$.
Instrumental variables	
$Contract3U_{t-2}$	Average value amongst the academic inventors of the patent of the total amount of contracts received by their university over the past three years. This variable has been averaged over all academic inventors who contributed to a given patent. We used the natural logarithm of this variable $ln\ (Contract3U_{t-2} + 1)$.
$GrantEI3_t$	Average value amongst the academic inventors of the patent of the amount of grants for equipment and infrastructure over the past three years. This variable has been averaged over all academic inventors who contributed to a given patent. We used the natural logarithm of this variable $ln\ (GrantEI3_t + 1)$.
$Loop_t$	Average value amongst the academic inventors of the patent of the number of innovation loops to which they have contributed (such a loop exists when the research of the named academic inventors of the patent has been funded by the assignee of the patent) to which they have contributed: $Loop_t$

APPENDIX B –TEST ROBUSTNESS FOR PATENT OWNERSHIP STRUCTURE

Table B.1 : Impact of academic assignees and government assignees on the number of forward citations [$NbFCit5_t$] – Zero-inflated negative binomial model results (robustness test FC (13–17))

Variables	FC (13)	FC (14)	FC (15)	FC (16)	FC (17)
$Grant3_t$	-0.0077	-0.0038	-0.0034	-0.0036	-0.0042
	(0.0096)	(0.0100)	(0.0102)	(0.0100)	(0.0100)
Age_t	0.3712***	0.3806***	0.3806***	0.3902***	0.3806***
	(0.0501)	(0.0498)	(0.0498)	(0.0502)	(0.0497)
$[Age_t]^2$	-0.0176***	-0.0182***	-0.0182***	-0.0185***	-0.0182***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
$MaxChair_t$	0.1234*	0.0832	0.0824	0.0805	0.0827
	(0.0632)	(0.0640)	(0.0641)	(0.0640)	(0.0638)
$ArtCit3_t$	-0.0843**	-0.0509	-0.0507	-0.0506	-0.0493
	(0.0363)	(0.0384)	(0.0384)	(0.0384)	(0.0384)
$BtwCentArt3_t$	0.0541	0.0105	0.0100	0.0090	0.0162
	(0.0598)	(0.0620)	(0.0621)	(0.0621)	(0.0622)
$CliqnessArt3_t$	-0.2039*	-0.1924*	-0.1905*	-0.2035*	-0.1881*
	(0.1057)	(0.1066)	(0.1072)	(0.1066)	(0.1065)
$[CliqnessArt3_t]^2$	0.0206**	0.0188**	0.0186**	0.0199**	0.0186**
	(0.0092)	(0.0091)	(0.0092)	(0.0091)	(0.0091)
$BtwCentPat3_t$	-0.0623***	-0.0781***	-0.0778***	-0.0794***	-0.0788***
	(0.0233)	(0.0247)	(0.0247)	(0.0248)	(0.0247)
$CliqnessPat3_t$	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loop	-0.1241	-0.0749	-0.0760	-0.0760	-0.0731
	(0.1193)	(0.1214)	(0.1215)	(0.1213)	(0.1213)
dNanoEx	0.6402***	0.6262***	0.6268***	0.6362***	0.6322***
	(0.1212)	(0.1205)	(0.1205)	(0.1209)	(0.1205)
$dGovAssignee_t$		-0.7768***	-0.7124	3.3786	-0.3944
		(0.2854)	(0.4700)	(2.5934)	(0.4402)
$dAcAssignee_t$		-0.4415***	-0.4421***	-0.4386***	-0.4412***
		(0.1399)	(0.1399)	(0.1397)	(0.1397)
$dGovAssignee_t \times Grant3_t$			-0.0088		
			(0.0509)		
$dGovAssignee_t \times Age_t$				-0.7210	
				(0.4692)	
$dGovAssignee_t \times [Age_t]^2$				0.0282	
				(0.0197)	
$dGovAssignee_t \times BtwCentArt3_t$					-0.3743
					(0.3195)
Constant	-0.9836***	-0.9006**	-0.9049**	-0.9417***	-0.9211***
	(0.3501)	(0.3506)	(0.3514)	(0.3517)	(0.3504)
Inflate					
$Grant3_t$	-0.0080	0.0021	0.0019	0.0013	0.0008
	(0.0699)	(0.0568)	(0.0566)	(0.0575)	(0.0558)
Age_t	0.1901	0.0454	0.0453	0.0473	0.0450
	(0.1825)	(0.0593)	(0.0592)	(0.0591)	(0.0584)

Table B.1 : Impact of academic assignees and government assignees on the number of forward citations [$NbFCit5_t$] – Zero-inflated negative binomial model results (robustness test FC (13–17)) (Cont'd and end)

Variables	**FC (13)**	**FC (14)**	**FC (15)**	**FC (16)**	**FC (17)**
$MaxChair_t$	2.4458**	0.7605*	0.7582*	0.7450	0.7550*
	(1.1628)	(0.4472)	(0.4456)	(0.4574)	(0.4427)
$BtwCentArt3_t$	-1.6670**	-1.9219	-1.9221	-1.8973	-1.9153
	(0.7080)	(1.1784)	(1.1751)	(1.1927)	(1.1775)
$CliqnessArt3_t$	0.3738	0.0411	0.0414	0.0389	0.0433
	(0.2418)	(0.1403)	(0.1400)	(0.1395)	(0.1373)
$ArtCit3_t$	0.2966	0.7215*	0.7218*	0.7160*	0.7179*
	(0.2741)	(0.4108)	(0.4096)	(0.4181)	(0.4072)
$BtwCentPat3_t$	-0.4346*	-0.4942*	-0.4938*	-0.4872*	-0.4949*
	(0.2279)	(0.2772)	(0.2763)	(0.2783)	(0.2740)
Constant (Inflate)	-9.9839*	-3.1570**	-3.1528**	-3.1434**	-3.1238**
	(5.2268)	(1.5146)	(1.5076)	(1.5461)	(1.4951)
Constant (lnalpha)	0.3635***	0.3056***	0.3055***	0.2992***	0.3017***
	(0.0799)	(0.0908)	(0.0907)	(0.0920)	(0.0913)
Nb observations	1110	1110	1110	1110	1110
Log Likelihood	-1733.70	-1727.58	-1727.57	-1726.12	-1726.89
Chi Square	98.26	110.50	110.53	113.42	111.88
P value	0.0000	0.0000	0.0000	0.0000	0.0000
Zero obs	543.00	543.00	543.00	543.00	543.00

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

Table B.2 : Impact of academic assignees and government assignees on the number of forward citations [$NbFCit5_t$] – Zero-inflated negative binomial model results (robustness test FC (18–21))

Variables	**FC (18)**	**FC (19)**	**FC (20)**	**FC (21)**
$Grant3_t$	-0.0031	-0.0043	-0.0071	-0.0039
	(0.0100)	(0.0102)	(0.0103)	(0.0100)
Age_t	0.3800***	0.3893***	0.3750***	0.3727***
	(0.0498)	(0.0501)	(0.0499)	(0.0534)
$[Age_t]^2$	-0.0182***	-0.0185***	-0.0180***	-0.0179***
	(0.0021)	(0.0021)	(0.0021)	(0.0023)
$MaxChair_t$	0.0818	0.0812	0.0853	0.0824
	(0.0639)	(0.0640)	(0.0644)	(0.0638)
$ArtCit3_t$	-0.0502	-0.0485	-0.0518	-0.0507
	(0.0384)	(0.0384)	(0.0384)	(0.0384)
$BtwCentArt3_t$	0.0079	0.0134	0.0147	0.0111
	(0.0621)	(0.0624)	(0.0619)	(0.0621)
$CliqnessArt3_t$	-0.1892*	-0.1998*	-0.1905*	-0.1945*
	(0.1066)	(0.1076)	(0.1066)	(0.1067)
$[CliqnessArt3_t]^2$	0.0185**	0.0197**	0.0188**	0.0189**
	(0.0091)	(0.0092)	(0.0091)	(0.0091)
$BtwCentPat3_t$	-0.0772***	-0.0797***	-0.0809***	-0.0776***
	(0.0247)	(0.0251)	(0.0247)	(0.0247)
$CliqnessPat3_t$	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loop	-0.0778	-0.0742	-0.0734	-0.0769
	(0.1214)	(0.1213)	(0.1211)	(0.1223)

Table B.2 : Impact of academic assignees and government assignees on the number of forward citations [NbFCit5$_t$] – Zero-inflated negative binomial model results (robustness test FC (18–21)) (Cont'd and end)

Variables	**FC (18)**	**FC (19)**	**FC (20)**	**FC (21)**
dNanoEx	0.6272***	0.6402***	0.6302***	0.6278***
	(0.1205)	(0.1211)	(0.1205)	(0.1205)
dGovAssignee$_t$	-0.6753**	3.8675	-0.7800***	-0.7759***
	(0.3200)	(2.7428)	(0.2852)	(0.2853)
dAcAssignee$_t$	-0.4408***	-0.4357***	-0.8545**	-0.7481
	(0.1398)	(0.1397)	(0.3464)	(0.8153)
dGovAssignee$_t$ × Grant3$_t$		0.0340		
		(0.0600)		
dGovAssignee$_t$ × Age$_t$		-0.7693		
		(0.5050)		
dGovAssignee$_t$ × [Age$_t$]^2		0.0307		
		(0.0215)		
dGovAssignee$_t$ × BtwCentArt3$_t$		-0.3998		
		(0.3359)		
dGovAssignee × BtwCentPat3$_t$	-0.2663	-0.4121		
	(0.3754)	(0.4449)		
dAcAssignee$_t$ × Grant3$_t$			0.0422	
			(0.0324)	
dAcAssignee$_t$× Age$_t$				0.0598
				(0.1461)
dAcAssignee$_t$ × [Age$_t$]^2				-0.0026
				(0.0064)
Constant	-0.9060***	-0.9545***	-0.8565**	-0.8524**
	(0.3505)	(0.3519)	(0.3519)	(0.3737)
Inflate				
Grant3$_t$	0.0022	0.0010	0.0072	0.0025
	(0.0567)	(0.0580)	(0.0592)	(0.0574)
Age$_t$	0.0458	0.0481	0.0485	0.0454
	(0.0591)	(0.0587)	(0.0622)	(0.0596)
MaxChair$_t$	0.7581*	0.7451	0.7988*	0.7631*
	(0.4454)	(0.4660)	(0.4644)	(0.4516)
BtwCentArt3$_t$	-1.9246	-1.8909	-1.9298	-1.9446
	(1.1775)	(1.2172)	(1.2595)	(1.1883)
CliqnessArt3$_t$	0.0409	0.0399	0.0400	0.0380
	(0.1395)	(0.1371)	(0.1500)	(0.1414)
ArtCit3$_t$	0.7223*	0.7110*	0.7232	0.7315*
	(0.4087)	(0.4203)	(0.4423)	(0.4156)
BtwCentPat3$_t$	-0.4945*	-0.4899*	-0.5013*	-0.4965*
	(0.2762)	(0.2789)	(0.2948)	(0.2806)
Constant (Inflate)	-3.1561**	-3.1288**	-3.3094**	-3.1706**
	(1.5085)	(1.5701)	(1.6032)	(1.5321)
Constant (lnalpha)	0.3047***	0.2940***	0.3020***	0.3054***
	(0.0908)	(0.0932)	(0.0905)	(0.0905)
Nb observations	1110	1110	1110	1110
Log Likelihood	-1727.31	-1725.05	-1726.74	-1727.50
Chi Square	111.04	115.57	112.18	110.67
P value	0.0000	0.0000	0.0000	0.0000
Zero obs	543.00	543.00	543.00	543.00

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

Table B.3 : Impact of academic assignees and government assignees on the number of forward citations [$NbFCit5_t$] – Zero-inflated negative binomial model results (robustness test FC (22–25))

Variables	**FC (22)**	**FC (23)**	**FC (24)**	**FC (25)**
Grant3$_t$	-0.0064	-0.0046	-0.0111	-0.0125
	(0.0104)	(0.0101)	(0.0107)	(0.0114)
Age$_t$	0.3842***	0.3821***	0.3730***	0.3834***
	(0.0498)	(0.0498)	(0.0532)	(0.0538)
[Age$_t$]^2	-0.0182***	-0.0183***	-0.0178***	-0.0181***
	(0.0021)	(0.0021)	(0.0022)	(0.0023)
MaxChair$_t$	0.0837	0.0822	0.0861	0.0849
	(0.0642)	(0.0640)	(0.0647)	(0.0647)
ArtCit3$_t$	-0.0434	-0.0524	-0.0455	-0.0419
	(0.0387)	(0.0384)	(0.0390)	(0.0394)
BtwCentArt3$_t$	0.0359	0.0129	0.0468	0.0513
	(0.0640)	(0.0621)	(0.0644)	(0.0653)
CliqnessArt3$_t$	-0.1861*	-0.1923*	-0.1848*	-0.1927*
	(0.1060)	(0.1065)	(0.1058)	(0.1067)
[CliqnessArt3$_t$]^2	0.0186**	0.0189**	0.0188**	0.0198**
	(0.0090)	(0.0091)	(0.0090)	(0.0091)
BtwCentPat3$_t$	-0.0832***	-0.0820***	-0.0896***	-0.0933***
	(0.0262)	(0.0254)	(0.0270)	(0.0297)
CliqnessPat3$_t$	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loop	-0.0717	-0.0650	-0.0585	-0.0567
	(0.1212)	(0.1222)	(0.1226)	(0.1224)
dNanoEx	0.6193***	0.6224***	0.6214***	0.6339***
	(0.1204)	(0.1206)	(0.1207)	(0.1220)
dGovAssignee$_t$	-0.7803***	-0.7836***	-0.7899***	3.8427
	(0.2850)	(0.2857)	(0.2849)	(2.7312)
dAcAssignee$_t$	-0.1809	-0.4828***	-0.9506	-0.8815
	(0.1954)	(0.1530)	(0.8282)	(0.8271)
dGovAssignee$_t$ × Grant3$_t$				0.0423
				(0.0598)
dGovAssignee$_t$ × Age$_t$				-0.7654
				(0.5034)
dGovAssignee$_t$ × [Age$_t$]^2				0.0304
				(0.0215)
dGovAssignee$_t$ × BtwCentArt3$_t$				-0.4542
				(0.3342)
dGovAssignee$_t$ × BtwCentPat3$_t$				-0.4035
				(0.4433)
dAcAssignee$_t$ × Grant3$_t$			0.0472	0.0485
			(0.0339)	(0.0339)
dAcAssignee$_t$× Age$_t$			0.0451	0.0361
			(0.1540)	(0.1538)
dAcAssignee$_t$ × [Age$_t$]^2			-0.0014	-0.0012
			(0.0067)	(0.0067)
dAcAssignee$_t$× BtwCentArt3$_t$	-0.2744*		-0.3196**	-0.3322**
	(0.1421)		(0.1475)	(0.1478)
dAcAssignee$_t$× BtwCentPat3$_t$		0.0534	0.0529	0.0545
		(0.0812)	(0.0834)	(0.0832)
		0.5113	0.5259	0.5125
Constant	-0.9828***	-0.9025**	-0.8987**	-0.9625***
	(0.3524)	(0.3505)	(0.3713)	(0.3734)

Table B.3 : Impact of academic assignees and government assignees on the number of forward citations [NbFCit5t] – Zero-inflated negative binomial model results (robustness test FC (22–25)) (Cont'd and end)

Variables	FC (22)	FC (23)	FC (24)	FC (25)
$Grant3_t$	-0.0064	0.0010	-0.0003	-0.0051
	(0.0548)	(0.0563)	(0.0583)	(0.0630)
Age_t	0.0478	0.0462	0.0531	0.0570
	(0.0549)	(0.0586)	(0.0575)	(0.0566)
$MaxChair_t$	0.6844	0.7517*	0.7240	0.6740
	(0.4581)	(0.4445)	(0.4874)	(0.5508)
$BtwCentArt3_t$	-1.7426	-1.9137	-1.7461	-1.6209
	(1.2182)	(1.1782)	(1.3125)	(1.4179)
$CliqnessArt3_t$	0.0450	0.0409	0.0425	0.0398
	(0.1257)	(0.1382)	(0.1319)	(0.1256)
$ArtCit3_t$	0.6607	0.7162*	0.6600	0.6187
	(0.4206)	(0.4103)	(0.4506)	(0.4784)
$BtwCentPat3_t$	-0.4539*	-0.4849*	-0.4508*	-0.4331
	(0.2534)	(0.2733)	(0.2710)	(0.2668)
Constant (Inflate)	-2.9091*	-3.1333**	-3.0872*	-2.9406
	(1.5325)	(1.5127)	(1.6841)	(1.8450)
Constant (lnalpha)	0.2867***	0.3035***	0.2797***	0.2610**
	(0.1007)	(0.0914)	(0.1013)	(0.1168)
Nb observations	1110	1110	1110	1110
Log Likelihood	-1725.71	-1727.37	-1724.19	-1721.44
Chi Square	114.25	110.93	117.29	122.78
P value	0.0000	0.0000	0.0000	0.0000
Zero obs	543.00	543.00	543.00	543.00

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

Table B.4 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [$HerfIndexBWCit_t$] – Regression results (robustness test HBC (12–15))

Variables	HBC (12)	HBC (13)	HBC (14)	HBC (15)
$Grant3_t$	-3.6579***	-3.6259***	-3.5805***	-3.5856***
	(0.7841)	0.7806	0.7980	0.7806
$[Grant3_t]^2$	0.2978***	0.2968***	0.2944***	0.2926***
	(0.0632)	(0.0629)	(0.0644)	(0.0629)
$NbClaims_t$	2.9728***	2.8988***	2.8976***	2.6623**
	(1.0517)	(1.0475)	(1.0484)	(1.0585)
Age_t	-2.2616***	-2.1145***	-2.1241***	-2.1391***
	(0.7764)	(0.7745)	(0.7754)	(0.7742)
$[Age_t]^2$	0.1396***	0.1312***	0.1316***	0.1318***
	(0.0331)	(0.0331)	(0.0331)	(0.0331)
$MaxChair_t$	-1.3123	-1.4395	-1.4480	-1.4304
	(1.0359)	(1.0320)	(1.0330)	(1.0315)
$ArtCit3_t$	0.9243	1.0090	1.0086	1.0287
	(0.6529)	(0.6513)	(0.6526)	(0.6510)
$BtwCentArt3_t$	-15.4000***	-14.1000***	-14.1000***	-14.1000***
	(4.0541)	(4.0525)	(4.0577)	(4.0501)
$[BtwCentArt3_t]^2$	2.5502***	2.3033***	2.2919***	2.3119***
	(0.7653)	(0.7654)	(0.7668)	(0.7650)

Table B.4 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [HerfIndexBWCit$_t$] – Regression results (robustness test HBC (12–15)) (Cont'd and end)

Variables	HBC (12)	HBC (13)	HBC (14)	HBC (15)
CliqnessArt3$_t$	0.4144	0.3718	0.3579	0.4490
	(0.6334)	(0.6315)	(0.6327)	(0.6332)
BtwCentPat3$_t$	1.0514**	0.7663*	0.7812*	0.7387*
	(0.4169)	(0.4233)	(0.4267)	(0.4234)
CliqnessPat3$_t$	0.0010***	0.0010***	0.0010***	0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	1.9252	2.1148	2.0605	2.1545
	(2.1736)	(2.2173)	(2.2218)	(2.2161)
dNanoEx	2.4129	2.3534	2.3181	2.4415
	(2.4072)	(2.3965)	(2.4000)	(2.3958)
dGovAssignee$_t$		-14.4000***	-10.9000	-40.4000**
		(4.9656)	(8.7998)	(17.9318)
dAcAssignee$_t$		-5.3922**	-5.4022**	-5.4477**
		(2.4889)	(2.4910)	(2.4877)
dGovAssignee$_t$ × Grant3$_t$			-1.3230	
			(4.2070)	
dGovAssignee$_t$ × [Grant3$_t$]^2			0.0752	
			(0.3370)	
dGovAssignee$_t$ × NbClaims$_t$				9.9747
				(6.5996)
Constant	60.9051***	62.5982***	62.5582***	63.0079***
	(6.0684)	(6.0867)	(6.0926)	(6.0892)
Nb observations	1110	1110	1110	1110
Log Likelihood	-5283.18	-5277.07	-5276.94	-5275.91
R^2	0.10	0.11	0.11	0.11
R^2 Adjusted	0.09	0.10	0.10	0.10
P value	0.0000	0.0000	0.0000	0.0000

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

Table B.5 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Regression results (robustness tests HBC (16–19))

Variables	HBC (16)	HBC (17)	HBC (18)	HBC (19)
Grant3$_t$	-3.6484***	-3.5613***	-3.6141***	-3.5094***
	0.7811	0.7865	0.7812	0.8000
[Grant3$_t$]^2	0.2994***	0.2904***	0.2950***	0.2874***
	(0.0629)	(0.0635)	(0.0630)	(0.0646)
NbClaims$_t$	2.9519***	2.8640***	2.8740***	2.6436**
	(1.0488)	(1.0490)	(1.0492)	(1.0605)
Age$_t$	-2.0508***	-2.1041***	-2.0986***	-2.0707***
	(0.7790)	(0.7753)	(0.7756)	(0.7801)
[Age$_t$]^2	0.1293***	0.1306***	0.1303***	0.1307***
	(0.0333)	(0.0331)	(0.0331)	(0.0334)
MaxChair$_t$	-1.4557	-1.4587	-1.4365	-1.4733
	(1.0327)	(1.0346)	(1.0324)	(1.0356)
ArtCit3$_t$	1.0181	1.0205	1.0147	1.0638
	(0.6515)	(0.6530)	(0.6516)	(0.6545)

Table B.5 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [HerfIndexBWCit$_t$] – Regression results (robustness tests HBC (16–19)) (Cont'd and end)

Variables	HBC (16)	HBC (17)	HBC (18)	HBC (19)
BtwCentArt3$_t$	-14.2000***	-14.0000***	-14.1000***	-14.2000***
	(4.0544)	(4.0786)	(4.0539)	(4.0843)
[BtwCentArt3$_t$]^2	2.3037***	2.3009***	2.3091***	2.3236***
	(0.7656)	(0.7693)	(0.7658)	(0.7709)
CliqnessArt3$_t$	0.3778	0.3918	0.3755	0.4879
	(0.6317)	(0.6334)	(0.6318)	(0.6378)
BtwCentPat3$_t$	0.7660*	0.7421*	0.7465*	0.7175*
	(0.4236)	(0.4247)	(0.4255)	(0.4287)
CliqnessPat3$_t$	0.0010***	0.0010***	0.0010***	0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	2.0625	2.1421	2.1308	2.0538
	(2.2186)	(2.2193)	(2.2183)	(2.2225)
dNanoEx	2.5024	2.3484	2.3828	2.6914
	(2.4005)	(2.4016)	(2.3982)	(2.4149)
dGovAssignee$_t$	37.7652	-9.6071	-15.7000***	31.7268
	(46.8636)	(7.6027)	(5.6690)	(49.1253)
dAcAssignee$_t$	-5.3495**	-5.4145**	-5.4165**	-5.3932**
	(2.4906)	(2.4906)	(2.4903)	(2.4928)
dGovAssignee$_t$ × Grant3$_t$				-1.8590
				(4.7144)
dGovAssignee$_t$ × [Grant3$_t$]^2				0.1429
				(0.3893)
dGovAssignee$_t$ × NbClaims$_t$				13.7743*
				(8.0662)
dGovAssignee$_t$ × Age$_t$	-7.9299			-11.2000
	(7.7856)			(8.9052)
dGovAssignee$_t$ × [Age$_t$]^2	0.2780			0.3640
	(0.3085)			(0.3542)
dGovAssignee$_t$ × BtwCentArt3$_t$		4.6194		3.8870
		(33.1080)		(36.4719)
dGovAssignee$_t$ × [BtwCentArt3$_t$]^2		-1.8944		-1.1252
		(7.0657)		(7.8615)
dGovAssignee$_t$ × BtwCentPat3$_t$			2.2066	0.6103
			(4.7291)	(6.1411)
Constant	62.0143***	62.4970***	62.6476***	62.2379***
	(6.1093)	(6.0935)	(6.0898)	(6.1211)
Nb observations	1110	1110	1110	1110
Log Likelihood	-5276.36	-5276.72	-5276.96	-5274.05
R^2	0.11	0.11	0.11	0.11
R^2 Adjusted	0.10	0.10	0.10	0.09
P value	0.0000	0.0000	0.0000	0.0000

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

Table B.6 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations – Regression results (to test model robustness HBC (20–23))

Variables	**HBC (20)**	**HBC (21)**	**HBC (22)**	**HBC (23)**
$Grant3_t$	-3.9543***	-3.4916***	-3.5979***	-3.6123***
	0.8043	0.7732	0.7791	0.7789
$[Grant3_t]^2$	0.3216***	0.2869***	0.2958***	0.2969***
	(0.0647)	(0.0623)	(0.0627)	(0.0627)
$NbClaims_t$	2.9935***	0.4664	2.8931***	2.8727***
	(1.0489)	(1.1529)	(1.0454)	(1.0451)
Age_t	-2.1260***	-2.2335***	-2.3959***	-2.8269***
	(0.7748)	(0.7671)	(0.7824)	(0.8445)
$[Age_t]^2$	0.1333***	0.1373***	0.1341***	0.1534***
	(0.0331)	(0.0328)	(0.0330)	(0.0360)
$MaxChair_t$	-1.3389	-1.3990	-1.4320	-1.4053
	(1.0339)	(1.0217)	(1.0300)	(1.0298)
$ArtCit3_t$	1.0494	0.8774	0.9464	0.9320
	(0.6515)	(0.6453)	(0.6505)	(0.6503)
$BtwCentArt3_t$	-14.1000***	-14.8000***	-14.4000***	-14.5000***
	(4.0668)	(4.0140)	(4.0457)	(4.0451)
$[BtwCentArt3_t]^2$	2.2941***	2.4087***	2.3154***	2.3342***
	(0.7692)	(0.7580)	(0.7639)	(0.7637)
$CliqnessArt3_t$	0.3728	0.3915	0.3595	0.3546
	(0.6320)	(0.6252)	(0.6303)	(0.6301)
$BtwCentPat3_t$	0.7361*	0.7456*	0.7813*	0.7943*
	(0.4251)	(0.4190)	(0.4225)	(0.4224)
$CliqnessPat3_t$	0.0010***	0.0010***	0.0010***	0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	1.7478	3.1189	2.4125	2.1947
	(2.2273)	(2.2048)	(2.2165)	(2.2215)
dNanoEx	2.3626	2.3128	2.4555	2.3310
	(2.3959)	(2.3724)	(2.3921)	(2.3929)
$dGovAssignee_t$	-14.4000***	-14.2000***	-14.3000***	-14.2000***
	(4.9637)	(4.9158)	(4.9557)	(4.9546)
$dAcAssignee_t$	-8.5723	-37.5000***	-20.2000***	-32.2000***
	(5.5021)	(7.0837)	(6.8502)	(11.1811)
$dAcAssignee_t \times Grant3_t$	4.1242*			
	(2.4502)			
$dAcAssignee_t \times [Grant3_t]^2$	-0.3241*			
	(0.1946)			
$dAcAssignee_t \times NbClaims_t$		12.5190***		
		(2.5929)		
$dAcAssignee_t \times Age_t$			1.2406**	3.8637*
			(0.5333)	(2.0107)
$dAcAssignee_t \times [Age_t]^2$				-0.1188
				(0.0878)
Constant	62.5415***	69.3201***	65.9054***	68.2413***
	(6.0939)	(6.1842)	(6.2386)	(6.4708)
Nb observations	1110	1110	1110	1110
Log Likelihood	-5275.62	-5265.35	-5274.32	-5273.39
R^2	0.11	0.13	0.11	0.12
R^2 Adjusted	0.10	0.11	0.10	0.10
P value	0.0000	0.0000	0.0000	0.0000

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

Table B.7 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [$HerfIndexBWCit_t$] – Regression results (to test model robustness HBC (24–27))

Variables	HBC (24)	HBC (25)	HBC (26)	HBC (27)
$Grant3_t$	-3.4633***	-3.7338***	-3.7465***	-3.5822***
	0.7860	0.7785	0.8067	0.8298
$[Grant3_t]^2$	0.2814***	0.3020***	0.2999***	0.2853***
	(0.0635)	(0.0627)	(0.0653)	(0.0674)
$NbClaims_t$	3.0140***	2.7911***	0.6050	0.2043
	(1.0489)	(1.0443)	(1.1460)	(1.1626)
Age_t	-2.0523***	-2.0610***	-2.8694***	-2.8182***
	(0.7748)	(0.7719)	(0.8343)	(0.8408)
$[Age_t]^2$	0.1306***	0.1272***	0.1586***	0.1580***
	(0.0330)	(0.0330)	(0.0355)	(0.0359)
$MaxChair_t$	-1.4844	-1.5157	-1.3735	-1.4146
	(1.0315)	(1.0286)	(1.0181)	(1.0211)
$ArtCit3_t$	1.0886*	0.8617	0.8244	0.8894
	(0.6525)	(0.6507)	(0.6439)	(0.6468)
$BtwCentArt3_t$	-13.7000***	-13.1000***	-13.9000***	-13.9000***
	(4.0556)	(4.0531)	(4.0208)	(4.0515)
$[BtwCentArt3_t]^2$	2.3582***	2.1163***	2.3686***	2.4028***
	(0.7655)	(0.7651)	(0.7605)	(0.7657)
$CliqnessArt3_t$	0.4057	0.4990	0.5288	0.6794
	(0.6314)	(0.6306)	(0.6236)	(0.6299)
$BtwCentPat3_t$	0.7173*	0.4597	0.4176	0.3397
	(0.4239)	(0.4338)	(0.4332)	(0.4398)
$CliqnessPat3_t$	0.0010***	0.0010***	0.0010***	0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	1.9277	2.6764	3.0346	3.0417
	(2.2183)	(2.2170)	(2.2087)	(2.2131)
dNanoEx	2.1690	2.1931	1.9599	2.3012
	(2.3971)	(2.3883)	(2.3606)	(2.3768)
$dGovAssignee_t$	-14.5000***	-14.9000***	-14.7000***	19.7058
	(4.9620)	(4.9507)	(4.8835)	(48.2929)
$dAcAssignee_t$	-1.1225	-9.1473***	-68.4000***	-68.7000***
	(3.5644)	(2.7758)	(13.4556)	(13.4848)
$dGovAssignee_t \times Grant3_t$				-1.7783
				(4.6356)
$dGovAssignee_t \times [Grant3_t]^2$				0.1454
				(0.3828)
$dGovAssignee_t \times NbClaims_t$				16.3965**
				(7.9354)
$dGovAssignee_t \times Age_t$				-10.6000
				(8.7489)
$dGovAssignee_t \times [Age_t]^2$				0.3402
				(0.3480)
$dGovAssignee_t \times BtwCentArt3_t$				3.7172
				(35.8107)
$dGovAssignee_t \times [BtwCentArt3_t]^2$				-1.2110
				(7.7180)
$dGovAssignee_t \times BtwCentPat3_t$				0.8541
				(6.0299)

Table B.7 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [HerfIndexBWCit$_t$] – Regression results (to test model robustness HBC (24–27)) (Cont'd and end)

Variables	**HBC (24)**	**HBC (25)**	**HBC (26)**	**HBC (27)**
dAcAssignee$_t$ × Grant3$_t$			4.8840*	4.7368*
			(2.5720)	(2.5791)
dAcAssignee$_t$ × [Grant3$_t$]^2			-0.3730*	-0.3591*
			(0.2062)	(0.2068)
dAcAssignee$_t$ × NbClaims$_t$			12.5752***	12.9711***
			(2.5868)	(2.5950)
dAcAssignee$_t$ × Age$_t$			3.9609*	3.8884*
			(2.0357)	(2.0392)
dAcAssignee$_t$ × [Age$_t$]^2			-0.1175	-0.1158
			(0.0887)	(0.0889)
dAcAssignee$_t$ ×	-4.1888*		-5.3030**	-5.6224**
BtwCentArt3$_t$	(2.5052)		(2.6489)	(2.6701)
dAcAssignee$_t$ ×		4.3246***	3.5249**	3.5912**
BtwCentPat3$_t$		(1.4365)	(1.4550)	(1.4572)
Constant	60.8792***	63.3674***	73.7807***	73.5680***
	(6.1680)	(6.0697)	(6.5633)	(6.6081)
Nb observations	1110	1110	1110	1110
Log Likelihood	-5275.65	-5272.48	-5253.79	-5249.93
R^2	0.11	0.12	0.15	0.15
R^2 Adjusted	0.10	0.10	0.13	0.13
P value	0.0000	0.0000	0.0000	0.0000

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

APPENDIX C – TEST ROBUSTNESS FOR PATENT–GRANT PAIRS

Table C.1 : Impact of patent–grant pairs on the number of forward citations [$NbFCit5_t$] – Zero-inflated negative binomial model results (to test model robustness FC (26–30))

Variables	**FC (26)**	**FC (27)**	**FC (28)**	**FC(29)**	**FC (30)**
$Grant3_t$	-0.0058	-0.0061	-0.0063	-0.0063	-0.0065
	(0.0096)	(0.0096)	(0.0096)	(0.0096)	(0.0096)
Age_t	0.3780***	0.3732***	0.3693***	0.3713***	0.3669***
	(0.0499)	(0.0501)	(0.0503)	(0.0502)	(0.0504)
$[Age_t]^2$	-0.0181***	-0.0178***	-0.0177***	-0.0177***	-0.0175***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
$MaxChair_t$	0.0782	0.0939	0.0968	0.0904	0.0927
	(0.0628)	(0.0640)	(0.0639)	(0.0638)	(0.0636)
$ArtCit3_t$	-0.0515	-0.0599	-0.0588	-0.0575	-0.0558
	(0.0382)	(0.0389)	(0.0388)	(0.0388)	(0.0387)
$BtwCentArt3_t$	0.0241	0.0208	0.0266	0.0249	0.0319
	(0.0611)	(0.0614)	(0.0613)	(0.0616)	(0.0615)
$CliqnessArt3_t$	-0.1916*	-0.1759*	-0.1818*	-0.1782*	-0.1850*
	(0.1066)	(0.1066)	(0.1067)	(0.1064)	(0.1065)
$[CliqnessArt3_t]^2$	0.0182**	0.0175*	0.0174*	0.0176*	0.0175*
	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)
$BtwCentPat3_t$	-0.0718***	-0.0770***	-0.0742***	-0.0770***	-0.0741***
	(0.0237)	(0.0239)	(0.0239)	(0.0238)	(0.0238)
$CliqnessPat3_t$	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$dAcAssignee_t$	-0.3869***	-0.3351***	-0.3501***	-0.3391***	-0.3548***
	(0.1157)	(0.1174)	(0.1176)	(0.1175)	(0.1175)
dNanoEx	0.6262***	0.6687***	0.6526***	0.6633***	0.6452***
	(0.1205)	(0.1223)	(0.1223)	(0.1224)	(0.1224)
$dPGP_t$		-0.8005***	-3.3708**	-0.6102	-3.3121**
		(0.3048)	(1.5736)	(0.4251)	(1.5949)
$dPGP_t \times CliqnessArt3_t$			0.5489*		0.5921*
			(0.3295)		(0.3401)
$dPGP_t \times BtwCentArt3_t$				-0.2209	-0.3036
				(0.3441)	(0.3629)
Constant	-0.8934**	-0.8819**	-0.8510**	-0.8742**	-0.8408**
	(0.3514)	(0.3528)	(0.3544)	(0.3527)	(0.3542)
Inflate					
$Grant3_t$	0.0019	0.0010	-0.0003	0.0005	-0.0011
	(0.0531)	(0.0555)	(0.0549)	(0.0548)	(0.0540)
Age_t	0.0499	0.0439	0.0433	0.0453	0.0449
	(0.0620)	(0.0658)	(0.0656)	(0.0647)	(0.0643)
$MaxChair_t$	0.8083*	0.8734*	0.8747*	0.8576*	0.8556*
	(0.4212)	(0.4860)	(0.4833)	(0.4717)	(0.4679)
$BtwCentArt3_t$	-2.1895**	-2.2101*	-2.2164**	-2.2152**	-2.2178**
	(1.0937)	(1.1428)	(1.1213)	(1.1251)	(1.1052)
$CliqnessArt3_t$	0.0337	0.0577	0.0566	0.0532	0.0516
	(0.1466)	(0.1617)	(0.1614)	(0.1563)	(0.1552)
$ArtCit3_t$	0.8068**	0.7866**	0.7904**	0.7909**	0.7941**
	(0.3791)	(0.3989)	(0.3932)	(0.3923)	(0.3870)
$BtwCentPat3_t$	-0.5282*	-0.5214*	-0.5206*	-0.5224*	-0.5209*
	(0.2748)	(0.2827)	(0.2811)	(0.2807)	(0.2788)

Table C.1 : Impact of patent–grant pairs on the number of forward citations [NbFCit5$_t$] – Zero-inflated negative binomial model results (to test model robustness FC (26–30)) (Cont'd and end)

Variables	**FC (26)**	**FC (27)**	**FC (28)**	**FC(29)**	**FC (30)**
Constant (Inflate)	-3.3830**	-3.4693**	-3.4575**	-3.4409**	-3.4216**
	(1.4682)	(1.6021)	(1.5796)	(1.5713)	(1.5446)
Lnalpha					
Constant (lnalpha)	0.3244***	0.3178***	0.3132***	0.3151***	0.3090***
	(0.0851)	(0.0854)	(0.0853)	(0.0855)	(0.0855)
Nb observations	1110	1110	1110	1110	1110
Log Likelihood	-1730.3	-1726.91	-1725.43	-1726.7	-1725.07
Chi Square	105.078	111.849	114.801	112.275	115.532
P value	0.0000	0.0000	0.0000	0.0000	0.0000
Zero obs	543	543	543	543	543

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

Table C.2 : Impact of patent–grant pairs on the Herfindahl index of forward citations [*HerfIndexFCit5$_t$*] – Regression results (robustness test HFC (12–16))

Variable	**HFC (12)**	**HFC (13)**	**HFC(14)**	**HFC (15)**	**HFC(16)**
Grant3$_t$	-0.2627	-0.2723*	-0.2721*	-0.2737*	-0.2734*
	(0.1625)	(0.1622)	(0.1622)	(0.1622)	(0.1622)
Age$_t$	-2.1436***	-1.9837***	-1.9948***	-2.0246***	-2.0640***
	(0.7045)	(0.7063)	(0.7103)	(0.7073)	(0.7128)
[Age$_t$]^2	0.0930***	0.0849***	0.0853***	0.0866***	0.0881***
	(0.0300)	(0.0302)	(0.0303)	(0.0302)	(0.0304)
MaxChair$_t$	0.8024	0.7327	0.7332	0.7237	0.7240
	(0.9350)	(0.9336)	(0.9340)	(0.9335)	(0.9339)
ArtCit3$_t$	2.6479*	2.8469*	2.8568*	2.7930*	2.8172*
	(1.5149)	(1.5140)	(1.5161)	(1.5148)	(1.5163)
[ArtCit3$_t$]^2	-0.5853	-0.6394*	-0.6423*	-0.6139*	-0.6198*
	(0.3690)	(0.3689)	(0.3696)	(0.3697)	(0.3701)
BtwCentArt3$_t$	0.5638	0.6028	0.6063	0.7119	0.7364
	(0.9824)	(0.9804)	(0.9812)	(0.9858)	(0.9876)
CliqnessArt3$_t$	-0.5803	-0.6176	-0.6275	-0.6299	-0.6622
	(0.5709)	(0.5700)	(0.5739)	(0.5701)	(0.5746)
BtwCentPat3$_t$	0.3637	0.4091	0.4129	0.4009	0.4118
	(0.3791)	(0.3788)	(0.3798)	(0.3789)	(0.3798)
CliqnessPat3$_t$	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
dAcAssignee$_t$	1.2685	0.8951	0.8912	0.8872	0.8739
	(1.8928)	(1.8954)	(1.8965)	(1.8953)	(1.8963)
dNanoEx	-2.7560	-3.1934	-3.2025	-3.2503	-3.2854
	(2.1569)	(2.1603)	(2.1621)	(2.1609)	(2.1630)
dPGP		9.9647**	7.1507	15.0625**	6.9757
		(4.2138)	(18.7986)	(6.4038)	(18.7967)
dPGP ×			0.6466		2.0011
CliqnessArt3$_t$			(4.2092)		(4.3727)

Table C.2 : Impact of patent–grant pairs on the Herfindahl index of forward citations [HerfIndexFCit5$_t$] – Regression results (robustness test HFC (12–16)) (Cont'd and end)

Variable	**HFC(12)**	**HFC (13)**	**HFC(14)**	**HFC (15)**	**HFC(16)**
dPGP ×				-4.9829	-5.5914
BtwCentArt3$_t$				(4.7136)	(4.8992)
Constant	93.2998***	92.5549***	92.6474***	92.7172***	93.0234***
	(4.9076)	(4.9075)	(4.9465)	(4.9097)	(4.9568)
Nb observations	1110	1110	1110	1110	1110
Log Likelihood	-5181.46	-5178.64	-5178.63	-5178.07	-5177.96
R^2	0.0189	0.0238	0.0239	0.0248	0.0250
R^2 Adjusted	0.0081	0.0123	0.0114	0.0124	0.0116
P value	0.0508	0.0142	0.0218	0.0157	0.0223

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

APPENDIX D – FIRST STAGE REGRESSION FOR PATENT–PAPER PAIRS MODELS

Table D.1 : First stage regression results: $[Contract3_t]^a$ as an endogenous variable associated with the model including the number of claims [$NbClaims_t$] as well as Herfindahl index of forward citations [$HerfIndexFCit5_t$] as a dependent variable – Regression results

Variable	*Contract* (1)	*Contract* (2)
$[Contract3U_{t-2}]^a$	0.2506***	0.2690***
	(0.0297)	(0.0295)
$[GrantEI3_{t-1}]^a$	0.0673**	0.0731***
	(0.0277)	(0.0277)
Loop	0.4603***	0.4537***
	(0.0584)	(0.0588)
$[Grant3_t]^a$	0.3225***	0.2783***
	(0.0367)	(0.0349)
$[Age_t]^a$	-0.0548**	-0.0656***
	(0.0251)	(0.0250)
$[Age_t^a]^2$	-0.0288	-0.0209
	(0.0179)	(0.0179)
$[MaxChair_t]^a$	0.0234	0.0333
	(0.0274)	(0.0245)
$[ArtCit3_t]^a$	0.1003***	0.0963***
	(0.0276)	(0.0278)
$[BtwCentArt3_t]^a$	0.0017	-0.0187
	(0.0308)	(0.0284)
$[BtwCentPat3_t]^a$	0.2042***	0.1846***
	(0.0408)	(0.0391)
$[(BtwCentPat3_t)^a]^2$	-0.1737***	-0.1649***
	(0.0290)	(0.0296)
$dAcAssignee_t$	-0.2138***	-0.2152***
	(0.0699)	(0.0629)
dNanoEx	-0.1336**	-0.1317**
	(0.0643)	(0.0649)
$Similarity_t^a$	-0.0043	-0.0105
	(0.0247)	(0.0252)
$dAcAssignee_t \times [(Grant3_t)^a]$	-0.1856***	
	(0.0683)	
$dAcAssignee_t \times [MaxChair_t]^a$	0.0619	
	(0.0559)	
$dAcAssignee_t \times [(BtwCentArt3_t)^a]$	-0.1265**	
	(0.0621)	
$dAcAssignee_t \times [(BtwCentPat3_t)^a]$	-0.0832	
	(0.0813)	
$Similarity_t \times [(Grant3_t)^a]$		0.0002
		(0.0305)
$Similarity_t^a \times [MaxChair_t]^a$		-0.0075
		(0.0262)
$Similarity_t^a \times [(BtwCentArt3_t)^a]$		-0.0167
		(0.0259)

Table D.1 : First stage regression results: [Contract3$_t$]a as an endogenous variable associated with the model including the number of claims [NbClaims$_t$] as well as Herfindahl index of forward citations [HerfIndexFCit5t] as a dependent variable – Regression results (Cont'd and end)

Variable	***Contract* (1)**	***Contract* (2)**
Similarity$_t$ ^{a} × [(BtwCentPat3$_t$) ^{a}]		-0.0284
		(0.0279)
Constant	0.1669***	0.1554***
	(0.0460)	(0.0468)
Nb observations	1083	1083
R^2	0.4556	0.4488
R^2 Adjusted	0.4464	0.4395
P value	0.0000	0.0000

Notes: (a) All the variables have been calculated by Z Score (Z) = x – μ / σ, μ=mean and σ = standard deviation

APPENDIX E – ENDOGENEITY TEST FOR PATENT–PAPER PAIRS

Table E.1 : IV Regression Two-stage least squares (2SLS) with number of forward citations [(NbFCit5$_t$)], to test endogeneity (in the model including patent–paper pairs similarity [*Similarity$_t$*])

Variables	**FC (31)**	**FC (32)**
[Contract3$_t$] [a]	-0.0574	-0.0345
	(0.0727)	(0.0695)
[Grant3$_t$] [a]	0.0044	0.0260
	(0.0468)	(0.0425)
[Age$_t$] [a]	-0.1778***	-0.1802***
	(0.0221)	(0.0221)
[Age$_t$ [a]]^2	-0.0684***	-0.0673***
	(0.0161)	(0.0159)
[MaxChair$_t$] [a]	0.0257	0.0075
	(0.0238)	(0.0212)
[ArtCit3$_t$] [a]	-0.0353	-0.0410
	(0.0253)	(0.0251)
[BtwCentArt3$_t$] [a]	0.0744***	0.0497**
	(0.0263)	(0.0243)
[BtwCentPat3$_t$] [a]	-0.0066	0.0167
	(0.0389)	(0.0367)
[(BtwCentPat3$_t$)[a]]^2	-0.0592**	-0.0567*
	(0.0292)	(0.0290)
dAcAssignee$_t$	-0.1177*	-0.1446***
	(0.0620)	(0.0550)
dNanoEx	0.3213***	0.3184***
	(0.0576)	(0.0577)
Similarity$_t$ [a]	-0.0439**	-0.0463**
	(0.0218)	(0.0221)
dAcAssignee$_t$ × [(Grant3$_t$) [a]]	0.0952	
	(0.0621)	
dAcAssignee$_t$ × MaxChair$_t$ [a]	-0.0827*	
	(0.0498)	
dAcAssignee$_t$ × [(BtwCentArt3$_t$) [a]]	-0.1242**	
	(0.0567)	
dAcAssignee$_t$ × [(BtwCentPat3$_t$) [a]]	0.1296*	
	(0.0719)	
Similarity$_t$ × [(Grant3$_t$) [a]]		0.0492*
		(0.0268)
Similarity$_t$ [a] × [MaxChair$_t$] [a]		-0.0067
		(0.0231)
Similarity$_t$ [a] × [(BtwCentArt3$_t$) [a]]		-0.0045
		(0.0229)
Similarity$_t$ [a] × [(BtwCentPat3$_t$) [a]]		0.0403
		(0.0245)
Constant	0.7229***	0.7118***
	(0.0442)	(0.0438)
Nb observations	1083	1083

Table E.1 : IV Regression Two-stage least squares (2SLS) with number of forward citations [($NbFCit5_t$)], to test endogeneity (in the model including patent–paper pairs similarity [Similarityt]) (Cont'd and end)

Variables	**FC (31)**	**FC (32)**
Chi Square	147.7570	141.5850
R^2	0.11183	0.111459
R^2 Adjusted	0.0985	0.0981
Sargan	0.1642	0.1085
Wu-Hausman	0.1901	0.2994

Notes: [(a)] All the variables have been calculated by Z Score (Z) = x – μ / σ, μ=mean and σ = standard deviation. Moreover, ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses. In order to test endogeneity in our model, we used IV Regression Two-stage least squares (2SLS) with number of forward citations [(*$NbFCit5_t$*)] to validate instrumental variables (through Sargan test) and to assess endogeneity (through Wu-Hausman measurement) in the model including patent–paper pairs similarity [*Similarity*].

Table E.2 : IV Regression Two-stage least squares (2SLS) with Herfindahl index of backward citations [*$HerfIndexBWCit_t$*], to test endogeneity (in the model including patent–paper pairs similarity [*$Similarity_t$*])

Variables	**HBC (28)**	**HBC (29)**
[$Contract3_t$] [a]	0.0293	0.0356*
	(0.0216)	(0.0207)
[$Grant3_t$] [a]	-0.0266*	-0.0238*
	(0.0142)	(0.0130)
[Age_t] [a]	0.0183***	0.0179**
	(0.0071)	(0.0071)
$[Age_t{}^a]^2$	0.0087*	0.0100*
	(0.0052)	(0.0052)
[$MaxChair_t$] [a]	0.0057	0.0002
	(0.0077)	(0.0069)
[$ArtCit3_t$] [a]	0.0035	0.0024
	(0.0081)	(0.0081)
[$BtwCentArt3_t$] [a]	0.0169**	0.0075
	(0.0084)	(0.0078)
[($BtwCentPat3_t$] [a]	0.0012	0.0112
	(0.0123)	(0.0117)
$[(BtwCentPat3_t)^a]^2$	-0.0075	-0.0129
	(0.0092)	(0.0092)
$dAcAssignee_t$	0.0101	0.0018
	(0.0196)	(0.0178)
dNanoEx	-0.0037	-0.0039
	(0.0183)	(0.0184)
$Similarity_t$ [a]	-0.0034	-0.0028
	(0.0071)	(0.0072)
$dAcAssignee_t \times [(Grant3_t)^a]$	0.0189	
	(0.0200)	
$dAcAssignee_t \times MaxChair_t{}^a$	-0.0280*	
	(0.0163)	
$dAcAssignee_t \times [(BtwCentArt3_t)^a]$	-0.0541***	
	(0.0186)	

Table E.2 : IV Regression Two-stage least squares (2SLS) with Herfindahl index of backward citations [$HerfIndexBWCit_t$], to test endogeneity (in the model including patent–paper pairs similarity [$Similarity_t$]) (Cont'd and end)

Variables	**HBC (28)**	**HBC (29)**
$dAcAssignee_t \times [(BtwCentPat3_t)^a]$	0.0495**	
	(0.0226)	
$Similarity_t \times [(Grant3_t)^a]$		-0.0005
		(0.0086)
$Similarity_t^a \times [MaxChair_t]^a$		-0.0006
		(0.0075)
$Similarity_t^a \times [(BtwCentArt3_t)^a]$		-0.0099
		(0.0075)
$Similarity_t^a \times [(BtwCentPat3_t)^a]$		0.0208***
		(0.0078)
Constant	0.7926***	0.7948***
	(0.0142)	(0.0141)
Nb observations	986	986
Chi Square	33.8496	28.5664
R^2	0.0323	0.0259
R^2 Adjusted	0.0163	0.0098
Sargan	0.8981	0.7587
Wu-Hausman	0.4965	0.3689

Notes: [(a)] All the variables have been calculated by Z Score (Z) = x – μ / σ, μ=mean and σ = standard deviation. Moreover, ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses. In order to test endogeneity in our model, we used IV Regression Two-stage least squares (2SLS) with Herfindahl index of backward citations [$HerfIndexBWCit_t$] to validate instrumental variables (through Sargan test) and to assess endogeneity (through Wu-Hausman measurement) in the model including patent–paper pairs similarity [*Similarity*].

APPENDIX F – ENDOGENEITY TEST FOR PUBLIC ASSIGNEES

Table F.1 : IV Regression Two-stage least squares (2SLS) with number of forward citations [NbFCit5$_t$], to test endogeneity (in the model related to public assignees)

Variable	**FC (33)**
Grant3$_t$	-0.0037
	(0.0063)
Age$_t$	0.1376***
	(0.0199)
[Age$_t$]^2	-0.0067***
	(0.0008)
MaxChair$_t$	0.0120
	(0.0243)
ArtCit3$_t$	-0.0294*
	(0.0152)
BtwCentArt3$_t$	0.0637**
	(0.0275)
CliqnessArt3$_t$	-0.0860*
	(0.0453)
[CliqnessArt3$_t$]^2	0.0094**
	(0.0040)
BtwCentPat3$_t$	-0.0289***
	(0.0108)
CliqnessPat3$_t$	0.0000
	(0.0000)
Loop	-0.0460
	(0.0529)
dNanoEx	0.3152***
	(0.0549)
dGovAssignee$_t$	1.9169*
	(1.0980)
dAcAssignee$_t$	0.0486
	(0.2609)
dGovAssignee$_t$ × Age$_t$	-0.3255*
	(0.1812)
dGovAssignee$_t$ × [Age$_t$]^2	0.0123*
	(0.0073)
dGovAssignee$_t$ × BtwCentArt3$_t$	-0.1672
	(0.1248)
dGovAssignee$_t$ × BtwCentPat3$_t$	-0.0381
	(0.1222)
dAcAssignee$_t$ × Age$_t$	-0.0226
	(0.0471)
dAcAssignee$_t$ × [Age$_t$]^2	0.0010
	(0.0020)
dAcAssignee$_t$ × BtwCentArt3$_t$	-0.0915
	(0.0591)
dAcAssignee$_t$ × BtwCentPat3$_t$	0.0364
	(0.0343)
Constant	0.1704
	(0.1448)
Nb Observations	1110
Chi Square	154.0940

Table F.1 : IV Regression Two-stage least squares (2SLS) with number of forward citations [$NbFCit5_t$], to test endogeneity (in the model related to public assignees) (Cont'd and end)

Variable	**FC (33)**
R^2	0.1211
R^2 Adjusted	0.1032
P value	0.0000
Sargan	0.3796
Wu-Hausman	0.3558

Notes: ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses. Moreover, in order to test endogeneity in our model, we used IV Regression Two-stage least squares (2SLS) with number of forward citations [($NbFCit5_t$)] to validate instrumental variables (through Sargan test) and to assess endogeneity (through Wu-Hausman measurement) in the model associated with academic assignees [*dAcAssigneet*] and government assignees [*dGovAssigneet*].

Table F.2 : IV Regression Two-stage least squares (2SLS) with number of claims [$NbClaims_t$], to test endogeneity (in the model related to public assignees)

Variable	**CL (12)**
$Grant3_t$	0.0024
	(0.0083)
Age_t	0.0127*
	(0.0067)
$MaxChair_t$	-0.0043
	(0.0299)
$ArtCit3_t$	-0.0367**
	(0.0185)
$BtwCentArt3_t$	-0.0338
	(0.0341)
$CliqnessArt3_t$	-0.0352**
	(0.0178)
$BtwCentPat3_t$	-0.0191
	(0.0151)
$CliqnessPat3_t$	0.0001***
	(0.0000)
$(CliqnessPat3_t)^2$	0.0000***
	(0.0000)
Loop	-0.0571
	(0.0646)
dNanoEx	0.4003***
	(0.0667)
$dGovAssignee_t$	-0.1608
	(0.5823)
$dAcAssignee_t$	-0.0898
	(0.2008)
$dGovAssignee_t \times Age_t$	0.0138
	(0.0417)
$dGovAssignee_t \times BtwCentArt3_t$	-0.1079
	(0.1526)

Table F.2 : IV Regression Two-stage least squares (2SLS) with number of claims [$NbClaims_t$], to test endogeneity (in the model related to public assignees) (Cont'd and end)

Variable	**CL (12)**
$dGovAssignee_t \times BtwCentPat3_t$	0.1446
	(0.1471)
$dAcAssignee_t \times Age_t$	-0.0117
	(0.0158)
$dAcAssignee_t \times BtwCentArt3_t$	0.1283*
	(0.0729)
$dAcAssignee_t \times BtwCentPat3_t$	0.0324
	(0.0422)
Constant	2.5107***
	(0.1358)
Nb Observations	1110
Chi Square	101.0510
R^2	0.0833
R^2 Adjusted	0.0673
P value	0.0000
Sargan	0.3731
Wu-Hausman	0.7867

Notes: ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses. Furthermore, in order to test endogeneity in our model, we used IV Regression Two-stage least squares (2SLS) with number of claims [($NbClaims_t$)] to validate instrumental variables (through Sargan test) and to assess endogeneity (through Wu-Hausman measurement) in the model associated with academic assignees [*dAcAssigneet*] and government assignees [*dGovAssigneet*].

Table F.3 : IV Regression Two-stage least squares (2SLS) Herfindahl index of backward citations [$HerfIndexBWCit_t$], to test endogeneity (in the model related to public assignees)

Variable	**HBC (30)**	**HBC (31)**	**HBC(32)**
$Grant3_t$	0.1707	-3.6809***	0.1841
	(0.2742)	(1.0422)	(0.3100)
Age_t	-2.8709***	-1.7022	-2.5304***
	(0.8501)	(1.1074)	(0.9664)
$[Age_t]^2$	0.1630***	0.0969*	0.1507***
	(0.0362)	(0.0570)	(0.0490)
$MaxChair_t$	-1.7194	-1.6943	-1.7051
	(1.0645)	(1.1824)	(1.0814)
$ArtCit3_t$	1.0927*	1.6471	0.9131
	(0.6492)	(1.1965)	(1.0067)
$BtwCentArt3_t$	-18.3000***	-11.6000**	-18.7000***
	(4.3606)	(4.9068)	(4.8490)
$[BtwCentArt3_t]^2$	3.6349***	2.2096**	3.6657***
	(0.8069)	(0.8874)	(0.8359)
$CliqnessArt3_t$	0.6236	1.3282	0.4150
	(0.6298)	(1.2792)	(1.0572)
$BtwCentPat3_t$	0.5453	0.1977	0.5597
	(0.4641)	(0.5578)	(0.5015)
$CliqnessPat3_t$	0.0008***	0.0008*	0.0009**
	(0.0003)	(0.0004)	(0.0004)

Table F.3 : IV Regression Two-stage least squares (2SLS) Herfindahl index of backward citations [*HerfIndexBWCit*$_t$], to test endogeneity (in the model related to public assignees) (Cont'd and end)

Variable	**HBC (30)**	**HBC (31)**	**HBC(32)**
Loop	0.9830	2.8861	1.2004
	(2.2582)	(2.5732)	(2.3074)
dNanoEx	1.9904	-5.4342	4.3772
	(2.3885)	(10.9062)	(9.0446)
dGovAssignee$_t$	33.4574	78.3231	25.8963
	(47.0963)	(79.8419)	(60.4809)
dAcAssignee$_t$	-28.8000***	-16.0000*	-17.0000**
	(11.1477)	(9.1867)	(8.1395)
dGovAssignee$_t$ × Age$_t$	-5.0357	-13.8000	-3.8456
	(7.8733)	(14.5135)	(10.2152)
dGovAssignee$_t$ × [Age$_t$]^2	0.1293	0.4859	0.0859
	(0.3176)	(0.5729)	(0.4065)
dGovAssignee$_t$ × BtwCentArt3$_t$	-1.7334	0.8382	0.0008
	(34.1091)	(42.2198)	(35.2573)
dGovAssignee$_t$ ×	-1.4610	-0.7137	-1.9859
[BtwCentArt3$_t$]^2	(7.3649)	(9.3236)	(7.7374)
dGovAssignee$_t$ × BtwCentPat3$_t$	4.3165	-1.7083	5.5917
	(5.2077)	(10.8047)	(6.9898)
dAcAssignee$_t$ × Age$_t$	4.0080**	1.2922*	1.1034*
	(2.0146)	(0.6655)	(0.6148)
dAcAssignee$_t$ × BtwCentArt3$_t$	8.7623	-9.6758*	11.3099
	(10.3163)	(5.5733)	(13.7255)
dAcAssignee$_t$ ×	-3.1595		-3.4298
[BtwCentArt3$_t$]^2	(1.9222)		(2.1950)
NbClaims$_t$	2.7231***	23.1035	-3.1045
	(1.0429)	(27.8550)	(22.6838)
dGovAssignee$_t$ × [Grant3$_t$]^2		0.2541	
		(0.5255)	
dGovAssignee$_t$ × Grant3$_t$		-2.7738	
		(5.9024)	
[Grant3$_t$]^2		0.2818***	
		(0.0784)	
Constant	62.8097***	8.5052	76.3706
	(6.4620)	(75.9231)	(62.3383)
Nb observations	1110	1110	1110
Chi Square	145.2530	114.3930	132.0290
R^2	0.1136		0.0866
R^2 Adjusted	0.0932		0.0664
P value	0.0000	0.0000	0.0000
Sargan	0.8727	0.9505	
Wu-Hausman	0.0968	0.4073	0.2944

Notes: ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses. In order to test endogeneity in our model, we used IV Regression Two-stage least squares (2SLS) for Herfindahl index of backward citations [*HerfIndexBWCit*$_t$] to validate instrumental variables (through Sargan test) and to assess endogeneity (through Wu-Hausman measurement) in the model associated with academic assignees [*dAcAssigneet*] and government assignees [*dGovAssigneet*].

Table F.4 : IV Regression Two-stage least squares (2SLS) with Herfindahl index of forward citations [HerfIndexFCit5$_t$], to test endogeneity (in the model related to public assignees)

Variable	**HFC 17)**
Grant3$_t$	-0.2326
	(0.2484)
Age$_t$	-1.9446**
	(0.7759)
[Age$_t$]^2	0.0787**
	(0.0329)
MaxChair$_t$	0.8567
	(0.9507)
ArtCit3$_t$	2.6851*
	(1.5249)
[ArtCit3$_t$]^2	-0.5766
	(0.3694)
BtwCentArt3$_t$	0.3293
	(1.0692)
CliqnessArt3$_t$	-0.6935
	(0.5693)
BtwCentPat3$_t$	0.2513
	(0.4223)
CliqnessPat3$_t$	0.0002
	(0.0002)
Loop	-2.5532
	(2.0615)
dNanoEx	-2.7444
	(2.1440)
dGovAssignee$_t$	20.7692
	(42.8907)
dAcAssignee$_t$	-4.7334
	(10.1798)
dGovAssignee$_t$ × Age$_t$	-8.6043
	(7.0807)
dGovAssignee$_t$ × [Age$_t$]^2	0.4065
	(0.2839)
dGovAssignee$_t$ × BtwCentArt3$_t$	7.4070
	(4.8816)
dGovAssignee$_t$ × BtwCentPat3$_t$	7.6975
	(4.7473)
dAcAssignee$_t$ × Age$_t$	0.3158
	(1.8395)
dAcAssignee$_t$ × [Age$_t$]^2	0.0130
	(0.0799)
dAcAssignee$_t$ × BtwCentPat3$_t$	-0.4546
	(1.3422)
Constant	94.8889***
	(5.2831)
Nb Observations	1110
Chi Square	33.7925
R^2	0.0306
R^2 Adjusted	0.0110
P value	0.0516
Sargan	0.2939

Table F.4 : IV Regression Two-stage least squares (2SLS) with Herfindahl index of forward citations [HerfIndexFCit5$_t$], to test endogeneity (in the model related to public assignees) (Cont'd and end)

Variable	**HFC 17)**
Wu-Hausman	0.9445

Notes: ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses. In order to test endogeneity in our model, we used IV Regression Two-stage least squares (2SLS) with Herfindahl index of forward citations [HerfIndexFCit5$_t$] to validate instrumental variables (through Sargan test) and to assess endogeneity (through Wu-Hausman measurement) in the model associated with academic assignees [*dAcAssignee$_t$*] and government assignees [*dGovAssignee$_t$*].

APPENDIX G –ENDOGENEITY TEST FOR PATENT–GRANT PAIRS

Table G.1 : IV Regression Two-stage least squares (2SLS) used with number of forward citations [$NbFCit5_t$], to test endogeneity (in the model linking to patent–grant pairs [$dPGP_t$])

Variable	**FC (34)**
$Grant3_t$	-0.0008
	(0.0061)
Age_t	0.1190***
	(0.0183)
$[Age_t]^2$	-0.0059***
	(0.0008)
$MaxChair_t$	0.0165
	(0.0243)
$ArtCit3_t$	-0.0321**
	(0.0151)
$BtwCentArt3_t$	0.0498*
	(0.0257)
$CliqnessArt3_t \times 10^{3}$	-0.0812*
	(0.0448)
$[CliqnessArt3_t \times 10^{3}]^2$	0.0085**
	(0.0039)
$BtwCentPat3_t$	-0.0221**
	(0.0103)
$CliqnessPat3_t$	0.0000
	(0.0000)
$dAcAssignee_t$	-0.1273***
	(0.0485)
dNanoEx	0.3243***
	(0.0549)
$dPGP_t$	-0.5512
	(0.4930)
$dPGP_t \times CliqnessArt3_t$	0.0946
	(0.1310)
$dPGP_t \times [CliqnessArt3_t]^2$	-0.0004
	(0.0007)
$dPGP_t \times BtwCentArt3_t$	-0.0376
	(0.1267)
Constant	0.2685**
	(0.1365)
Nb observations	1110
Chi Square	149.8400
R^2	0.1189
R^2 Adjusted	0.1060
Sargan	0.3622
Wu-Hausman	0.6416

Notes: ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses. Furthermore, in order to test endogeneity in our model, we used IV Regression Two-stage least squares (2SLS) with number of forward citations [($NbFCit5_t$)] to validate instrumental variables (through Sargan test) and to assess endogeneity (through Wu-Hausman measurement) in our analysis model that is associated with patent–grant pairs [*dPGP*].

Table G.2 : IV Regression Two-stage least squares (2SLS) used with number of claims [$NbClaims_t$], to test endogeneity (in the model linking to patent–grant pairs [$dPGP_t$])

Variable	**CL (13)**
$Grant3_t$	0.0013
	(0.0077)
Age_t	0.0131**
	(0.0060)
$MaxChair_t$	-0.0055
	(0.0299)
$ArtCit3_t$	-0.0397**
	(0.0185)
$BtwCentArt3_t$	-0.0204
	(0.0318)
$CliqnessArt3_t$	-0.0354**
	(0.0178)
$BtwCentPat3_t$	-0.0161
	(0.0146)
$CliqnessPat3_t$	0.0001***
	(0.0000)
$[CliqnessPat3_t]^2$	0.0000***
	(0.0000)
$dAcAssignee_t$	-0.0229
	(0.0591)
dNanoEx	0.4020***
	(0.0671)
$dPGP_t$	-0.2377
	(0.5821)
$dPGP_t \times CliqnessArt3_t$	0.0357
	(0.1355)
$dPGP_t \times BtwCentArt3_t$	0.1115
	(0.1521)
Constant	2.4737***
	(0.1305)
Nb observations	1110
Chi Square	92.0642
R^2	0.0765
R^2 Adjusted	0.0647
Sargan	0.3576
Wu-Hausman	0.8078

Notes: ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses. Furthermore, in order to test endogeneity in our model, we used IV Regression Two-stage least squares (2SLS) with number of claims [($NbClaims_t$)] to validate instrumental variables (through Sargan test) and to assess endogeneity (through Wu-Hausman measurement) in our analysis that is linked to patent–grant pairs [*dPGP*].

Table G.3 : IV Regression Two-stage least squares (2SLS) with Herfindahl index of backward citations [$HerfIndexBWCit_t$] (including patent–grant pairs [$dPGP_t$] variable)

Variable	**HBC (33)**	**HBC (34)**	**HBC (35)**
$Grant3_t$	0.3428	-4.1803***	0.3550
	(0.2630)	(1.2270)	(0.3040)
Age_t	-2.3779***	-1.4098	-2.4245**
	(0.7947)	(1.2771)	(0.9829)
$[Age_t]^2$	0.1473***	0.0839	0.1505***
	(0.0338)	(0.0690)	(0.0517)
$MaxChair_t$	-1.6251	-1.3833	-1.6257
	(1.0695)	(1.3425)	(1.0712)
$ArtCit3_t$	1.1204*	1.9400	1.0574
	(0.6566)	(1.3255)	(1.0205)
$BtwCentArt3_t$	-18.3000***	-12.3000**	-18.5000***
	(4.0085)	(5.9993)	(4.3480)
$[BtwCentArt3_t]^2$	3.4082***	2.0658*	3.4208***
	(0.7321)	(1.0667)	(0.7497)
$CliqnessArt3_t$	0.3951	1.3940	0.3235
	(0.6414)	(1.4439)	(1.0949)
$BtwCentPat3_t$	1.1129**	0.5973	1.1389**
	(0.4512)	(0.6721)	(0.5553)
$CliqnessPat3_t$	0.0008***	0.0007	0.0008**
	(0.0003)	(0.0005)	(0.0004)
$dAcAssignee_t$	-3.4481	-2.0706	-3.4910
	(2.1050)	(2.8175)	(2.1742)
dNanoEx	2.0596	-8.8536	2.7983
	(2.4291)	(12.7737)	(9.4649)
$dPGP_t$	8.0108	16.8291	7.1501
	(20.8142)	(30.1423)	(23.4128)
$dPGP_t \times CliqnessArt3_t$	-1.9978	-3.8345	-1.8476
	(4.8351)	(6.6901)	(5.1875)
$dPGP_t \times BtwCentArt3_t$	5.6570	1.6362	6.0017
	(8.9663)	(12.6479)	(9.9429)
$dPGP_t \times [BtwCentArt3_t]^2$	-0.0784	-0.0193	-0.0810
	(0.1496)	(0.1948)	(0.1531)
$NbClaims_t$	2.7497***	31.9741	0.8443
	(1.0565)	(32.2286)	(23.6151)
$[Grant3_t]^2$		0.3333***	
		(0.0930)	
Constant	58.4500***	-15.9000	63.5665
	(6.1912)	(86.4824)	(63.6504)
Nb observations	1110	1110	1110
Chi Square	102.4500	69.9641	95.2508
R^2	0.0802		0.0772
R^2 Adjusted	0.0658		0.0629
Sargan	0.9355	0.8741	
Wu-Hausman	0.0583	0.2441	0.1661

Notes: ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses. Moreover, in order to test endogeneity in our model, we used IV Regression Two-stage least squares (2SLS) for Herfindahl index of backward citations [$HerfIndexBWCit_t$] to validate instrumental variables (through Sargan test) and to assess endogeneity (through Wu-Hausman measurement) in our analysis including patent–grant pairs [dPGP].

Table G.4 : IV Regression Two-stage least squares (2SLS) used with Herfindahl index of forward citations [HerfIndexFCit5$_t$], to test endogeneity (including patent–grant pairs [$dPGP_t$] variable)

Variable	**HFC (18)**
Grant3$_t$	-0.3114
	(0.2324)
Age$_t$	-2.0438***
	(0.7132)
[Age$_t$]^2	0.0873***
	(0.0303)
MaxChair$_t$	0.7724
	(0.9515)
ArtCit3$_t$	2.8438*
	(1.5099)
[ArtCit3$_t$]^2	-0.6242*
	(0.3679)
BtwCentArt3$_t$	0.7837
	(1.0025)
CliqnessArt3$_t$	-0.6586
	(0.5707)
BtwCentPat3$_t$	0.3802
	(0.4019)
CliqnessPat3$_t$	0.0002
	(0.0002)
dAcAssignee$_t$	0.8912
	(1.8841)
dNanoEx	-3.3055
	(2.1493)
dPGP$_t$	7.0275
	(18.6626)
dPGP$_t$ × CliqnessArt3$_t$	1.9966
	(4.3413)
dPGP$_t$ × BtwCentArt3$_t$	-5.5991
	(4.8640)
Constant	93.1212***
	(4.9400)
Nb observations	1110
Chi Square	27.3899
R^2	0.0250
R^2 Adjusted	0.0116
Sargan	0.1726
Wu-Hausman	0.8220

Notes: ***, **, * show significance at the 1%, 5%, and 10% levels. Standard errors are presented in parentheses. Furthermore, in order to test endogeneity in our model, we used IV Regression Two-stage least squares (2SLS) with Herfindahl index of forward citations [$HerfIndexFCit5_t$] to validate instrumental variables (through Sargan test) and to assess endogeneity (through Wu-Hausman measurement) in our analysis that is linked to patent–grant pairs [$dPGP$].

APPENDIX H – EXTRA FINAL MODELS

Table H.1 : Impact of academic assignees and government assignees on the number of forward citations [$NbFCit5_t$] – Tobit results FC (35–38)

Variables	FC (35)	FC (36)	FC (37)	FC (38)
$Grant3_t$	0.0053	0.0043	0.0021	0.0042
	(0.0081)	(0.0082)	(0.0084)	(0.0080)
Age_t	0.2787***	0.2845***	0.2780***	0.2887***
	(0.0389)	(0.0392)	(0.0389)	(0.0425)
$[Age_t]^2$	-0.0137***	-0.0139***	-0.0137***	-0.0141***
	(0.0016)	(0.0017)	(0.0016)	(0.0018)
$MaxChair_t$	0.0209	0.0187	0.0202	0.0212
	(0.0447)	(0.0447)	(0.0448)	(0.0447)
$ArtCit3_t$	-0.0661**	-0.0639**	-0.0653**	-0.0650**
	(0.0287)	(0.0287)	(0.0287)	(0.0288)
$BtwCentArt3_t$	0.0747	0.0795*	0.0790*	0.0788*
	(0.0474)	(0.0476)	(0.0474)	(0.0476)
$CliqnessArt3_t$	-0.1451*	-0.1527*	-0.1493*	-0.1520*
	(0.0830)	(0.0838)	(0.0829)	(0.0830)
$[CliqnessArt3_t]^2$	0.0156**	0.0166**	0.0161**	0.0163**
	(0.0073)	(0.0074)	(0.0073)	(0.0073)
$BtwCentPat3_t$	-0.0308*	-0.0330*	-0.0346*	-0.0329*
	(0.0186)	(0.0186)	(0.0187)	(0.0185)
$CliqnessPat3_t$	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loop	-0.0618	-0.0589	-0.0586	-0.0573
	(0.0977)	(0.0976)	(0.0976)	(0.0982)
dNanoEx	0.5378***	0.5510***	0.5407***	0.5396***
	(0.1018)	(0.1020)	(0.1018)	(0.1019)
$dGovAssignee_t$	-0.3129	3.1564	-0.4532**	-0.4521**
	(0.2511)	(2.1022)	(0.2247)	(0.2248)
$dAcAssignee_t$	-0.2142*	-0.2107*	-0.4068	0.0800
	(0.1110)	(0.1108)	(0.2544)	(0.5586)
$dGovAssignee_t \times Grant3_t$		0.0169		
		(0.0442)		
$dGovAssignee_t \times Age_t$		-0.5216		
		(0.3662)		
$dGovAssignee_t \times [Age_t]^2$		0.0191		
		(0.0153)		
$dGovAssignee_t \times BtwCentArt3_t$		-0.2936		
		(0.2464)		
$dGovAssignee_t \times BtwCentPat3_t$	-0.3543	-0.3667		
	(0.3139)	(0.3373)		
$dAcAssignee_t \times Grant3_t$			0.0200	
			(0.0238)	
$dAcAssignee_t \times Age_t$				-0.0505
				(0.0998)
$dAcAssignee_t \times [Age_t]^2$				0.0019
				(0.0043)
Constant	-0.7516***	-0.7842***	-0.7190***	-0.7997***
	(0.2751)	(0.2764)	(0.2760)	(0.2954)
Constant (Sigma)	1.1260***	0.1231***	1.1257***	1.1263***
	(0.0377)	(0.0376)	(0.0377)	(0.0377)

Table H.1 : Impact of academic assignees and government assignees on the number of forward citations [NbFCit5$_t$] – Tobit results FC (35–38) (Cont'd and end)

Variables	FC (35)	FC (36)	FC (37)	FC (38)
Nb observations	1110	1110	1110	1110
Chi Square	144.60	148.63	143.78	143.36
Pseudo R^2	0.0548	0.0563	0.0545	0.0543
P value	0.0000	0.0000	0.0000	0.0000

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

Table H.2 : Impact of academic assignees and government assignees on the number of forward citations [NbFCit5$_t$] – Tobit results FC (39–42)

Variables	FC (39)	FC (40)	FC (41)	FC (42)
Grant3$_t$	0.0034	0.0037	-0.0003	-0.0008
	(0.0080)	(0.0081)	(0.0086)	(0.0088)
Age$_t$	0.2824***	0.2804***	0.2910***	0.2971***
	(0.0390)	(0.0389)	(0.0425)	(0.0429)
[Age$_t$]^2	-0.0138***	-0.0138***	-0.0142***	-0.0143***
	(0.0016)	(0.0016)	(0.0018)	(0.0018)
MaxChair$_t$	0.0205	0.0210	0.0178	0.0148
	(0.0447)	(0.0447)	(0.0447)	(0.0446)
ArtCit3$_t$	-0.0631**	-0.0665**	-0.0631**	-0.0608**
	(0.0288)	(0.0288)	(0.0288)	(0.0288)
BtwCentArt3$_t$	0.0940*	0.0792*	0.0999**	0.1043**
	(0.0494)	(0.0475)	(0.0496)	(0.0499)
CliqnessArt3$_t$	-0.1531*	-0.1495*	-0.1501*	-0.1539*
	(0.0828)	(0.0829)	(0.0829)	(0.0838)
[CliqnessArt3$_t$]^2	0.0165**	0.0162**	0.0165**	0.0171**
	(0.0073)	(0.0073)	(0.0073)	(0.0074)
BtwCentPat3$_t$	-0.0343*	-0.0348*	-0.0402**	-0.0413**
	(0.0186)	(0.0191)	(0.0193)	(0.0195)
CliqnessPat3$_t$	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loop	-0.0629	-0.0532	-0.0551	-0.0553
	(0.0976)	(0.0981)	(0.0985)	(0.0984)
dNanoEx	0.5361***	0.5371***	0.5370***	0.5498***
	(0.1018)	(0.1019)	(0.1019)	(0.1020)
dGovAssignee$_t$	-0.4542**	-0.4543**	-0.4653**	3.2200
	(0.2245)	(0.2249)	(0.2247)	(2.1008)
dAcAssignee$_t$	-0.0836	-0.2428**	-0.0218	0.0339
	(0.1574)	(0.1234)	(0.5645)	(0.5643)
dGovAssignee$_t$ × Grant3$_t$				0.0226
				(0.0442)
dGovAssignee$_t$ × Age$_t$				-0.5345
				(0.3659)
dGovAssignee$_t$ × [Age$_t$]^2				0.0195
				(0.0153)
dGovAssignee$_t$ ×				-0.3247
BtwCentArt3$_t$				(0.2465)
dGovAssignee$_t$ ×				-0.3561
BtwCentPat3$_t$				(0.3364)

Table H.2 : Impact of academic assignees and government assignees on the number of forward citations [$NbFCit5_t$] – Tobit results FC (39–42) (Cont'd and end)

Variables	FC (39)	FC (40)	FC (41)	FC (42)
$dAcAssignee_t \times Grant3_t$			0.0284	0.0291
			(0.0247)	(0.0248)
$dAcAssignee_t \times Age_t$			-0.0654	-0.0717
			(0.1034)	(0.1033)
$dAcAssignee_t \times [Age_t]^2$			0.0027	0.0028
			(0.0044)	(0.0044)
$dAcAssignee_t \times BtwCentArt3_t$	-0.1313		-0.1422	-0.1508
	(0.1117)		(0.1157)	(0.1157)
$dAcAssignee_t \times BtwCentPat3_t$		0.0335	0.0387	0.0388
		(0.0663)	(0.0678)	(0.0677)
Constant	-0.7815***	-0.7426***	-0.8148***	-0.8664***
	(0.2773)	(0.2751)	(0.2952)	(0.2971)
Constant (Sigma)	1.1252***	1.1260***	1.1238***	1.1204***
	(0.0376)	(0.0377)	(0.0376)	(0.0375)
Nb observations	1110	1110	1110	1110
Chi Square	144.46	143.33	146.22	152.11
Pseudo R^2	0.0548	0.0543	0.0554	0.0577
P value	0.0000	0.0000	0.0000	0.0000

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

Table H.3 : Impact of academic assignees and government assignees on the number of claims [$NbClaims_t$] – Regression results CL (14–18)

Variables	CL (14)	CL(15)	CL(16)	CL(17)	CL(18)
$Grant3_t$	0.0009	0.0012	0.0012	0.0009	0.0008
	(0.0052)	(0.0052)	(0.0053)	(0.0052)	(0.0052)
Age_t	0.0140**	0.0132**	0.0132**	0.0123**	0.0131**
	(0.0060)	(0.0060)	(0.0060)	(0.0061)	(0.0060)
$MaxChair_t$	-0.0037	-0.0035	-0.0035	-0.0026	-0.0046
	(0.0292)	(0.0292)	(0.0292)	(0.0292)	(0.0292)
$ArtCit3_t$	-0.0368**	-0.0355*	-0.0355*	-0.0356*	-0.0347*
	(0.0185)	(0.0186)	(0.0186)	(0.0186)	(0.0186)
$BtwCentArt3_t$	-0.0199	-0.0206	-0.0206	-0.0188	-0.0167
	(0.0309)	(0.0309)	(0.0310)	(0.0310)	(0.0311)
$CliqnessArt3_t$	-0.0355**	-0.0361**	-0.0362**	-0.0361**	-0.0349**
	(0.0177)	(0.0177)	(0.0177)	(0.0177)	(0.0178)
$BtwCentPat3_t$	-0.0195	-0.0206	-0.0206	-0.0205	-0.0212
	(0.0133)	(0.0135)	(0.0135)	(0.0135)	(0.0135)
$CliqnessPat3_t$	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$[CliqnessPat3_t]^2$	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loop	-0.0795	-0.0674	-0.0675	-0.0649	-0.0655
	(0.0617)	(0.0634)	(0.0635)	(0.0635)	(0.0634)
dNanoEx	0.3994***	0.3980***	0.3980***	0.3945***	0.3994***
	(0.0670)	(0.0670)	(0.0671)	(0.0671)	(0.0670)
$dGovAssignee_t$		-0.0134	-0.0114	-0.4977	0.1591
		(0.1416)	(0.2474)	(0.5049)	(0.2117)

Table H.3 : Impact of academic assignees and government assignees on the number of claims [*$NbClaims_t$*] – Regression results CL (14–18) (Cont'd and end)

Variables	**CL (14)**	**CL(15)**	**CL(16)**	**CL(17)**	**CL(18)**
$dAcAssignee_t$		-0.0665	-0.0665	-0.0685	-0.0670
		(0.0711)	(0.0711)	(0.0711)	(0.0711)
$dGovAssignee_t \times Grant3_t$			-0.0003		
			(0.0259)		
$dGovAssignee_t \times Age_t$				0.0377	
				(0.0378)	
$dGovAssignee_t \times BtwCentArt3_t$					-0.1631
					(0.1488)
Constant	2.4729***	2.4934***	2.4933***	2.5035***	2.4879***
	(0.1263)	(0.1283)	(0.1285)	(0.1287)	(0.1284)
Nb observations	1110	1110	1110	1110	1110
Log Likelihood	-1335.09	-1334.64	-1334.64	-1334.14	-1334.03
R^2	0.0772	0.0779	0.0779	0.0788	0.0789
R^2 Adjusted	0.0679	0.0670	0.0661	0.0670	0.0672
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table H.4 : Impact of academic assignees and government assignees on the number of claims [*$NbClaims_t$*] – Regression results CL (19–22)

Variables	**CL (19)**	**CL(20)**	**CL (21)**	**CL (22)**
$Grant3_t$	0.0005	0.0009	0.0031	0.0011
	(0.0052)	(0.0054)	(0.0055)	(0.0052)
Age_t	0.0128**	0.0124**	0.0131**	0.0141**
	(0.0060)	(0.0061)	(0.0060)	(0.0066)
$MaxChair_t$	-0.0032	-0.0038	-0.0023	-0.0036
	(0.0292)	(0.0293)	(0.0292)	(0.0292)
$ArtCit3_t$	-0.0349*	-0.0346*	-0.0357*	-0.0353*
	(0.0186)	(0.0186)	(0.0186)	(0.0186)
$BtwCentArt3_t$	-0.0191	-0.0162	-0.0218	-0.0197
	(0.0309)	(0.0312)	(0.0309)	(0.0310)
$CliqnessArt3_t$	-0.0358**	-0.0353**	-0.0366**	-0.0360**
	(0.0177)	(0.0178)	(0.0177)	(0.0177)
$BtwCentPat3_t$	-0.0213	-0.0208	-0.0191	-0.0208
	(0.0135)	(0.0135)	(0.0135)	(0.0135)
$CliqnessPat3_t$	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$[CliqnessPat3_t]^2$	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loop	-0.0644	-0.0639	-0.0664	-0.0688
	(0.0634)	(0.0636)	(0.0634)	(0.0636)
dNanoEx	0.3992***	0.3980***	0.3964***	0.3975***
	(0.0670)	(0.0672)	(0.0670)	(0.0671)
$dGovAssignee_t$	-0.1177	-0.0712	-0.0117	-0.0135
	(0.1615)	(0.5980)	(0.1416)	(0.1417)
$dAcAssignee_t$	-0.0687	-0.0700	0.0830	-0.0057
	(0.0711)	(0.0712)	(0.1539)	(0.1974)

Table H.4 : Impact of academic assignees and government assignees on the number of claims [*$NbClaims_t$*] – Regression results CL (19–22) (Cont'd and end)

Variables	**CL (19)**	**CL(20)**	**CL (21)**	**CL (22)**
$dGovAssignee_t \times Grant3_t$		-0.0175		
		(0.0282)		
$dGovAssignee_t \times Age_t$		0.0178		
		(0.0424)		
$dGovAssignee_t \times BtwCentArt3_t$		-0.1267		
		(0.1533)		
$dGovAssignee \times BtwCentPat3_t$	0.1817	0.1732		
	(0.1352)	(0.1549)		
$dAcAssignee_t \times Grant3_t$			-0.0160	
			(0.0146)	
$dAcAssignee_t \times Age_t$				-0.0051
				(0.0153)
Constant	2.5023***	2.4980***	2.4821***	2.4806***
	(0.1284)	(0.1291)	(0.1287)	(0.1341)
Nb observations	1110	1110	1110	1110
Log Likelihood	-1333.73	-1333.05	-1334.03	-1334.59
R^2	0.0794	0.0806	0.0789	0.0780
R^2 Adjusted	0.0677	0.0662	0.0672	0.0662
P value	0.0000	0.0000	0.0000	0.0000

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

Table H.5 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*$HerfIndexBWCit_t$*]– Tobit results HBC (36–40)

Variables	**HBC (36)**	**HBC (37)**	**HBC (38)**	**HBC (39)**	**HBC (40)**
$Grant3_t$	-4.0048***	-3.9735***	-3.9252***	-3.8236***	-3.7596***
	(0.8859)	(0.8811)	(0.8806)	(0.8722)	(0.8713)
$[Grant3_t]^2$	0.3270***	0.3264***	0.3214***	0.3154***	0.3089***
	(0.0714)	(0.0710)	(0.0710)	(0.0702)	(0.0702)
$NbClaims_t$	3.3849***	3.3119***	3.0255**	0.5512	0.1171
	(1.1891)	(1.1832)	(1.1947)	(1.2972)	(1.3126)
Age_t	-2.5498***	-2.3791***	-2.4100***	-2.5039***	-2.5454***
	(0.8749)	(0.8718)	(0.8711)	(0.8629)	(0.8617)
$[Age_t]^2$	0.1578***	0.1479***	0.1487***	0.1546***	0.1558***
	(0.0373)	(0.0372)	(0.0372)	(0.0369)	(0.0368)
$MaxChair_t$	-1.5007	-1.6468	-1.6381	-1.5881	-1.5756
	(1.1716)	(1.1663)	(1.1650)	(1.1538)	(1.1518)
$ArtCit3_t$	1.1048	1.2052	1.2308*	1.0588	1.0856
	(0.7383)	(0.7356)	(0.7350)	(0.7283)	(0.7271)
$BtwCentArt3_t$	-17.6000***	-16.1000***	-16.1000***	-16.8000***	-16.8000***
	(4.5861)	(4.5807)	(4.5757)	(4.5358)	(4.5280)
$[BtwCentArt3_t]^2$	2.8890***	2.5973***	2.6075***	2.7019***	2.7176***
	(0.8652)	(0.8647)	(0.8637)	(0.8562)	(0.8547)
$CliqnessArt3_t$	0.5308	0.4734	0.5659	0.4999	0.6142
	(0.7151)	(0.7125)	(0.7142)	(0.7051)	(0.7064)
$BtwCentPat3_t$	1.2289***	0.9080*	0.8764*	0.8791*	0.8393*
	(0.4726)	(0.4789)	(0.4788)	(0.4737)	(0.4733)
$CliqnessPat3_t$	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	1.9606	2.2170	2.2637	3.3603	3.4518
	(2.4573)	(2.5023)	(2.4996)	(2.4868)	(2.4829)

Table H.5 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*]– Tobit results HBC (36–40) (Cont'd and end)

Variables	**HBC (36)**	**HBC (37)**	**HBC (38)**	**HBC (39)**	**HBC (40)**
dNanoEx	3.1025	3.0217	3.1236	2.9644	3.0877
	(2.7131)	(2.6985)	(2.6966)	(2.6693)	(2.6658)
dGovAssignee$_t$		-16.1000***	-48.6000**	-15.9000***	-55.6000***
		(5.6640)	(20.7079)	(5.6001)	(20.5159)
dAcAssignee$_t$		-6.3483**	-6.4085**	-44.0000***	-45.2000***
		(2.8181)	(2.8150)	(8.1643)	(8.1718)
dGovAssignee$_t$ × NbClaims$_t$			12.3585		15.1263**
			(7.5681)		(7.5011)
dAcAssignee$_t$ × NbClaims$_t$				14.6161***	15.0532***
				(2.9752)	(2.9780)
Constant	57.2654***	59.2069***	59.7010***	66.7906***	67.6249***
	(6.8629)	(6.8740)	(6.8730)	(6.9714)	(6.9717)
Constant (Sigma)	31.9057***	31.7270***	31.6915***	31.3837***	31.3289***
	(0.7571)	(0.7527)	(0.7518)	(0.7444)	(0.7430)
Nb observations	1110	1110	1110	1110	1110
Chi Square	115.56	127.72	130.39	151.79	155.86
Pseudo R^2	0.0115	0.0128	0.0130	0.0152	0.0156
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table H.6 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results HBC (41 – 45)

Variables	**HBC (41)**	**HBC (42)**	**HBC (43)**	**HBC (44)**	**HBC (45)**
Grant3$_t$	-3.8996***	-3.8653***	-4.0043***	-3.9461***	-3.8917***
	(0.8995)	(0.8987)	(0.8810)	(0.8796)	(0.8868)
[Grant3$_t$]^2	0.3219***	0.3184***	0.3298***	0.3246***	0.3182***
	(0.0726)	(0.0725)	(0.0710)	(0.0709)	(0.0715)
NbClaims$_t$	3.3094***	3.0208**	3.3750***	3.0043**	3.2635***
	(1.1831)	(1.1945)	(1.1836)	(1.1930)	(1.1837)
Age$_t$	-2.3923***	-2.4237***	-2.2929***	-2.3160***	-2.3635***
	(0.8720)	(0.8712)	(0.8761)	(0.8743)	(0.8719)
[Age$_t$]^2	0.1486***	0.1494***	0.1452***	0.1466***	0.1470***
	(0.0372)	(0.0372)	(0.0375)	(0.0374)	(0.0372)
MaxChair$_t$	-1.6591	-1.6508	-1.6636	-1.6741	-1.6675
	(1.1664)	(1.1651)	(1.1661)	(1.1638)	(1.1677)
ArtCit3$_t$	1.2076	1.2286*	1.2160*	1.2589*	1.2193*
	(0.7365)	(0.7358)	(0.7352)	(0.7340)	(0.7370)
BtwCentArt3$_t$	-16.0000***	-16.0000***	-16.2000***	-16.2000***	-15.9000***
	(4.5824)	(4.5772)	(4.5787)	(4.5695)	(4.6044)
[BtwCentArt3$_t$]^2	2.5852***	2.5912***	2.5956***	2.6089***	2.5988***
	(0.8654)	(0.8644)	(0.8642)	(0.8624)	(0.8681)
CliqnessArt3$_t$	0.4584	0.5496	0.4792	0.6133	0.5012
	(0.7130)	(0.7145)	(0.7122)	(0.7137)	(0.7140)
BtwCentPat3$_t$	0.9220*	0.8970*	0.9050*	0.8647*	0.8771*
	(0.4823)	(0.4820)	(0.4788)	(0.4782)	(0.4800)
CliqnessPat3$_t$	0.0012***	0.0012***	0.0011***	0.0011***	0.0012***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	2.1493	2.1898	2.1594	2.1701	2.2564
	(2.5049)	(2.5021)	(2.5015)	(2.4963)	(2.5021)

Table H.6 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results HBC (41 – 45) (Cont'd and end)

Variables	HBC (41)	HBC (42)	HBC (43)	HBC (44)	HBC (45)
dNanoEx	2.9745	3.0818	3.1963	3.4547	3.0201
	(2.6996)	(2.6975)	(2.7006)	(2.6982)	(2.7017)
dGovAssignee$_t$	-11.7000	-44.0000**	49.3545	35.2546	-9.5928
	(9.9853)	(22.0235)	(52.8270)	(53.1508)	(8.6442)
dAcAssignee$_t$	-6.3626**	-6.4217**	-6.3081**	-6.3402**	-6.3746**
	(2.8179)	(2.8148)	(2.8173)	(2.8114)	(2.8172)
dGovAssignee$_t$ ×		12.4865		17.8992**	
NbClaims$_t$		(7.5931)		(8.1500)	
dGovAssignee$_t$ ×	-2.1370	-1.8106			
Grant3$_t$	(4.7922)	(4.7945)			
dGovAssignee$_t$ ×	0.1352	0.1008			
[Grant3$_t$]^2	(0.3829)	(0.3832)			
dGovAssignee$_t$ ×			-10.2000	-14.5000	
Age$_t$			(8.7877)	(8.9988)	
dGovAssignee$_t$ ×			0.3672	0.4915	
[Age$_t$]^2			(0.3482)	(0.3526)	
dGovAssignee$_t$ ×					8.6342
BtwCentArt3$_t$					(37.7633)
dGovAssignee$_t$ ×					-3.0996
[BtwCentArt3$_t$]^2					(8.0870)
Constant	59.1633***	59.6462***	58.4996***	58.8448***	59.0602***
	(6.8745)	(6.8729)	(6.8925)	(6.8802)	(6.8762)
Constant (Sigma)	31.7232***	31.6869***	31.7062***	31.6415***	31.7157***
	(0.7526)	(0.7517)	(0.7522)	(0.7506)	(0.7524)
Nb observations	1110	1110	1110	1110	1110
Chi Square	128.06	130.77	129.35	134.19	128.73
Pseudo R^2	0.0128	0.0131	0.0129	0.0134	0.0129
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table H.7 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results HBC (46 – 50)

Variables	HBC (46)	HBC (47)	HBC (48)	HBC (49)	HBC (50)
rant3$_t$	-3.8911***	-3.9608***	-3.9266***	-3.8097***	-4.3267***
	(0.8861)	(0.8814)	(0.8808)	(0.8991)	(0.9069)
[Grant3$_t$]^2	0.3180***	0.3245***	0.3217***	0.3131***	0.3527***
	(0.0715)	(0.0711)	(0.0710)	(0.0726)	(0.0729)
NbClaims$_t$	3.0326**	3.2847***	3.0256**	3.0086**	3.4105***
	(1.1947)	(1.1845)	(1.1947)	(1.1929)	(1.1834)
Age$_t$	-2.3991***	-2.3613***	-2.4133***	-2.3176***	-2.3945***
	(0.8715)	(0.8726)	(0.8723)	(0.8747)	(0.8713)
[Age$_t$]^2	0.1482***	0.1470***	0.1489***	0.1469***	0.1504***
	(0.0372)	(0.0373)	(0.0373)	(0.0374)	(0.0372)
MaxChair$_t$	-1.6491	-1.6445	-1.6383	-1.6848	-1.5403
	(1.1669)	(1.1662)	(1.1650)	(1.1656)	(1.1673)
ArtCit3$_t$	1.2349*	1.2120*	1.2301*	1.2750*	1.2457*
	(0.7364)	(0.7357)	(0.7351)	(0.7366)	(0.7352)
BtwCentArt3$_t$	-16.0000***	-16.1000***	-16.1000***	-16.2000***	-16.2000***
	(4.6011)	(4.5803)	(4.5757)	(4.5975)	(4.5937)

Table H.7 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results HBC (46 – 50) (Cont'd and end)

Variables	**HBC (41)**	**HBC (42)**	**HBC (43)**	**HBC (44)**	**HBC (45)**
$[BtwCentArt3_t]^2$	2.6072***	2.6034***	2.6066***	2.6269***	2.5907***
	(0.8674)	(0.8647)	(0.8638)	(0.8673)	(0.8686)
$CliqnessArt3_t$	0.5697	0.4775	0.5666	0.6073	0.4779
	(0.7155)	(0.7125)	(0.7142)	(0.7168)	(0.7124)
$BtwCentPat3_t$	0.8648*	0.8859*	0.8794*	0.8476*	0.8722*
	(0.4797)	(0.4812)	(0.4807)	(0.4830)	(0.4804)
$CliqnessPat3_t$	0.0012***	0.0012***	0.0012***	0.0011***	0.0011***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	2.2777	2.2345	2.2615	2.1421	1.8286
	(2.5001)	(2.5023)	(2.4998)	(2.4985)	(2.5111)
dNanoEx	3.1127	3.0566	3.1195	3.3798	3.0424
	(2.7007)	(2.6993)	(2.6972)	(2.7086)	(2.6954)
$dGovAssignee_t$	-42.0000*	-17.6000***	-48.9000**	45.3974	-16.2000***
	(25.3144)	(6.4748)	(20.9997)	(55.5026)	(5.6570)
$dAcAssignee_t$	-6.4146**	-6.3744**	-6.4052**	-6.3506**	-10.2000
	(2.8150)	(2.8183)	(2.8154)	(2.8115)	(6.2358)
$dGovAssignee_t$ ×	11.0529		12.5420	17.2524*	
$NbClaims_t$	(8.1005)		(7.9992)	(9.2732)	
$dGovAssignee_t$ ×				-3.3542	
$Grant3_t$				(5.4257)	
$dGovAssignee_t$ ×				0.2670	
$[Grant3_t]^2$				(0.4469)	
$dGovAssignee_t$ ×				-15.1000	
Age_t				(10.1526)	
$dGovAssignee_t$ ×				0.5080	
$[Age_t]^2$				(0.4033)	
$dGovAssignee_t$ ×	4.1476			8.6853	
$BtwCentArt3_t$	(37.8998)			(41.8561)	
$dGovAssignee_t$ ×	-1.4901			-2.1903	
$[BtwCentArt3_t]^2$	(8.1704)			(9.0495)	
$dGovAssignee_t$ ×		2.4750	-0.3993	-0.3069	
$BtwCentPat3_t$		(5.3365)	(5.6385)	(6.8812)	
$dAcAssignee_t$ ×					4.4804
$Grant3_t$					(2.7747)
$dAcAssignee_t$ ×					-0.3483
$[Grant3_t]^2$					(0.2204)
Constant	59.5763***	59.2616***	59.6996***	58.7647***	59.1942***
	(6.8809)	(6.8743)	(6.8730)	(6.8871)	(6.8739)
Constant (Sigma)	31.6898***	31.7237***	31.6915***	31.6368***	31.6861***
	(0.7518)	(0.7526)	(0.7518)	(0.7505)	(0.7517)
Nb observations	1110	1110	1110	1110	1110
Chi Square	130.59	127.93	130.39	134.75	130.32
Pseudo R^2	0.0131	0.0128	0.0130	0.0135	0.0130
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table H.8 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results HBC (51 – 55)

Variables	**HBC(51)**	**HBC (52)**	**HBC (53)**	**HBC(54)**	**HBC (55)**
Grant3$_t$	-4.2386***	-3.9551***	-3.8074***	-3.7914***	-3.6258***
	(0.8969)	(0.8783)	(0.8694)	(0.8867)	(0.8776)
[Grant3$_t$]^2	0.3449***	0.3266***	0.3157***	0.3091***	0.2966***
	(0.0721)	(0.0707)	(0.0700)	(0.0716)	(0.0709)
NbClaims$_t$	0.6004	3.2957***	0.5277	3.4367***	0.6583
	(1.2951)	(1.1796)	(1.2931)	(1.1840)	(1.2965)
Age$_t$	-2.5327***	-3.1751***	-3.3401***	-2.3124***	-2.4330***
	(0.8620)	(0.9480)	(0.9383)	(0.8716)	(0.8624)
[Age$_t$]^2	0.1580***	0.1720***	0.1807***	0.1474***	0.1541***
	(0.0369)	(0.0404)	(0.0400)	(0.0372)	(0.0368)
MaxChair$_t$	-1.4716	-1.6118	-1.5501	-1.6982	-1.6438
	(1.1541)	(1.1626)	(1.1500)	(1.1653)	(1.1525)
ArtCit3$_t$	1.1047	1.1148	0.9692	1.2919*	1.1507
	(0.7273)	(0.7338)	(0.7264)	(0.7366)	(0.7289)
BtwCentArt3$_t$	-16.9000***	-16.5000***	-17.2000***	-15.7000***	-16.3000***
	(4.5472)	(4.5678)	(4.5230)	(4.5848)	(4.5395)
[BtwCentArt3$_t$]^2	2.7200***	2.6245***	2.7309***	2.6525***	2.7609***
	(0.8598)	(0.8620)	(0.8535)	(0.8647)	(0.8561)
CliqnessArt3$_t$	0.5145	0.4511	0.4787	0.5102	0.5392
	(0.7046)	(0.7101)	(0.7027)	(0.7119)	(0.7043)
BtwCentPat3$_t$	0.8259*	0.9404**	0.9125*	0.8522*	0.8184*
	(0.4750)	(0.4774)	(0.4723)	(0.4794)	(0.4741)
CliqnessPat3$_t$	0.0011***	0.0011***	0.0011***	0.0012***	0.0012***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	2.9446	2.3415	3.4601	2.0116	3.1531
	(2.4932)	(2.5044)	(2.4884)	(2.5022)	(2.4858)
dNanoEx	3.0009	3.0058	2.9315	2.8173	2.7432
	(2.6647)	(2.6921)	(2.6629)	(2.6978)	(2.6679)
dGovAssignee$_t$	-15.9000***	-15.9000***	-15.7000***	-16.2000***	-16.0000***
	(5.5900)	(5.6453)	(5.5814)	(5.6562)	(5.5909)
dAcAssignee$_t$	-50.8000***	-37.8000***	-76.6000***	-1.5398	-39.1000***
	(10.1658)	(12.7342)	(14.9044)	(4.0368)	(8.5707)
dAcAssignee$_t$ ×	14.9836***		14.6826***		14.7581***
NbClaims$_t$	(2.9760)		(2.9714)		(2.9712)
dAcAssignee$_t$ ×	5.3238*				
Grant3$_t$	(2.7534)				
dAcAssignee$_t$ ×	-0.4020*				
[Grant3$_t$]^2	(0.2185)				
dAcAssignee$_t$ × Age$_t$		4.4093*	4.6839**		
		(2.2814)	(2.2603)		
dAcAssignee$_t$ ×		-0.1311	-0.1447		
[Age$_t$]^2		(0.0994)	(0.0985)		
dAcAssignee$_t$ ×				-4.7374*	-5.1288*
BtwCentArt3$_t$				(2.8549)	(2.8314)
Constant	67.0652***	65.6480***	73.4070***	57.3383***	64.8543***
	(6.9721)	(7.2833)	(7.3708)	(6.9567)	(7.0421)
Constant (Sigma)	31.3256***	31.6192***	31.2749***	31.6861***	31.3353***
	(0.7430)	(0.7500)	(0.7417)	(0.7517)	(0.7432)
Nb observations	1110	1110	1110	1110	1110
Chi Square	155.58	135.68	160.05	130.47	155.07

Table H.8 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results HBC (51 – 55) (Cont'd and end)

Variables	HBC(51)	HBC (52)	HBC (53)	HBC(54)	HBC (55)
Pseudo R^2	0.0155	0.0136	0.0160	0.0130	0.0155
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table H.9 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results HBC (56 – 59)

Variables	HBC (56)	HBC (57)	HBC (58)	HBC (59)
Grant3_t	-4.0946***	-3.9388***	-4.0898***	-3.8686***
	(0.8784)	(0.8703)	(0.9069)	(0.9286)
$[\text{Grant3}_t]^2$	0.3323***	0.3211***	0.3281***	0.3085***
	(0.0707)	(0.0700)	(0.0734)	(0.0754)
NbClaims_t	3.1936***	0.5383	0.7067	0.2428
	(1.1790)	(1.2927)	(1.2855)	(1.2985)
Age_t	-2.3128***	-2.4395***	-3.2094***	-3.1365***
	(0.8685)	(0.8603)	(0.9340)	(0.9377)
$[\text{Age}_t]^2$	0.1432***	0.1501***	0.1771***	0.1757***
	(0.0371)	(0.0368)	(0.0398)	(0.0400)
MaxChair_t	-1.7352	-1.6696	-1.5766	-1.6243
	(1.1619)	(1.1503)	(1.1465)	(1.1453)
ArtCit3_t	1.0412	0.9159	0.9918	1.0741
	(0.7346)	(0.7277)	(0.7244)	(0.7250)
BtwCentArt3_t	-14.9000***	-15.7000***	-15.7000***	-15.7000***
	(4.5802)	(4.5396)	(4.5393)	(4.5549)
$[\text{BtwCentArt3}_t]^2$	2.3807***	2.5018***	2.6370***	2.6822***
	(0.8642)	(0.8564)	(0.8582)	(0.8605)
CliqnessArt3_t	0.6146	0.6269	0.6520	0.8250
	(0.7111)	(0.7042)	(0.7012)	(0.7056)
BtwCentPat3_t	0.5634	0.5688	0.5085	0.4147
	(0.4906)	(0.4857)	(0.4881)	(0.4936)
CliqnessPat3_t	0.0012***	0.0012***	0.0011***	0.0011***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	2.8418	3.8875	3.3375	3.3425
	(2.5007)	(2.4860)	(2.4846)	(2.4797)
dNanoEx	2.8445	2.8058	2.6014	2.9614
	(2.6879)	(2.6607)	(2.6484)	(2.6560)
dGovAssignee_t	-16.7000***	-16.4000***	-16.3000***	31.3499
	(5.6432)	(5.5839)	(5.5448)	(54.3388)
dAcAssignee_t	-10.6000***	-46.6000***	-81.0000***	-81.3000***
	(3.1480)	(8.1987)	(15.4894)	(15.4607)
$\text{dGovAssignee}_t \times \text{NbClaims}_t$				20.0903**
				(9.0790)
$\text{dAcAssignee}_t \times \text{NbClaims}_t$		14.1339***	14.7948***	15.2454***
		(2.9714)	(2.9631)	(2.9605)
$\text{dGovAssignee}_t \times \text{Grant3}_t$				-3.2276
				(5.3123)
$\text{dGovAssignee}_t \times [\text{Grant3}_t]^2$				0.2669
				(0.4376)
$\text{dGovAssignee}_t \times \text{Age}_t$				-14.2000
				(9.9306)

Table H.9 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit*] – Tobit results HBC (56 – 59) (Cont'd and end)

Variables	HBC (56)	HBC (57)	HBC (58)	HBC (59)
dGovAssignee$_t$ × [Age$_t$]^2				0.4777
				(0.3945)
dGovAssignee$_t$ × BtwCentArt3$_t$				8.1352
				(40.9264)
dGovAssignee$_t$ × [BtwCentArt3$_t$]^2				-2.2146
				(8.8466)
dGovAssignee$_t$ × BtwCentPat3$_t$				0.0089
				(6.7304)
dAcAssignee$_t$ × Grant3$_t$			5.4869*	5.2856*
			(2.9158)	(2.9123)
dAcAssignee$_t$ × [Grant3$_t$]^2			-0.4137*	-0.3950*
			(0.2334)	(0.2333)
dAcAssignee$_t$ × Age$_t$			4.5052*	4.4055*
			(2.3014)	(2.2964)
dAcAssignee$_t$ × [Age$_t$]^2			-0.1259	-0.1233
			(0.1001)	(0.0999)
dAcAssignee$_t$ × BtwCentArt3$_t$			-6.2813**	-6.6850**
			(3.0206)	(3.0316)
dAcAssignee$_t$ × BtwCentPat3$_t$	4.8062***	4.3437***	3.8620**	3.9386**
	(1.6141)	(1.6010)	(1.6289)	(1.6251)
Constant	60.0498***	67.2892***	72.0060***	71.6971***
	(6.8519)	(6.9503)	(7.3607)	(7.3824)
Constant (Sigma)	31.5948***	31.2752***	31.0518***	30.9396***
	(0.7495)	(0.7418)	(0.7363)	(0.7336)
Nb observations	1110	1110	1110	1110
Chi Square	136.55	159.13	175.35	184.08
Pseudo R^2	0.0136	0.0159	0.0175	0.0184
P value	0.0000	0.0000	0.0000	0.0000

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

Table H.10 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results HBC (60 – 64)

Variables	HBC (60)	HBC (61)	HBC (62)	HBC (63)	HBC (64)
Grant3$_t$	-3.9237***	-3.8936***	-3.8166***	-3.9207***	-3.8036***
	(0.8887)	(0.8837)	(0.9022)	(0.8837)	(0.8893)
[Grant3$_t$]^2	0.3218***	0.3214***	0.3166***	0.3244***	0.3123***
	(0.0716)	(0.0712)	(0.0728)	(0.0712)	(0.0718)
Age$_t$	-2.6292***	-2.4565***	-2.4699***	-2.3773***	-2.4380***
	(0.8776)	(0.8745)	(0.8747)	(0.8788)	(0.8744)
[Age$_t$]^2	0.1635***	0.1533***	0.1540***	0.1507***	0.1522***
	(0.0374)	(0.0373)	(0.0373)	(0.0376)	(0.0373)
MaxChair$_t$	-1.4991	-1.6456	-1.6580	-1.6597	-1.6688
	(1.1760)	(1.1705)	(1.1706)	(1.1704)	(1.1718)
ArtCit3$_t$	1.0040	1.1105	1.1135	1.1187	1.1279
	(0.7401)	(0.7374)	(0.7383)	(0.7371)	(0.7387)
BtwCentArt3$_t$	-17.9000***	-16.4000***	-16.3000***	-16.5000***	-16.2000***
	(4.6017)	(4.5959)	(4.5976)	(4.5944)	(4.6194)
[BtwCentArt3$_t$]^2	2.9291***	2.6312***	2.6193***	2.6303***	2.6318***
	(0.8682)	(0.8676)	(0.8684)	(0.8672)	(0.8710)

Table H.10 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [$HerfIndexBWCit_t$] – Tobit results HBC (60 – 64) (Cont'd and end)

Variables	**HBC (60)**	**HBC (61)**	**HBC (62)**	**HBC (63)**	**HBC (64)**
$CliqnessArt3_t$	0.4086	0.3507	0.3357	0.3541	0.3838
	(0.7164)	(0.7136)	(0.7141)	(0.7133)	(0.7151)
$BtwCentPat3_t$	1.2660***	0.9387*	0.9523**	0.9360*	0.9038*
	(0.4741)	(0.4805)	(0.4839)	(0.4805)	(0.4816)
$CliqnessPat3_t$	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	1.8361	2.1374	2.0690	2.0855	2.1823
	(2.4658)	(2.5109)	(2.5135)	(2.5104)	(2.5105)
dNanoEx	4.4030	4.2896	4.2397	4.4691*	4.2677
	(2.6845)	(2.6700)	(2.6711)	(2.6735)	(2.6730)
$dGovAssignee_t$		-16.1000***	-11.7000	43.7205	-8.8515
		(5.6825)	(10.0170)	(52.9790)	(8.6678)
$dAcAssignee_t$		-6.5898**	-6.6045**	-6.5599**	-6.6154**
		(2.8263)	(2.8261)	(2.8258)	(2.8252)
$dGovAssignee_t \times$			-2.2185		
$Grant3_t$			(4.8088)		
$dGovAssignee_t \times$			0.1418		
$[Grant3_t]^2$			(0.3842)		
$dGovAssignee_t \times$				-9.3993	
Age_t				(8.8144)	
$dGovAssignee_t \times$				0.3402	
$[Age_t]^2$				(0.3493)	
$dGovAssignee_t \times$					9.3953
$BtwCentArt3_t$					(37.8921)
$dGovAssignee_t \times$					-3.4049
$BtwCentArt3_t]^2$					(8.1145)
Constant	66.2845***	68.0948***	68.0450***	67.6018***	67.7868***
	(6.1057)	(6.1145)	(6.1150)	(6.1272)	(6.1215)
Constant (Sigma)	32.0237***	31.8401***	31.8362***	31.8233***	31.8258***
	(0.7599)	(0.7555)	(0.7554)	(0.7550)	(0.7551)
Nb observations	1110	1110	1110	1110	1110
Chi Square	107.47	119.90	120.26	121.24	121.15
Pseudo R^2	0.0107	0.0120	0.0120	0.0121	0.0121
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table H.11 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [$HerfIndexBWCit_t$] – Tobit results HBC (65 – 68)

Variables	**HBC (65)**	**HBC (66)**	**HBC (67)**	**HBC (68)**
$Grant3_t$	-3.8780***	-3.7441***	-4.2118***	-3.8759***
	(0.8839)	(0.9028)	(0.9094)	(0.8809)
$[Grant3_t]^2$	0.3189***	0.3093***	0.3454***	0.3216***
	(0.0713)	(0.0729)	(0.0732)	(0.0710)
Age_t	-2.4326***	-2.3729***	-2.4707***	-3.2657***
	(0.8752)	(0.8784)	(0.8742)	(0.9508)
$[Age_t]^2$	0.1520***	0.1508***	0.1556***	0.1779***
	(0.0374)	(0.0376)	(0.0373)	(0.0405)
$MaxChair_t$	-1.6426	-1.7066	-1.5463	-1.6098
	(1.1703)	(1.1712)	(1.1718)	(1.1667)
$ArtCit3_t$	1.1203	1.1393	1.1443	1.0201
	(0.7375)	(0.7390)	(0.7371)	(0.7356)
$BtwCentArt3_t$	-16.4000***	-16.2000***	-16.4000***	-16.8000***
	(4.5951)	(4.6174)	(4.6100)	(4.5827)
$[BtwCentArt3_t]^2$	2.6387***	2.6321***	2.6205***	2.6589***
	(0.8676)	(0.8713)	(0.8717)	(0.8649)
$CliqnessArt3_t$	0.3574	0.3720	0.3495	0.3288
	(0.7136)	(0.7158)	(0.7136)	(0.7112)
$BtwCentPat3_t$	0.9097*	0.8932*	0.9095*	0.9713**
	(0.4828)	(0.4852)	(0.4821)	(0.4790)
$CliqnessPat3_t$	0.0012***	0.0012***	0.0012***	0.0011***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Loop	2.1610	2.0591	1.7792	2.2543
	(2.5107)	(2.5104)	(2.5205)	(2.5130)
dNanoEx	4.3212	4.4552*	4.3391	4.2627
	(2.6700)	(2.6821)	(2.6679)	(2.6639)
$dGovAssignee_t$	-18.0000***	47.8149	-16.2000***	-15.9000***
	(6.4932)	(55.4965)	(5.6767)	(5.6636)
$dAcAssignee_t$	-6.6211**	-6.6002**	-9.7915	-38.4000***
	(2.8263)	(2.8234)	(6.2558)	(12.7722)
$dGovAssignee_t \times Grant3_t$		-1.6595		
		(5.3803)		
$dGovAssignee_t \times [Grant3_t]^2$		0.0772		
		(0.4394)		
$dGovAssignee_t \times Age_t$		-7.0349		
		(9.4843)		
$dGovAssignee_t \times [Age_t]^2$		0.2104		
		(0.3811)		
$dGovAssignee_t \times$		15.8289		
$BtwCentArt3_t$		(41.8044)		
$dGovAssignee_t \times$		-4.9212		
$[BtwCentArt3_t]^2$		(8.9784)		
$dGovAssignee_t \times$	3.2064	5.0386		
$BtwCentPat3_t$	(5.3479)	(6.4935)		
$dAcAssignee_t \times Grant3_t$			4.0620	
			(2.7805)	
$dAcAssignee_t \times [Grant3_t]^2$			-0.3186	
			(0.2209)	
$dAcAssignee_t \times Age_t$				4.4918**

Table H.11 : Impact of academic assignees and government assignees on the Herfindahl index of backward citations [$HerfIndexBWCit_t$] – Tobit results HBC (65 – 68) (Cont'd and end)

Variables	**HBC (65)**	**HBC (66)**	**HBC (67)**	**HBC (68)**
				(2.2888)
dAcAssignee$_t$ × [Age$_t$]^2				-0.1349
				(0.0998)
Constant	68.0711***	67.2377***	68.2986***	74.5623***
	(6.1136)	(6.1325)	(6.1241)	(6.5683)
Constant (Sigma)	31.8345***	31.7918***	31.8062***	31.7309***
	(0.7553)	(0.7543)	(0.7547)	(0.7528)
Nb observations	1110	1110	1110	1110
Chi Square	120.26	123.63	122.04	127.89
Pseudo R^2	0.0120	0.0124	0.0122	0.0128
P value	0.0000	0.0000	0.0000	0.0000

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

Table H.12 : Impact of academic assignees and government assignees on the Herfindahl index of forward citations [$HerfIndexFCit5_t$] – Tobit results HFC (19 – 23)

Variables	**HFC (19)**	**HFC (20)**	**HFC (21)**	**HFC (22)**	**HFC (23)**
Grant3$_t$	-0.2675	-0.2787	-0.3451	-0.3180	-0.2631
	(0.2524)	(0.2526)	(0.2584)	(0.2527)	(0.2532)
Age$_t$	-6.9610***	-6.9142***	-6.8790***	-6.7160***	-6.9094***
	(1.2161)	(1.2167)	(1.2160)	(1.2191)	(1.2157)
[Age$_t$]^2	0.3348***	0.3344***	0.3325***	0.3223***	0.3344***
	(0.0515)	(0.0515)	(0.0515)	(0.0517)	(0.0515)
MaxChair$_t$	0.6491	0.6359	0.6517	0.7172	0.6737
	(1.4042)	(1.4046)	(1.4035)	(1.4013)	(1.4049)
ArtCit3$_t$	5.9785**	5.9387**	5.9346**	5.7786**	5.8239**
	(2.3217)	(2.3225)	(2.3210)	(2.3188)	(2.3253)
[ArtCit3$_t$]^2	-1.1393**	-1.1414**	-1.1342**	-1.1041*	-1.1185**
	(0.5653)	(0.5652)	(0.5648)	(0.5641)	(0.5656)
BtwCentArt3$_t$	-0.4260	-0.4024	-0.3281	-0.2372	-0.5590
	(1.4866)	(1.4864)	(1.4865)	(1.4847)	(1.4968)
CliqnessArt3$_t$	-1.1849	-1.1496	-1.1030	-1.1864	-1.1915
	(0.8473)	(0.8477)	(0.8473)	(0.8469)	(0.8487)
BtwCentPat3$_t$	0.7028	0.7235	0.6448	0.6710	0.7515
	(0.5729)	(0.5831)	(0.5862)	(0.5818)	(0.5837)
CliqnessPat3$_t$	0.0004	0.0003	0.0003	0.0004	0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Loop	-3.6996	-4.2953	-4.1195	-4.1290	-4.3467
	(2.9738)	(3.0501)	(3.0508)	(3.0412)	(3.0495)
dNanoEx	-7.0340**	-6.9694**	-6.9305**	-7.2687**	-7.0393**
	(3.2439)	(3.2436)	(3.2406)	(3.2443)	(3.2431)
dGovAssignee$_t$		-2.9325	-14.3000	56.2439	-9.4379
		(6.8522)	(11.6292)	(69.0434)	(10.1569)
dAcAssignee$_t$		2.5117	2.5098	2.3280	2.5272
		(3.4496)	(3.4467)	(3.4391)	(3.4482)
dGovAssignee$_t$ × Grant3$_t$			1.5028		
			(1.2434)		
dGovAssignee$_t$ × Age$_t$				-15.1000	
				(12.2114)	

Table H.12 : Impact of academic assignees and government assignees on the Herfindahl index of forward citations [*HerfIndexFCit5$_t$*] – Tobit results HFC (19 – 23) (Cont'd and end)

Variables	**HFC (19)**	**HFC (20)**	**HFC (21)**	**HFC (22)**	**HFC (23)**
dGovAssignee$_t$ × [Age$_t$]^2				0.7724	
				(0.5171)	
dGovAssignee$_t$ × BtwCentArt3$_t$					6.1288
					(7.1054)
Constant	123.0000***	122.0000***	123.0000***	122.0000***	123.0000***
	(8.0555)	(8.0974)	(8.0923)	(8.1083)	(8.0956)
Constant (Sigma)	36.4504***	36.4351***	36.4065***	36.3276***	36.4194***
	(1.0457)	(1.0454)	(1.0445)	(1.0421)	(1.0449)
Nb observations	1110	1110	1110	1110	1110
Chi Square	76.5717	77.3430	78.8039	82.5109	78.0882
Pseudo R^2	0.0100	0.0101	0.0103	0.0108	0.0102
P value	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table H.13 : Impact of academic assignees and government assignees on the Herfindahl index of forward citations [*HerfIndexFCit5$_t$*] – Tobit results HFC (24 – 27)

Variables	**HFC (24)**	**HFC (25)**	**HFC (26)**	**HFC (27)**
Grant3$_t$	-0.3598	-0.3523	-0.3169	-0.2721
	(0.2534)	(0.2572)	(0.2656)	(0.2526)
Age$_t$	-6.7849***	-6.6194***	-6.9522***	-7.4654***
	(1.2134)	(1.2134)	(1.2208)	(1.3482)
[Age$_t$]^2	0.3266***	0.3179***	0.3361***	0.3506***
	(0.0514)	(0.0514)	(0.0517)	(0.0566)
MaxChair$_t$	0.6912	0.8058	0.6194	0.6770
	(1.3995)	(1.3967)	(1.4051)	(1.4046)
ArtCit3$_t$	5.8664**	5.5605**	5.9062**	5.8207**
	(2.3159)	(2.3142)	(2.3233)	(2.3246)
[ArtCit3$_t$]^2	-1.1135**	-1.0478*	-1.1325**	-1.1235**
	(0.5633)	(0.5627)	(0.5654)	(0.5654)
BtwCentArt3$_t$	-0.2124	-0.4060	-0.3786	-0.5409
	(1.4820)	(1.4882)	(1.4870)	(1.4904)
CliqnessArt3$_t$	-1.1128	-1.2085	-1.1346	-1.1632
	(0.8440)	(0.8454)	(0.8482)	(0.8474)
BtwCentPat3$_t$	0.5816	0.6037	0.6905	0.7502
	(0.5830)	(0.5840)	(0.5872)	(0.5830)
CliqnessPat3$_t$	0.0004	0.0004	0.0003	0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Loop	-4.0799	-4.0863	-4.2955	-4.1032
	(3.0383)	(3.0317)	(3.0496)	(3.0696)
dNanoEx	-6.8987**	-7.2449**	-6.9448**	-6.9400**
	(3.2317)	(3.2357)	(3.2436)	(3.2441)
dGovAssignee$_t$	-13.4000*	47.8610	-2.9748	-2.8286
	(7.7535)	(71.0240)	(6.8511)	(6.8462)
dAcAssignee$_t$	2.3178	2.2525	-0.6713	-16.9000
	(3.4359)	(3.4252)	(7.6453)	(16.7846)

Table H.13 : Impact of academic assignees and government assignees on the Herfindahl index of forward citations [*HerfIndexFCit5$_t$*] – Tobit results HFC (24 – 27) (Cont'd and end)

Variables	**HFC (24)**	**HFC (25)**	**HFC (26)**	**HFC (27)**
$dGovAssignee_t \times Grant3_t$		0.0303		
		(1.3799)		
$dGovAssignee_t \times Age_t$		-16.3000		
		(12.6826)		
$dGovAssignee_t \times [Age_t]^2$		0.7829		
		(0.5418)		
$dGovAssignee_t \times BtwCentArt3_t$		11.7759		
		(7.4203)		
$dGovAssignee_t \times BtwCentPat3_t$	28.4374**	26.3826**		
	(11.9891)	(12.5547)		
$dAcAssignee_t \times Grant3_t$			0.3364	
			(0.7220)	
$dAcAssignee_t \times Age_t$				2.6324
				(3.0245)
$dAcAssignee_t \times [Age_t]^2$				-0.0739
				(0.1324)
Constant	122.0000***	122.0000***	123.0000***	127.0000***
	(8.0669)	(8.0723)	(8.1652)	(8.9103)
Constant (Sigma)	36.2965***	36.1841***	36.4300***	36.4111***
	(1.0408)	(1.0376)	(1.0453)	(1.0446)
Nb observations	1110	1110	1110	1110
Chi Square	86.0052	90.6246	77.5596	79.2735
Pseudo R^2	0.0112	0.0118	0.0101	0.0104
P value	0.0000	0.0000	0.0000	0.0000

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

Table H.14 : Impact of patent–grant pairs on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*]– Tobit results HBC (69 – 71)

Variables	**HBC (69)**	**HBC (70)**	**HBC (71)**
$Grant3_t$	-3.8546***	-3.8523***	-3.8469***
	(0.8820)	(0.8820)	(0.8828)
$[Grant3_t]^2$	0.3186***	0.3182***	0.3177***
	(0.0713)	(0.0713)	(0.0713)
$(NbClaims_t)$	3.3550***	3.3541***	3.3579***
	(1.1886)	(1.1886)	(1.1888)
Age_t	-2.4556***	-2.4243***	-2.4115***
	(0.8718)	(0.8758)	(0.8804)
$[Age_t]^2$	0.1531***	0.1515***	0.1510***
	(0.0373)	(0.0375)	(0.0376)
$MaxChair_t$	-1.5212	-1.5325	-1.5329
	(1.1711)	(1.1714)	(1.1714)
$ArtCit3_t$	1.2478*	1.2473*	1.2488*
	(0.7365)	(0.7364)	(0.7365)
$BtwCentArt3_t$	-16.8000***	-16.8000***	-16.8000***
	(4.5891)	(4.5913)	(4.5912)
$[BtwCentArt3_t]^2$	2.7211***	2.7329***	2.7329***
	(0.8636)	(0.8641)	(0.8641)
$CliqnessArt3_t$	0.3912	0.3855	0.3970
	(0.7152)	(0.7153)	(0.7199)

Table H.14 : Impact of patent–grant pairs on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*]– Tobit results HBC (69 – 71) (Cont'd and end)

Variables	**HBC (69)**	**HBC (70)**	**HBC (71)**
BtwCentPat3$_t$	1.0899**	1.1000**	1.0950**
	(0.4780)	(0.4787)	(0.4800)
CliqnessPat3$_t$	0.0011***	0.0011***	0.0011***
	(0.0003)	(0.0003)	(0.0003)
dAcAssignee$_t$	-3.3386	-3.4080	-3.4053
	(2.3656)	(2.3728)	(2.3729)
dNanoEx	2.9421	2.8557	2.8642
	(2.7100)	(2.7197)	(2.7203)
dPGP$_t$		1.9509	5.1673
		(5.2071)	(23.1908)
dPGP$_t$ × CliqnessArt3$_t$			-0.7388
			(5.1905)
Constant	58.6359***	58.4885***	58.3656***
	(6.9144)	(6.9254)	(6.9791)
Constant (Sigma)	31.8911***	31.8899***	31.8895***
	(0.7567)	(0.7567)	(0.7566)
Statistics			
Nb observations	1110	1110	1110
Chi Square	116.91	117.051	117.071
Pseudo R^2	0.0117	0.0117	0.0117
P value	0.0000	0.0000	0.0000

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

Table H.15 : Impact of patent–grant pairs on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results HBC (72 – 74)

Variables	**HBC (72)**	**HBC (73)**	**HBC (74)**
Grant3$_t$	-3.8361***	-3.8807***	-3.8748***
	(0.8829)	(0.8861)	(0.8863)
[Grant3$_t$]^2	0.3169***	0.3213***	0.3207***
	(0.0713)	(0.0716)	(0.0717)
NbClaims$_t$	3.2788***	3.2655***	3.2699***
	(1.2047)	(1.2046)	(1.2046)
Age$_t$	-2.4215***	-2.4025***	-2.3676***
	(0.8757)	(0.8774)	(0.8842)
[Age$_t$]^2	0.1514***	0.1504***	0.1491***
	(0.0375)	(0.0376)	(0.0378)
MaxChair$_t$	-1.5288	-1.5092	-1.5098
	(1.1713)	(1.1717)	(1.1717)
ArtCit3$_t$	1.2544*	1.2202*	1.2191*
	(0.7366)	(0.7384)	(0.7384)
BtwCentArt3$_t$	-16.8000***	-17.1000***	-17.1000***
	(4.5916)	(4.6010)	(4.6013)
[BtwCentArt3$_t$]^2	2.7412***	2.7556***	2.7570***
	(0.8643)	(0.8644)	(0.8644)
CliqnessArt3$_t$	0.3798	0.3913	0.4194
	(0.7154)	(0.7154)	(0.7208)
BtwCentPat3$_t$	1.0997**	1.1174**	1.1067**
	(0.4787)	(0.4795)	(0.4806)

Table H.15 : Impact of patent–grant pairs on the Herfindahl index of backward citations [*HerfIndexBWCit$_t$*] – Tobit results HBC (72 – 74) (Cont'd and end)

Variables	**HBC (72)**	**HBC (73)**	**HBC (74)**
CliqnessPat3$_t$	0.0012***	0.0012***	0.0012***
	(0.0003)	(0.0003)	(0.0003)
dAcAssignee$_t$	-3.5178	-3.4815	-3.4748
	(2.3901)	(2.3901)	(2.3901)
dNanoEx	2.7683	2.8721	2.8954
	(2.7291)	(2.7337)	(2.7345)
dPGP$_t$	-5.3643	-8.3549	-1.5733
	(19.9155)	(20.5129)	(29.5809)
dPGP$_t$ × CliqnessArt3$_t$			-1.7204
			(5.4069)
dPGP$_t$ × NbClaims$_t$	2.6957	2.3746	2.4420
	(7.0838)	(7.0980)	(7.1008)
dPGP$_t$ × BtwCentArt3$_t$		5.9256	6.2607
		(9.9508)	(10.0059)
dPGP$_t$ × [BtwCentArt3$_t$]^2		-0.0471	-0.0433
		(0.1655)	(0.1659)
Constant	58.6333***	58.6444***	58.3535***
	(6.9351)	(6.9360)	(6.9958)
Constant (Sigma)	31.8868***	31.8795***	31.8777***
	(0.7566)	(0.7564)	(0.7564)
Nb observations	1110	1110	1110
Chi Square	117.196	117.662	117.763
Pseudo R^2	0.0117	0.0118	0.0118
P value	0.0000	0.0000	0.0000

APPENDIX I – *T*-TEST AND TEST OF VARIANCE

Table I.1 : Mean comparison between patent–paper pairs / non-patent–paper pairs groups for forward citation

Over	Nb Observations	Mean	Std.Err.	[95% Conf.	Interval]
($NbFCit5_t$)]					
No patent–paper pairs	940	0.6073	0.0233	0.5615	0.6530
Patent–paper pairs	170	0.5471	0.0465	0.4558	0.6383

Table I.2 : Test of variances for patent–paper pairs / non-patent–paper pairs

Group	Obs	Mean	Std.Err.	Std.Dev.	[95% Conf.	Interval]
No patent–paper pairs	940	0.6073	0.0233	0.7151	0.5615	0.6530
Patent–paper pairs	170	0.5471	0.0465	0.6063	0.4553	0.6389
Combined	1110	0.5980	0.0210	0.6996	0.5568	0.6392

ratio = sd(0) / sd(1) f = 1.3914

Ho: ratio = 1 degrees of freedom = 939, 169

Ha: ratio < 1 Ha: ratio!= 1 Ha: ratio > 1

$\Pr(F < f) = 0.9961$ $2*\Pr(F > f) = 0.0078$ $\Pr(F > f) = 0.0039$

Table I.3 : Two-sample *t*-test with equal variances patent–paper pairs / non-patent–paper pairs

Group	Obs	Mean	Std.Err.	Std.Dev.	[95% Conf.	Interval]
No patent–paper pairs	940	0.6073	0.0233	0.7151	0.5615	0.6530
Patent–paper pairs	170	0.5471	0.0465	0.6063	0.4553	0.6389
Combined	1110	0.5980	0.0210	0.6996	0.5568	0.6392
Diff		0.0602	0.0583		-0.0542	0.1746

diff = mean(0) - mean(1) t = 1.0321

Ho: diff = 0 degrees of freedom = 1108

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0

$\Pr(T < t) = 0.8489$ $\Pr(|T| > |t|) = 0.3022$ $\Pr(T > t) = 0.1511$

Table I.4 : Mean comparison between exclusive academic assignees / non-academic assignees groups for forward citation

Group	Obs	Mean	Std.Err.	Std.Dev.	[95% Conf.	Interval]
($NbFCit5_t$)]						
Not Academic Assignees	1075	0.6019	0.0214	0.7029	0.5598	0.6439
Academic Assignees	35	0.4802	0.0991	0.5863	0.2788	0.6816
Combined	1110	0.5980	0.0210	0.6996	0.5568	0.6392

Table I.5 : Test of variance for exclusive academic assignees / non-academic assignees

Group	Obs	Mean	Std.Err.	Std.Dev.	[95% Conf.	Interval]
Not Academic Assignees	1075	0.6019	0.0214	0.7029	0.5598	0.6439
Academic Assignees	35	0.4802	0.0991	0.5863	0.2788	0.6816
Combined	1110	0.5980	0.0210	0.6996	0.5568	0.6392

ratio = sd(0) / sd(1) f = 1.4374
Ho: ratio = 1 degrees of freedom = 1074, 34
Ha: ratio < 1 Ha: ratio!= 1 Ha: ratio > 1
Pr($F < f$) = 0.9055 2*Pr($F > f$) = 0.1890 Pr($F > f$) = 0.0945

Table I.6 : t-test with equal variances for exclusive academic assignees / non-academic assignees

Group	Obs	Mean	Std.Err.	Std.Dev.	[95% Conf.	Interval]
Not Academic Assignees	1075	0.6019	0.0214	0.7029	0.5598	0.6439
Academic Assignees	35	0.4802	0.0991	0.5863	0.2788	0.6816
Combined	1110	0.5980	0.0210	0.6996	0.5568	0.6392
Diff		0.1217	0.1202		-0.1141	0.3575

diff = mean(0) - mean(1) t = 1.0127
Ho: diff = 0 degrees of freedom = 1108
Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr($T < t$) = 0.8443 Pr($|T| > |t|$) = 0.3114 Pr($T > t$) = 0.1557

Table I.7 : Mean comparison between exclusive government assignee / non-government assignee groups for forward citations

Over	Nb Observations	Mean	Std.Err.	[95% Conf.	Interval]
($NbFCit5_t$)]					
Not Government Assignees	932	0.6127	0.0233	0.5670	0.6584
Government Assignees	178	0.5212	0.0476	0.4277	0.6146

Table I.8 : Test of variances for exclusive government assignees / non-government assignees

Group	Obs	Mean	Std.Err.	Std.Dev.	[95% Conf.	Interval]
Not Government Assignees	932	0.6127	0.0233	0.7106	0.5670	0.6584
Government Assignees	178	0.5212	0.0476	0.6354	0.4272	0.6152
Combined	1110	0.5980	0.0210	0.6996	0.5568	0.6392

ratio = sd(0) / sd(1) f = 1.2507
Ho: ratio = 1 degrees of freedom = 931, 177
Ha: ratio < 1 Ha: ratio!= 1 Ha: ratio > 1
Pr($F < f$) = 0.9680 2*Pr($F > f$) = 0.0639 Pr($F > f$) = 0.0320

Table I.9 : *t*-test with unequal variances for exclusive government assignees / non-government assignees

Group	Obs	Mean	Std.Err.	Std.Dev.	[95% Conf.	Interval]
Not Government Assignees	932	0.6127	0.0233	0.7106	0.5670	0.6584
Government Assignees	178	0.5212	0.0476	0.6354	0.4272	0.6152
Combined	1110	0.5980	0.0210	0.6996	0.5568	0.6392
Diff		0.0915	0.0530		-0.0128	0.1959

diff = mean(0) - mean(1) t = 1.7267
Ho: diff = 0 Satterthwaite's degrees of freedom = 268.74
Ha: diff < 0 Ha: diff!= 0 Ha: diff > 0
$\Pr(T < t) = 0.9573$ $\Pr(|T| > |t|) = 0.0854$ $\Pr(T > t) = 0.0427$

Table I.10 : Mean estimation for patent–grant pairs / non-patent–grant pairs groups for forward citation

Over	Nb Observations	Mean	Std.Err.	[95% Conf.	Interval]
($NbFCit5_t$)]					
No patent–grant pairs	1069	0.6110	0.0214	0.5689	0.6531
Patent–grant pairs	41	0.2597	0.0879	0.0872	0.4322

Table I.11 : Test of variance for patent–grant pairs / non-patent–grant pairs

Group	Obs	Mean	Std.Err.	Std.Dev.	[95% Conf.	Interval]
No patent–grant pairs	1069	0.6110	0.0214	0.7013	0.5689	0.6531
Patent–grant pairs	41	0.2597	0.0879	0.5629	0.0821	0.4374
Combined	1110	0.5980	0.0210	0.6996	0.5568	0.6392

ratio = sd(0) / sd(1) f = 1.5524
Ho: ratio = 1 degrees of freedom = 1068, 40
Ha: ratio < 1 Ha: ratio!= 1 Ha: ratio > 1
$\Pr(F < f) = 0.9585$ $2*\Pr(F > f) = 0.0829$ $\Pr(F > f) = 0.0415$

Table I.12 : Test of means if unequal variance between groups for patent–grant pairs / non-patent–grant pairs

Group	Obs	Mean	Std.Err.	Std.Dev.	[95% Conf.	Interval]
No patent–grant pairs	1069	0.6110	0.0214	0.7013	0.5689	0.6531
Patent–grant pairs	41	0.2597	0.0879	0.5629	0.0821	0.4374
Combined	1110	0.5980	0.0210	0.6996	0.5568	0.6392
Diff		0.3513	0.0905		0.1690	0.5336

diff = mean(0) - mean(1) t = 3.8824
Ho: diff = 0 Satterthwaite's degrees of freedom = 44.8991
Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
$\Pr(T < t) = 0.9998$ $\Pr(|T| > |t|) = 0.0003$ $\Pr(T > t) = 0.0002$

APPENDIX J – STANDARD TERMS, APA FORMAT

Table J.1 : Guide to usage of en dash (–) and hyphen (-) in key phrases in this research

University–industry linkages	en dash (–)	Refers to the links between university and industry
Authors-inventors	hyphen (-)	Refers to authors who are also inventors (same person)
Author–inventor	en dash (–)	Refers to an author who is paired with an inventor (different people)
Patent–paper pair	en dash (–)	Indicates a pair consisting of a patent and a paper
Patent–grant pair	en dash (–)	Indicates a pair consisting of a patent and grant
Co-authorship	hyphen (-)	Collaborative network of authors
Co-invention	hyphen (-)	Collaborative network of inventors
Co-assignees	hyphen (-)	Collaborative network of assignees
Bayh–Dole Act	en dash (–)	US legislation allowing public patentees (including universities) with government funding to claim private patent ownership

Reference: (*Publication manual of the American Psychological Association* 2010, p. 97)

APPENDIX K – CORRELATION MATRIX

Table K.1 : Correlation matrix of the model linked to patent–paper pairs similarity [$Similarity_t$]

		1	2	3	4	5	6	7	8
[$Grant3_t$] [a]	1	1							
[$Contract3_t$] [a]	2	0.5590*	1						
[$Contract3U_{t-2}$] [a]	3	0.6009*	0.5243*	1					
[$GrantEI3_{t-1}$] [a]	4	0.4830*	0.3333*	0.3325*	1				
[Age_t] [a]	5	0.0478	0.0302	0.0586	0.1199*	1			
[$MaxChair_t$] [a]	6	0.2571*	0.2187*	0.1950*	0.3312*	0.0872*	1		
[$ArtCit3_t$] [a]	7	0.1705*	0.1824*	0.0949*	0.1194*	0.1932*	0.0890*	1	
[$BtwCentArt3_t$] [a]	8	0.2231*	0.1762*	0.2408*	0.1738*	-0.0104	0.0483	0.4939*	1
$CliqnessArt3_t$	9	0.0111	0.0743*	0.0433	0.0458	-0.2250*	-0.033	0.1018*	0.3290*
[$CliqnessPat3_t$] [a]	10	0.1428*	-0.015	0.0590*	0.0825*	0.0983*	0.0431	-0.1390*	-0.2850*
[$BtwCentPat3_t$] [a]	11	-0.3587*	-0.1526*	-0.2229*	-0.0822*	0.0646*	-0.0673*	0.1209*	0.1285*
Loop	12	0.2393*	0.3103*	0.1390*	0.1410*	0.0727*	0.0818*	0.0864*	-0.0610*
$dAcAssignee_t$	13	0.1216*	-0.0097	-0.025	0.0636*	-0.1127*	0.0391	0.0577	-0.012
dNanoEx	14	-0.0071	-0.0649*	-0.0036	0.0799*	0.0935*	-0.0251	-0.0429	0.0108
$Similarity_t$ [a]	15	0.0856*	0.0177	-0.0223	0.0041	-0.1585*	-0.0113	0.1253*	0.1381*

		9	10	11	12	13	14	15
$CliqnessArt3_t$	9	1						
[$CliqnessPat3_t$] [a]	10	-0.2286*	1					
[$BtwCentPat3_t$] [a]	11	0.2561*	-0.4697*	1				
Loop	12	-0.1775*	0.0990*	-0.1417*	1			
$dAcAssignee_t$	13	-0.1416*	0.1299*	-0.2380*	0.2458*	1		
dNanoEx	14	-0.1183*	0.1229*	-0.1135*	-0.0349	0.0077	1	
$Similarity_t$ [a]	15	0.1314*	-0.1021*	0.0334	0.1054*	0.2618*	-0.1275*	1

Note: [(a)] All the variables have been calculated by Z Score (Z) = x – μ / σ, μ=mean and σ = standard deviation. Furthermore, * corresponds to a 1% significance level.

Table K.2 : Correlation matrix of the model related to academic [$dAcAssignee_t$] and government assignees [$dGovAssignee_t$]

Variables		1	2	3	4	5	6	7	8
$NbFCit5_t$	1	1							
$NbClaims_t$	2	0.1166*	1						
$HerfIndexFCit5_t$	3	-0.1213*	0.0288	1					
$HerfIndexBWCit_t$	4	-0.0146	0.1068*	0.0642*	1				
$Grant3_t$	5	0.0359	0.0047	-0.0539	-0.0021	1			
Age_t	6	-0.1205*	0.0749*	0.0016	0.1566*	0.0639*	1		
$MaxChair_t$	7	0.0089	0.0041	0.011	-0.0375	0.2571*	0.1194*	1	
$ArtCit3_t$	8	-0.0783*	-0.0844*	0.0205	0.0545	0.1705*	0.1773*	0.0890*	1
$BtwCentArt3_t$	9	0.0468	-0.0993*	-0.0071	-0.0095	0.2231*	-0.0181	0.0483	0.4939*
$CliqnessArt3_t$	10	0.0633*	-0.1281*	-0.0397	-0.0382	0.024	-0.0811*	-0.0392	0.1715*
$BtwCentPat3_t$	11	-0.0493	-0.0446	0.0235	0.0118	-0.3587*	0.1032*	-0.0673*	0.1209*
$CliqnessPat3_t$	12	0.0042	0.0986*	0.0129	0.0860*	0.1428*	0.0695*	0.0431	-0.1390*
Loop	13	-0.0545	-0.0078	-0.0399	0.0081	0.2393*	0.1028*	0.0818*	0.0864*
dNanoEx	14	0.1387*	0.1890*	-0.025	0.0526	-0.0071	0.0082	-0.0251	-0.0429
$dGovAssignee_t$	15	-0.0304	0.0025	-0.0367	-0.0920*	0.0109	0.0033	-0.0301	-0.0182
$dAcAssignee_t$	16	-0.048	-0.0382	-0.002	-0.0814*	0.1629*	-0.1085*	0.0427	0.0422

Variables		9	10	11	12	13	14	15	16
$BtwCentArt3_t$	9	1							
$CliqnessArt3_t$	10	0.3822*	1						
$BtwCentPat3_t$	11	0.1285*	0.2478*	1					
$CliqnessPat3_t$	12	-0.2850*	-0.2405*	-0.4697*	1				
Loop	13	-0.0610*	-0.1069*	-0.1417*	0.0990*	1			
dNanoEx	14	0.0108	-0.1055*	-0.1135*	0.1229*	-0.0349	1		
$dGovAssignee_t$	15	0.0019	0.0151	-0.1060*	0.0306	-0.0973*	0.0176	1	
$dAcAssignee_t$	16	-0.0257	-0.0876*	-0.2281*	0.1272*	0.2463*	-0.0079	-0.0789*	1

Note: * corresponds to a 1% significance level.

Table K.3 : Correlation matrix of the model including patent–grant pairs [$dPGP_t$]

Variables		1	2	3	4	5	6	7	8
$NbFCit5_t$	1	1							
$NbClaims_t$	2	0.1166*	1						
$HerfIndexFCit5_t$	3	-0.1213*	0.0288	1					
$HerfIndexBWCit_t$	4	-0.0146	0.1068*	0.0642*	1				
$Grant3_t$	5	0.0359	0.0047	-0.0539	-0.0021	1			
Age_t	6	-0.1205*	0.0749*	0.0016	0.1566*	0.0639*	1		
$MaxChair_t$	7	0.0089	0.0041	0.011	-0.0375	0.2571*	0.1194*	1	
$ArtCit3_t$	8	-0.0783*	-0.0844*	0.0205	0.0545	0.1705*	0.1773*	0.0890*	1
$BtwCentArt3_t$	9	0.0468	-0.0993*	-0.0071	-0.0095	0.2231*	-0.0181	0.0483	0.4939*
$CliqnessArt3_t$	10	0.0633*	-0.1281*	-0.0397	-0.0382	0.024	-0.0811*	-0.0392	0.1715*
$BtwCentPat3_t$	11	-0.0493	-0.0446	0.0235	0.0118	-0.3587*	0.1032*	-0.0673*	0.1209*
$CliqnessPat3_t$	12	0.0042	0.0986*	0.0129	0.0860*	0.1428*	0.0695*	0.0431	-0.1390*
Loop	13	-0.0545	-0.0078	-0.0399	0.0081	0.2393*	0.1028*	0.0818*	0.0864*
$dAcAssignee_t$	14	-0.0673*	-0.0135	0.0144	-0.0712*	0.1325*	-0.0716*	0.0383	0.0608*
dNanoEx	15	0.1387*	0.1890*	-0.025	0.0526	-0.0071	0.0082	-0.0251	-0.0429
$dPGP_t$	16	-0.0947*	0.0317	0.0725*	0.0239	0.0577	0.045	0.0431	0.013

Variables		9	10	11	12	13	14	15	16
$BtwCentArt3_t$	9	1							
$CliqnessArt3_t$	10	0.3822*	1						
$BtwCentPat3_t$	11	0.1285*	0.2478*	1					
$CliqnessPat3_t$	12	-0.2850*	-0.2405*	-0.4697*	1				
Loop	13	-0.0610*	-0.1069*	-0.1417*	0.0990*	1			
$dAcAssignee_t$	14	0.0157	-0.0944*	-0.2153*	0.0870*	0.2965*	1		
dNanoEx	15	0.0108	-0.1055*	-0.1135*	0.1229*	-0.0349	0.0041	1	
$dPGP_t$	16	-0.004	-0.0322	-0.0995*	0.0451	0.0202	0.0925*	0.1068*	1

Note: * corresponds to a 1% significance level.