Effect of Inventors' Characteristics on Commercialization Potential of their Inventions: The Case of Nanotechnology in Canada

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Abstract

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Innovation may significantly contribute to building and maintaining competitive advantage of companies. It is therefore imperative to invest in research activities which will lead to innovative accomplishments that can be successfully patented. However, only a small portion of these patents will ever be commercialized in the form of a new product introduction or a patent license. The main purpose of this thesis is to examine various factors which might increase the commercialization potential of the patented inventions. We investigate the impact of collaboration patterns of inventors and also their various individual characteristics and the attributes related to their work on the commercialization potential of the inventions. While focusing on Canadian nanotechnology innovation ecosystem we exploit the data spanning 25 years of United States Patent Trademark Office (USPTO) patent documents. Based on the co-inventorship information captured in the patents the network of inventors' collaborations is developed. To evaluate collaboration patterns of inventors the relevant structural properties assessing collaborative intensity and access to knowledge and ideas through the network are measured. Furthermore, various attributes and features of inventors related to their education, working experience and to the characteristics of their workplace are collected via Google and LinkedIn. The statistical model assessing the impact of the various collaboration and individual characteristics of inventors on the commercialization potential of their inventions is then developed. The results show that those inventors who collaborate with higher number of other inventors and those who occupy more central positions in the collaboration network and thus enjoy an enhanced access to knowledge and ideas tend to produce inventions with higher commercialization potential. Moreover, the results also indicate that having graduate education in engineering and being employed in non-academic institution, especially in companies with lower number of employees are factors which may enhance the commercialization potential of the patented inventions as well.

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Contents

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List of acronyms

Acronym	Definition
AFM	Atomic Force Microscopy
CSV	Comma-Separated Values
EDX	Energy Dispersive X-ray Spectroscopy
EELS	Electron Energy-Loss Spectroscopy
EPO	European Patent Office
FDI	Foreign Direct Investment
FLEED	Finnish Linked Employer-Employee data of Statistics Finland
HRTEM	High-Resolution Transmission Electron Microscopy
JPO	Japanese Patent Office
KDE	Kernel Density Estimate
NEMS	Nanoelectromechanical Systems
OLS	Ordinary Least Squares
PDMS	Polydimethylsiloxane
R&D	Research and Development
SEM	Scanning Electron Microscope
STM	Scanning Tunneling Microscopy
TEM	Transmission Electron Microscopes
USPTO	United States Patent Trademark Office

Chapter 1 Introduction and motivation

Innovation can create a lot of advantages for firms and individuals in any industrial and scientific field. Innovation also helps firms to keep their competitive advantages and enter new markets. Therefore, many firms invest a lot of money in research activities to increase their knowledge level and achieve new ideas and information. Hence, the concept of innovation is becoming a critical factor in firms' performance and survival because of the progress of the competitive environment (Alegre and Chiva 2008).

Patents can be used as an indicator of innovation (Lee and Lee 2013). The researchers used the number of patents (Narin et al. 1987), citations (Guan and Zhao 2013), claims[1] (Beaudry and Schiffauerova 2011), and patent family size[2] (Y. Chang et al. 2010) to assess the quantity and quality of innovation performance but the patent evaluation is very difficult before their commercialization (Hsieh 2013) because if the patent cannot be commercialized, the main goal of patenting is missed. Therefore, the commercialization potential of patents is extremely important for organizations and individuals. Although the commercialization of patents is very important for organizations, it should be mentioned that patenting can be due to the different reasons including preventing others from exploiting the patented technology, and increasing the overall corporate value by enhancing the company's intellectual asset (S. Hunter 2005). The main reason of patenting is varied in different industries and sectors (Orsenigo and Sterzi

[1] Patent claims are a series of numbered expression that define the boundaries of the invention by mentioning exactly what is claimed by the invention and clarify what the patent does and not does cover (Beaudry and Schiffauerova 2011).

[2] Patent family size is the number of countries in which an invention is protected by a patent (Kabore and Park 2019).

2010). For example, in aerospace industry the main reason of patenting is the protecting the innovation from the competitors (Klein 2018).

Many factors can affect the commercialization potential of patents like patent ownership (Giuri et al. 2013), number of inventors (Su and Lin 2018), individual characteristics of inventors (Wu et al. 2015), number of references (Su and Lin 2018), patent policy (Gong and Peng 2018), etc. The focus of this study is investigating the effect of individual characteristics and collaboration patterns of inventors on the commercialization potential of their inventions.

Many studies showed that the collaboration between inventors may increase the quantity and quality of innovation (Beaudry and Schiffauerova 2011; Guan and Zhao 2013; Schilling and Phelps 2007). This collaboration can be measured by creating the network of inventors (Schilling and Phelps 2007).

In the network of inventors, the flow of knowledge has a great effect on the productivity and the quality of innovation because the knowledge can lead to the creation of new ideas and methods for the inventors in the network (Schilling and Phelps 2007). The level of access to a variety of knowledge helps inventors to make inventions with higher quality and economic value. Therefore, it is very important at individuals' and organizations' level to be well-connected in the network to keep their advantages among the competitors because nowadays the knowledge and good ideas make differences among inventors and organizations.

As mentioned above being well-connected in the network creates a lot of advantages for the inventors in the networks. Therefore, there is a need to have a better understanding of the networks. The process of diffusion of knowledge and ideas in the network can have an impact on inventors' and organizations' performance in any industrial and scientific field. Besides, the information about networks in different fields can help governments or international organizations to make their policies and manipulate the networks to increase their efficiency.

In addition, the individual characteristics of inventors might have an impact on the commercialization potential of inventors' patents. The investigation of the impact of individual characteristics of inventors such as age, experience, education, industrial or academic affiliation, and available funds might be helpful to have a comprehensive understanding of the impact of inventors' characteristics on the commercialization potential of inventors' patents.

In this study, the collaboration patterns and some individual characteristics of inventors will be studied, and some light will be shed on their effect on the commercialization potential of patents.

The data used in this study are taken from the field of nanotechnology in Canada. This segment of the industry is of great importance for Canada, it is a relatively new industry with a great potential for growth. In addition, nanotechnology provides a significant contribution to science and innovation, many jobs, and large exports.

The content of this thesis will provide a deeper understanding of the effect of the collaboration network and individual characteristics on the commercialization potential of patents in the nanotechnology industry in Canada. The results can serve as a basis to design government or organization policies and strategies.

Chapter 2 Literature review

2.1 Introduction

In this chapter, the related literature that investigated the effect of collaboration network and individual characteristics on innovation and commercialization potential is reviewed in detail. The following concepts have been reviewed: the concept of innovation and patent commercialization, the collaboration network characteristics and measures, and the literature related to the individual characteristics. At the end of this chapter, the research gaps in the literature and the objectives of this thesis will be discussed.

2.2 Innovation

The origin of the word innovation belongs to the Latin word "Innovare" which means "to make something new" (Mohd Zawawi et al. 2016). In another study, innovation is defined as the entrepreneurs' specific tool to exploit changes for a variety of businesses or services (Drucker 1985). But the modern definition for innovation is "a new idea, creative thoughts, new imaginations in the form of device or method " (Merriam-Webster 2020).

As mentioned before, innovation is very important in any industry. Therefore, the activities or any factors that can affect innovation must be important for firms to keep their competitive advantages and an interesting subject for researchers to investigate. Researchers examined the effect of various factors including individual and institutional factors (Wu et al. 2015), collaboration patterns (Beaudry and Schiffauerova 2011), and policies (Gong and Peng 2018) on the innovation in the different fields.

There is an important issue that is finding the proper index to measure the innovation accurately. There are a lot of studies that considered patents as the innovation indicator, for instance, some studies considered the number of patents as an indicator for the quantity of innovation and did not consider the innovation quality (Demirkan and Demirkan 2012; Liang and Liu 2018). In other studies, researchers have used a few indicators including the number of claims (Beaudry and Schiffauerova 2011), patent family size (Guan and Zhao 2013), and patent commercialization (Gong and Peng 2018; Su and Lin 2018; Wu et al. 2015) to represent the quality of patents and innovation.

2.3 Patent commercialization

For the individuals who work in the academic or industrial fields patenting can be helpful to enhance their career position and credits. As mentioned before, patenting can be used for protecting innovation from other competitors, increasing the corporate's intellectual asset, and the commercialization. The commercialization of patents is beneficial for patent owners because they can earn money from the commercialized patents (Porey 2010). Since the proportion of commercialized patents to all patents is low, patent commercialization is a very important issue for patent owners in many industries and sectors, and finding the parameters which can have an impact on the commercialization potential of patents is very useful in a variety of industries (Griffin 1997).

Many studies investigated patent commercialization from different perspectives, while focusing on different aspects such as the effect of patent policy (Gong and Peng 2018; Sternitzke 2010), patent-based measures[3] (Cohen et al. 2000; Su and Lin 2018; Wagner and Wakeman 2016), and individual characteristics of inventors (Giuri et al. 2013; Weick and Eakin 2005; Wu et al. 2015). Some of the most important research studies are reviewed below.

Webster and Jensen (2011) found that there is a negative relationship between being a refused patent and commercialization. They found out when a patent application of an invention has

[3] Patent-based measures are common indicators that indicate a category of parameters like nonpatent reference count, foreign reference count, claim count, and family size that can be found in the patent documents.

been refused, the probability of attempting market launch and mass production of the product based on this invention will be decreased.

Giuri et al. (2013) investigated the commercialization potential of academic patents to find out how the patent ownership affects the probability of patent commercialization. They studied the commercialization of patents in a sample of 858 universities and public research organizations that were filed with the European Patent Office from 2003 to 2005 across 22 countries. Their results suggested that university ownership and the institutional intellectual property regime positively affect the probability of commercialization potential of patents. This means the inventions which have been patented in the countries with institutional intellectual property regime have higher commercialization potential. In addition, if the assignee of a patent is a university the commercialization potential will be higher.

Another study in patent commercialization has been carried out by Su and Lin (2018). They considered the patent-based measures that have effects on the probability of patent approval and the speed of patent commercialization in the United States pharmaceutical industry. A total of 2943 drugs and 4660 corresponding patents have been investigated to find out which parameters have an impact on the probability of FDA approval (and thus subsequent commercialization) and on product commercialization speed (the time that elapses between initial development of a new drug and the ultimate commercialization as the introduction of a new drug into the marketplace). They found that inventor count, nonpatent reference count, foreign reference count, and claim count increase the speed and the probability of patent commercialization.

In another study, Wu et al. (2015) investigated the effect of individual and institutional factors on the likelihood that a patent with a university assignee will be licensed. They found that the probability of licensing is significantly correlated with individual factors including inventors' tendency towards commercialization of research, additional research implemented during the patent review, and collaboration with researchers who work in the industry. Besides, they found that institutional factors including the proportion of the fund coming from industry, university technology transfer office (TTO) service effectiveness, and perceived TTO's coverage of patenting fees have a positive effect on licensing.

Gong and Peng (2018) investigated the effect of patent policy on the potential commercialization of patents. This study is based on the data collected from 64 universities that were directly under the Ministry of Education in China from 2009 to 2015. They found out that China's enactment of incentivized patent policy, which aimed at promoting scientific research and patent applications, has increased the number of university patents but not increased the university patent commercialization potential in China. According to the results, they suggested that patent policies focusing on the number of patent applications in the short term can increase the number of patent applications, but it negatively affects the university's sustainable development in the long run by reducing the enthusiasm of the university patent commercialization.

In the above articles, the parameters including patent policy, individual characteristics of inventors, and the patent-based measures that affect patent commercialization have been reviewed. However, the effect of collaboration among individuals and organizations on the commercialization potential of patents has not been so far discussed in previous literature. There is substantial evidence that innovation performance at the level of individuals and firms is related to the collaboration patterns (Demirkan and Demirkan 2012; Muller and Peres 2019), but the impact on commercialization has been neglected. In addition, there is only one study (Wu et al. 2015) that has investigated the impact of some individual characteristics on patent commercialization. And these two parameters – inventors' collaboration patterns and several individual characteristics such as their education level or their experience – are going to be the main focus of this thesis in which we will shed some light on their effects on the commercialization. In the following two sections, we are first going to discuss collaboration networks while highlighting the effects of the collaboration network structure on innovation, and then we shift the focus on the individual characteristics of inventors and the related literature.

2.4 Network

In everyday life, people are involved various networks such as those of their friends, colleagues, and families. The concept of networks has been used in engineering for the management of complex systems for a long time, especially in transport and communications. Sociologists in the 1960 and 1970s used the concept of the network to understand norms, exchange, and power (Cook 2014). In the 1980s the concept of the network had become one of the most important tools in the social sciences (DeBresson and Amesse 1991).

2.4.1 Networks of innovators

Nowadays, organizations and firms work together to take advantage of the knowledge and resource trading among themselves. In contrast with a belief that working alone and keeping the ideas disguised is better than collaboration, many studies showed that collaboration with other people can lead to remarkable and outstanding results (Trodd 1999). In many studies, in which the effect of collaboration on innovation in the form of patents and publications has been investigated, it was found that collaboration can boost innovation at the individual's and firm's levels (Ahuja 2000; Beaudry and Schiffauerova 2011; Liang and Liu 2018; Schilling and Phelps 2007; Wang 2016).

Many studies investigated the effect of collaboration networks on knowledge transfer (Ioanid et al. 2018). The studies showed that the collaboration network can facilitate knowledge transfer and help the innovators in the network to contribute to innovation activities including patents, research papers, books, or new technologies (Ahuja 2000; Eslami et al. 2013; Guan and Zhao 2013).

Scientists and inventors often collaborate, which provides them with easier access to knowledge and any other kind of resources such as equipment or funding from the other scientists or inventors. This cooperation can be represented as a network in which the nodes are inventors or scientists, and they are connected by edges. These edges represent common collaborations. However, in many cases, their collaborations cannot be traced by any official trace or contracts because these are rare among scientists or inventors. Therefore, these relationships are traced through the outcomes of their common activities. For scientific networks, the result of cooperation can be a publication, where the collaboration is traced by a co-authorship of an article, paper, book, etc., whereas in the network of inventors, the traceable outcome of cooperation is usually an invention where the collaborations are evidenced by co-inventorship of a patent. Consequently, the information on the co-authorship can be extracted from journal articles and the co-inventorship information can be found in the patents' documents (Eslami et al. 2013).

2.5 Structural properties of a network

Many researchers proposed the social and economic importance of networking among organizations and individuals (Ahuja 2000; Eslami et al. 2013; Ioanid et al. 2018; Liang and Liu 2018; Wang 2016). It was also proposed that the successful flow of knowledge and innovation depends on the collaboration patterns and shapes of the networks of researchers and inventors, and thus on structural properties of the collaboration network (Chen et al. 2017; Eslami et al. 2013; Schilling and Phelps 2007). The collaboration network structural properties are suggested to be able not only to shape innovation (Keeling and Eames 2005; Muller and Peres 2019; Newman 2001) but also to affect the innovation potential of firms (Schilling and Phelps 2007). The structural properties of networks are represented by various measures and indexes. Some of these indexes explain the number of direct and indirect connections that a node has and some of them give us some information about the position of the node, some indexes clarify the role of nodes in the networks and some indexes give us information about the whole structure of the networks. In the following section, the most important and frequent indexes are explained.

2.5.1 Degree centrality

The simplest centrality (being in the center of the network) measure is degree centrality. The degree centrality of a node is the number of collaborators of the node (Beaudry and Schiffauerova 2011). The inventors with a high degree centrality have a more central position in the network and some studies showed that the central position of an inventor can help the inventor to be more productive and produce innovation with higher quality (Beaudry and Schiffauerova 2011; Liang and Liu 2018).

2.5.2 Betweenness centrality

Betweenness centrality is an indicator that detects the amount of power of a node to control the flow of information, knowledge, and ideas in the network. A higher value for betweenness centrality means that the inventor has access to greater amount of knowledge, information, and ideas. It was also shown that these inventors have better innovation performance than others (Beaudry and Schiffauerova 2011).

Betweenness centrality and degree centrality give different information about the position of an inventor in the network (Golbeck 2013). Betweenness centrality indicates the ability of inventors to play a role as a bridge between different groups of inventors in the network, but the degree centrality indicates the number of inventors’ collaborators.

2.5.3 Closeness centrality

Closeness centrality measures how close a node is to all other nodes in the network. When a node is close to all other nodes the value of closeness centrality is high and if it is far from other nodes the value is low (McKnight 2014). Closeness centrality indicates how fast an innovator takes to spread information to all other innovators in the network. If an innovator has a high closeness centrality, it may be able to spread information quickly. These innovators in the network might be important players of the network (McKnight 2014).

2.5.4 Eigenvector centrality

Eigenvector centrality is used as a measure of the influence of a node in the network. Each node in the network will be given a score or value, the higher score indicates the greater influence of the node within the network (Abbasi et al. 2011). According to this definition, an innovator with a few connections in the network has a very high eigenvector centrality if he/she has connections to very well-connected innovators in the network (Hansen et al. 2020).

2.5.5 Clustering coefficient

In graph theory, the clustering coefficient is a measure of the degree to which the nodes in the network are clustered. This measure tells how the neighbors of a node are well-connected together. The clustering coefficient contributes to the easy diffusion of resources and provides a trustful environment for a group of firms (Schilling and Phelps 2007). Schilling and Phelps (2007) found out that the firms that are highly clustered and have a high reach (short average path lengths to a wide range of firms) have a better innovation performance in terms of the number of patents.

2.5.6 Network size

Network size is the number of nodes in a network. As a new innovator joins the network, there will be more chances for collaboration which will provide more opportunities for knowledge exchange for every other innovator and researcher in the network. Network size affects the overall scientific and innovation performance in the network (Beaudry and Schiffauerova 2011; Eslami et al. 2013).

2.6 Effect of collaboration network on innovation

A lot of novel ideas that lead to scientific publications or technological advances are the result of collaborations between scientists or inventors (Eslami et al. 2013). Many studies have been carried out to find the effect of collaboration network on scientific and innovation performance (Ahuja 2000; Beaudry and Schiffauerova 2011; Demirkan and Demirkan 2012; Eslami et al. 2013; Muller and Peres 2019; Wang 2016). To reach that goal, researchers used various indexes to explain the features of the networks, some of which were briefly introduced in the previous section. This section reviews the studies which investigated the effect of those features on scientific and innovation performance at the individual or organizational level.

Ahuja (2000) investigated the effect of collaboration network structure on innovation performance in the chemical industry. He represented innovation by the number of patents and created their network based on firms. He found that the number of direct ties[4] and the number of indirect ties[5] both has a positive impact on innovation, but the number of direct ties has a stronger effect than indirect ties. Although the effects of direct and indirect ties are positive on innovation, but the interaction of the number of direct ties and indirect ties had a negative effect

[4] Direct ties are defined as a connection between two nodes that have a direct relation in the network.

[5] Indirect ties are defined as a connection between two nodes who have no direct relation but are connected through a third person in the network.

because having many direct and indirect ties for a node is not **necessarily** beneficial. After all, the firms with many direct ties may not take advantage of their indirect ties because of the limitation in the ability of the absorption of information. He also found that the increase of the structural holes[6] harms innovation.

Beaudry and Schiffauerova (2011) investigated the effect of collaboration and network indicators on the quality of patents in the field of nanotechnology in Canada. They used the number of patent claims as the patent quality indicator. They studied 1218 patents from 1794 inventors between 1989 to 2004. They found that degree centrality has a positive effect on patent quality. The results also showed that the patents that at least have one inventor with high betweenness centrality have higher quality. Another important issue that was clarified by this study was the role of the number of collaborations, where the result showed that it has a negative effect on patent quality.

In another study, Abbasi et al. (2011) investigated the effect of collaboration networks on the researcher's citation-based performance. They assessed the effect of degree centrality, betweenness centrality, and network efficiency[7] on scientific performance in the field of information systems. They used the data from the period of 2001 to 2005 and they built the network with 2139 publications. They used the multiple Poisson regression model and found

[6] Structural holes indicate the disconnections between nodes' neighbors in the network.

[7] The efficiency of a network is a measure of the ability of network to efficiently exchanges information (Liang and Liu 2018). Network efficiency can be calculated in both local and global scale in the network. In the global scale, network efficiency measures the exchange of information that is shared throughout the whole network. In the local scale, the network efficiency measures a network's resilience to failure, when a node is removed, its local efficiency describes how effectively information is transferred by its neighbours (Latora and Marchiori 2001).

that the degree centrality of a researcher and the network efficiency has a positive effect on scientific performance. They did not find any significant effect for betweenness centrality.

Eslami et al. (2013) investigated the impact of collaboration network structure on knowledge creation and technological performance of biotechnology in Canada. They extracted data from SCOPUS and United States Patent and Trademark Office (USPTO) between the years 1973 to 2005. They used degree centralization[8], betweenness centralization[9], clustering coefficient, small-world phenomena[10], and network size to find the effect of collaboration network's features on scientific and innovation performance. They defined the research productivity of researchers by the number of articles they have. The technological performance of researchers was defined as the number of patents, and the quality of technological production was defined as the number of patent claims. They found that degree centralization has a very strong negative effect on productivity and technological performance. This is explained by the assumption that authors with a high number of direct ties can have a negative influence on knowledge and technological diffusion by blocking the transmission of information (Chung and Hossain 2009). The results showed that the effect of betweenness centralization on productivity is not significant, but it harms technological performance. This means that the existence of nodes that have the power to control the flow of information through the network is not helpful for the diffusion of innovative ideas in the network. The small world had a positive effect on both productivity and technological performance. The clustering coefficient hurt productivity, but it

[8] Degree centralization is an indicator of variation in degree centrality of nodes in the network.

[9] Betweenness centralization is an indicator of variation in betweenness centrality of nodes in the network.

[10] The implication that everybody has an indirect relation to everyone else by a limited number of intermediaries.

had a positive effect on technological performance. They did not find any significant effect of network features on technological production.

Although the result of many studies showed that degree centrality and betweenness centrality have a positive effect on innovation performance Eslami et al. (2013) suggested the non-homogenous distribution of these indexes in the network can hurt innovation. For example, the existence of some inventors with very high betweenness centrality or degree centrality can harm the whole network performance.

In another study, Gonzalez-Brambila et al. (2013) investigated the effect of collaboration network including degree centrality, weighted degree centrality[11], structural hole, eigenvector centrality on research output. They used data from 1981 to 2002 and considered all scientific articles that have at least one author from Mexico. They found that researchers with high degree centrality and weighted degree centrality publish articles with a higher number of citations than other researchers. They also found that the researchers who were involved in a network with a higher number of structural holes have papers with more citations than others. They could not find any significant effect for the degree centrality, weighted degree centrality, and structural holes on the number of publications but the eigenvector centrality had a positive effect on the number of publications.

Chen et al. (2017) investigated the effect of degree centrality and structural holes on the performance of industrial and scientific institutes in the scientific collaboration network. They used data from the period between 1978 to 2015 and they considered scientific performance as the number of Science Citation Index Expanded (SCIE) articles. Their results showed that the position of institutes in the network is strongly related to the scientific performance of the institute. The degree centrality had an inverted U-shape effect in the "University-Research

[11] Weighted degree centrality is calculated by considering repetitive collaboration between nodes.

Institute" network and for the structural holes, the effect was positive. But in "Industry-Research Institute'' and "Industry-University-Research Institute" networks the effect of degree centrality was positive, and the effect of the structural holes was inverted U-shape.

Liang and Liu (2018) investigated the effect of network structure on innovation performance in solar photovoltaics technology in China from 2005 to 2013. They investigated the effect of direct ties, indirect ties, and network efficiency on the number of patents in the solar photovoltaics technology industry. They considered collaboration between the organizations and found that the number of direct ties has an inverted U-shape effect on the number of patents, and they also found a positive effect of indirect ties and network efficiency on the number of patents.

In summary, for the degree centrality in the network, Liang and Liu (2018) and Chen et al. (2017) found out an inverted U-shape on the number of patents and number of papers respectively. However, the results of other studies showed a positive effect for degree centrality on scientific and innovation performance (Abbasi et al. 2011; Ahuja 2000; Beaudry and Schiffauerova 2011; Gonzalez-Brambila et al. 2013). For the ability and power to control the flow of knowledge in the network, represented by betweenness centrality, Beaudry and Schiffauerova (2011) suggested that the presence of inventors with high betweenness centrality might increase the number of claims in a patent. But Eslami et al. (2013) suggested that the non-homogenous distribution of betweenness centrality in the network may decrease the innovation performance of whole network.

In the former paragraphs, several studies addressing the effect of collaboration network properties on scientific and innovation performance have been reviewed. They used different data from different fields and times and consequently reached different results. Therefore, we cannot generalize the results of one study to another similar network, but have at least gained some insight into the expected effects of each index in a particular context.

2.7 Individual characteristics of inventors

The previous section discussed collaboration network effects on the scientific and innovation performance of innovators. However, collaboration patterns are not the only drivers of research and innovation performance. Various other variables may play a role as well, for example, individual characteristics of inventors including their experience, education, age, workplace, gender, and nationality can all have an impact on the innovation performance of inventors (Balconi et al. 2004; Frosch 2011; Jones 2005; Toivanen and Väänänen 2016). In the following sections, some of the most commonly studied individual characteristics suggested as having an impact on the final outcome of innovative work are explained.

2.7.1 Experience

The experience of inventors in their professional job can have an impact on innovation performance (Frosch 2011). Experienced inventors might have more connections and better access to available funds and other resources for their innovative work (Lubango and Pouris 2007). Nevertheless, the impact has also been found negative in some research studies (Frosch 2011; Jones 2005). It is suggested that highly experienced inventors would usually be of older age, and therefore might have lower motivation to be involved in innovative activities (Frosch 2011; Jones 2005).

2.7.2 Firm size

The relationship between the size of firms and innovation performance has been analyzed in some studies (Maffini Gomes et al. 2009; Rogers 2004). Some researchers suggested that the large firms are more involved in innovative activities (Maffini Gomes et al. 2009). Rogers (2004) carried out a similar research study on various types of firms (manufacturing and non-manufacturing firms) in Australia. He found that in manufacturing firms, the small firms have better performance in innovation, and in non-manufacturing firms, the medium and large firms have a better innovation performance. As mentioned, the effect of firm size on innovation performance varies in different literature. It is undeniable that both small and large firms have advantageous and disadvantages in innovation performance (Rogers 2004). For instance, large firms may have access to a wider range of knowledge, human sources, and funds that can be used to outsource other firms as the information source for their technological innovations (Rogers 2004). In contrast, small firms can react to the new technologies faster and have less bureaucratic decision-making procedures to apply new innovative technologies to their product and services (Birley and Norburn 1985).

2.7.3 Education

There is some evidence that education has an impact on innovation and productivity. Junge et al. (2012) investigated the effect of the number of educated employees (employees with more than 16 years of schooling) in firms on the innovation and the productivity of firms. They did a survey to find which Danish organizations and firms are active in innovation activities (product, process, organizational, and marketing innovations) and found that the firms which used more educated employees were involved in more innovative activities. This result can be extended from firm level to individual level.

In another study by Toivanen and Väänänen (2016), The effect of inventors with MSc engineering education on the inventors' propensity to patent has been investigated. They identified individuals whose employer's name in the Finnish Linked Employer-Employee data of Statistics Finland (FLEED) is matched with the patent assignee in the USPTO database. They found 2328 inventors in the time range from 1988 to 1996 from FLEED, which contains the full Finnish working-age population. They used ordinary least squares (OLS) regression analysis and found out there is a positive relationship between the MSc engineering education and the inventors' tendency to patent.

2.7.4 Academic versus industrial working environment

Academic and technological worlds are very different in their objectives, motivations, and approaches (Bikard 2018). Partha and David (1994) describe the difference between these two worlds, where the science world is characterized by publication, supported by a priority-based reward system, and usually exists in research universities. In contrast, in the technology world, the ideas are produced for economic objectives and encoded in patents and other forms of protection. Balconi et al. (2004) explained that the differences consequently lies also in openness of these two worlds. In the academic world, each group of scientists belongs to a wide range of community of researchers of the same field. In contrast to the science world, in the technology world the instrument, methods, and results are shared with the other researchers within their own research team or company, but they are not shared outside the organizational boundaries.

Few studies investigated the effect of the academic versus industrial working environment on the performance of researchers and inventors. Beaudry and Schiffauerova (2011) investigated its effect on the patent quality in nanotechnology in Canada. Their result showed the inventors who work for firms have better innovation performance in terms of the number of claims in their patents.

In another study, Ebadi and Schiffauerova (2015) investigated the effect of the working environment type on the position of the researcher in the collaboration network of the funded researchers in Canada. They found a negative effect of academic working environment on betweenness centrality. They also found that academic researchers work in smaller groups in comparison with industrial researchers.

2.7.5 Age

Most previous research on age and innovation at the individual level shows that the capacity to create economically significant, novel achievements follows an inverted U-shape relationship with age (Frosch 2011; Jones 2005). It means that we have an increase in innovation performance until a certain age and after that increasing age harms innovation performance. The previous literature also shows that the most of inventions are produced by inventors between the age of 35 and 50 (Frosch 2011).

2.7.6 Gender

Although women make up 50 percent of the population, the portion of women among inventors is just 10 percent in USPTO (Sugimoto et al. 2015). Jensen et al. (2018) investigated the effect of gender in obtaining and maintaining patent rights, they examined 2.7 million US patent applications from 2001 to 2014 from USPTO. They found out the patent applications by women inventors were more likely to be rejected. They examined the effect of the name of women inventors and found out when the names of the women are rare and the gender cannot be identified from their names by the examiner of the patents, the rate of rejection will be decreased. This result showed that in 70 percent of cases, the lower probability of patent application grant with women inventors comes from the examiner side. Busolt and Kugele (2009) explained that this low contribution of women in the patents might be related to a wide range of reasons including differences in salary and lower motivation, lack of sufficient time because of parenting and children, and social mechanisms including access to power, authority, influence, reward systems, and networks.

Gender diversity can positively affect innovation in developed countries. Ritter-Hayashi et al. (2019) suggested that gender diversity among a firm's owners and employees as well as having a female top manager can help innovation in developing countries (Ritter-Hayashi et al. 2019; Schneider and Eckl 2016).

2.7.7 Individual characteristics' literature summary

This section summarizes the results of the reviewed research related to individual characteristics. Most of the literature suggested an inverted U-shape relationship between age/experience and innovation (Ebadi and Schiffauerova 2015; Frosch 2011; Jones 2005) but some researchers reported a positive effect of experience on innovation (Wang 2016). According to the previous literature, both small and large firms have advantages and disadvantages in the innovation process. The small firms have an agile decision making ability and faster reaction to new technologies in comparison with large firms, but the large firms have access to more fund to outsource information and technologies and they also have access to wider human resources and knowledge (Birley and Norburn 1985; Maffini Gomes et al. 2009; Rogers 2004). Junge et al. (2012) suggested that inventors with more than 16 years of education have a better innovation performance. For the field of education, Toivanen and Väänänen (2016) suggested that inventors with an MSc engineering education have a better innovation performance than other inventors. Researchers suggested that the innovation created in the technology world usually has better quality than the science world due to the different approaches, motivations, and objectives in the technology and science worlds (Beaudry and Schiffauerova 2011; Bikard 2018). Literature showed that only a small number of inventors in Of the USPTO patents are women (Sugimoto et al. 2015). They explained that gender discrimination in societies and the patent examiner insight have an impact on the low probability of patent grants to women inventors (Busolt and Kugele 2009; Jensen et al. 2018). The literature also suggested that gender diversity can boost innovation (Ritter-Hayashi et al. 2019; Schneider and Eckl 2016).

2.8 Research gaps

Based on the attention that collaboration networks have received in recent years, it is clear that the topic is significant, interesting, and useful for the study of social systems. In addition, the wide range of topics and their application in different fields provide a large field for implementing future research (Eslami et al. 2013).

Many studies have investigated the effect of collaboration networks on innovation (Beaudry and Schiffauerova 2011), in terms of patent citations count, patent claims count, etc. The effect of network measures such as degree and betweenness centrality on innovation performance is inconsistent according to different research studies (Beaudry and Schiffauerova 2011; Liang and Liu 2018). In addition, examining the effect of these variables on innovation performance in terms of patent commercialization has been neglected in previous literature.

The speed and the probability of patent commercialization have been investigated in a few studies (Giuri et al. 2013; Gong and Peng 2018; Porey 2010; Su and Lin 2018; Wu et al. 2015), but to our knowledge, there is no investigation on the commercialization potential of patents in nanotechnology industry in Canada. In addition, most of the discussed research work focuses on investigating the patent-based measures, patent policies, and inventors' research background. To our knowledge, there has been no research study on the effect of individual characteristics of inventors on the commercialization potential of their patents in the nanotechnology industry in Canada.

2.9 Research objectives

The main objective of this thesis is to examine the effect of collaboration patterns and individual characteristics of inventors on the commercialization potential of their patents in the nanotechnology industry in Canada. The sub-objectives of the thesis are the following:

1) Examine the effect of collaborative intensity among inventors on commercialization potential of their patents
2) Examine the effect of inventor’s access to knowledge and ideas on commercialization potential of their patents

3) Examine the effect of inventors' experience on commercialization potential of their patents
4) Examine the effect of inventors' firm size on commercialization potential of their patents
5) Examine the effect of inventors' education on commercialization potential of their patents

In the following paragraphs these sub-objectives are discussed and their originality highlighted in greater detail:

- The first sub-objective of this thesis is to find out whether the patents of the inventors who collaborate with a higher number of collaborators in the nanotechnology field in Canada have higher commercialization potential. Previous studies investigated the effect of the number of collaborators on innovation performance, but the effect on commercialization potential is unexplored.
- The second sub-objective is to investigate the impact of inventors' access to knowledge and ideas and the power to control the flow of knowledge in the network. The thesis intends to examine whether this power gained during collaboration has any effect on the commercialization potential of the patents created through this collaborative activity. Previous studies investigated the effect of inventor's access to knowledge and ideas on innovation performance, but the effect on commercialization potential is unexplored.
- Identifying the amount of experience of inventors and its effect on the commercialization potential of inventors' patents is another objective of this study. We are going to find out the distribution of experience of inventors, and finally, we are going to examine the effect of experience on the commercialization potential of

inventors' patents. As mentioned before, many studies investigated the effect of experience on innovation but none of them investigated the effect of experience on the commercialization potential of inventors' patents.

- We are going to examine the effect of the size of firms that the inventors work for on the patent commercialization potential, again in Canadian nanotechnology. Previous research already addressed the effect of firm size on innovation, but the effect of firm size on the patent commercialization potential remains unexplored.
- The final objective of this study is to find the effect of education on the commercialization potential of inventors' patents. The impact of the level and field of education on innovation performance has been investigated in many studies but none of them considered its role in the commercialization potential of inventors' patents in nanotechnology in Canada.

This study aims to shed some light on the inventors' characteristics in terms of their collaborative patterns and in terms of their individual aspects, which are all assumed to affect the commercialization potential of inventors' patents. The result of this thesis can be beneficial for the government, firms, and individuals. The government can use the results in policymaking, fund administration and allocation, and innovation processes facilitation. Firms can use these insights to modify their employment and motivation policies to encourage the creation of more commercial and potentially profitable innovations. Individual inventors can use the results of this study when searching for collaboration partners to find the right combinations of skills, education, and experience for their innovation team.

Chapter 3 Data and methodology

3.1 Data collection

This study will evaluate the network of Canadian nanotechnology inventors, with the main objective to examine the effect of collaboration network characteristics and individual characteristics of inventors on the commercialization potential of their inventions. Therefore, various data related to Canadian innovation and commercialization activities are needed.

This research requires the collection of the Canadian nanotechnology patent data spanning over 25 years (from 1990 to 2015). For this purpose, we need to select the database among available databases. Afterward, we have to define a suitable filter and strategy to find the nanotechnology patents to create our nanotechnology patent database. After the creation of our database, we create a collaboration network based on the collaboration between inventors.

The patent commercialization information of the patents will be extracted from the existing database that developed previously by Sarencheh et al. (2021).

In the final stage, we collect individual information of the inventors of the patent with commercialization information, including the level of education, the field of education, employer, graduation date of each degree. This data is collected via the search of the name of inventors in Google and LinkedIn. Each observation includes the individual and collaboration network characteristics of the inventors and their patent commercialization status. After that, the data is visualized to gain the first insight into the data collected.

3.2 Database Selection

Investigation on the patent information helps to evaluate a technology's originality, progressiveness, and commercial potential (National Bureau of Economic Research 1962). Therefore, patent analyses are used for different purposes such as monitoring trends, innovation patterns analyzing, or technology development strategies. To reach these goals researchers, need to select and extract the patent information from the appropriate database according to their objectives. There are a lot of patent databases, but the databases most commonly used in research are the United States Patent and Trademarks Office (USPTO), the European Patent Office (EPO), or the Japanese Patent Office (JPO) (Kim and Lee 2015).

In this study, we use USPTO to extract the patent information because it is free and comprehensive with more detailed information about the patent inventor's location. Besides, most of the Canadian inventors submit their patents not only in Canada but also in the US (Beaudry and Schiffauerova 2011). The main reason is that the market of nanotechnology in the United States is larger and the access to it is simpler than the Canadian market. High market accessibility has great importance for the inventors to have reasonable profit and satisfactory return of investment. Therefore, we select the USPTO database as a source of data to extract the Canadian nanotechnology patents.

3.3 Database Filtering

After the database selection, we need to extract the nanotechnology patents. To extract the needed data, we use appropriate keywords and define a suitable filter to access the nanotechnology patents.

Nanotechnology patents are extracted by the filters that had been developed by Porter et al. (2008). We apply this filter only on the abstract of the patents between 1990 to 2015 and at least one inventor resides in Canada to have more accurate results. We assume that if we run the filter through the complete patents' text such as description and references the results would be more comprehensive and we might obtain more of the results irrelevant to nanotechnology. The filter is applied in two steps, in the first step, the patents regarding the terms and conditions in Table 1 are extracted.

The main term in the first step is “nano” and 7 additional modules. We use the MolEnv-I (inclusive) and MolEnv-R (more restrictive) to modify and limit each category in the database.

Table 1 Terms corresponding to nanotechnology

Title	Terms
MolEnv-I (inclusive)	(monolayer or (mono-layer) or film or quantum or multilayer or (multi-layer) or array or molecul or polymer or (co-polymer) or copolymer or mater or biolog or supramolecul)
MolEnv-R (more restrictive)	(monolayer or (mono-layer) or film or quantum or multilayer or (multi-layer) or array)
1.Nano	nano
2.Quantum	(quantum dot OR quantum well OR quantum wire) NOT nano
3.Self-Assembly	(((SELF ASSEMBL) or (SELF ORGANIZ) or (DIRECTED ASSEMBL)) AND MolEnv-I) NOT nano
4.Terms to include as Nano without other delimiters	((molecul motor) or (molecul ruler) or (molecul wir) or (molecul devic) or (molecular engineering) or (molecular electronic) or (single molecul) or (fullerene) or (coulomb blockad) or (bionano) or

	(langmuir-blodgett) or (Coulomb- staircase) or (PDMS stamp)) NOT nano
5.Microscopy - terms to include but limit to the molecular environment	((TEM or STM or EDX or AFM or HRTEM or SEM or EELS) or (atom force microscop) or (tunnel microscop) or (scanning probe microscop) or (transmission electron microscop) or (scanning electron microscop) or (energy dispersive X-ray) or (X- ray photoelectron) or (electron energy loss spectroscop)) AND MolEnv-I) NOT nano
6.Nano-pertinent; Limit to the Molecular Environment – More Inclusively	(pebbles OR NEMS OR Quasicrystal OR (quasi-crystal)) AND MolEnv-I) NOT nano
7.Nano-pertinent; limit to the Molecular Environment – More Restrictive	(biosensor or (sol gel or solgel) or dendrimer or soft lithograph or molecular simul or quantum effect or molecular sieve or mesoporous material) AND (MolEnv-R)) NOT nano
8.Additional Items in Nano Journals	fullerene or ieee transactions on nano or journal of nano or nano or materials science & engineering C - biomimetic and supramolecular systems (in JOURNAL title field) NOT nano

In the first step, we collect patents and identify them as nanotechnology patents if we can detect one of these terms (1 or 2 or 3 or 4 or 5 or 6 or 7 or 8) in its title or abstract.

After the first step, we reach 693 patents from 1990 to 2015.

In the second step, we need to exclude the patents that are not related to nanotechnology, by excluding the records with the following terms:

plankton, nanoflagel, nanoalga, nanoprotist, nanofauna, nanoaryote, nanoheterotroph, nanophtalm, nanomeli, nanophyto, nanobacteri, nanos_, nanog_, nanor_, nanor_, nanoa_, nanoa_, nano-, nanog-, nanoa-, nanor-

We also remove any nano records containing only one of these terms and no other nano terms:

nanometer, nanosecond, nanomolar, nanogram, nanoliter, nano-second, nano-meter, nano-molar, nano-gram, nano-liter

After the second step, the number of patents reduced to 657 patents. As you can see, the second step removes 36 patents from the total number of patents from the first step.

3.4 Commercialization information

The original database that was developed by Sarencheh et al. (2021) is used to extract the commercialization info of patents. They defined that a patent as commercialized if the corresponding invention was converted to a commercialized product or if it was licensed. Both scenarios lead to profit for the patent owners. In this database, they considered the patent family as a proxy of innovation. Consequently, an invention is considered as valuable if any patent within a patent family had been licensed or practiced. Accordingly, they evaluated the commercialization potential of a patent, regarding the implementation of the patent in a product development process or licensing of the patent to other firms. In this study, we have 657 patents within the period from 1990 to 2015. The patent commercialization information of these patents is searched in the original database by matching the title, abstract, and the inventors of the patents. The commercialization information of 102 patents that are the result of collaboration between 186 unique inventors is found by matching these patents with the original database.

3.5 Individual characteristics information

For the related information to the individual characteristics of inventors, we collect data by searching the following information in Google and LinkedIn for the 186 unique inventors in the 102 patents with commercialization information.

1. Field of study in the undergraduate degree

2. Field of study in the graduate degree

3. Graduation date of the undergraduate degree

4. Graduation date of the graduate degree

5. Name of employer

The information of 58 inventors is not found anywhere in Google and LinkedIn, and the information on 28 inventors is found but the critical information including graduation date and the field of study is not found. Therefore, these inventors are removed from the database. For the rest of the 100 inventors, we have some null values for the graduation date of the undergraduate degree and the field of education in the undergraduate degree. To deal with this, we considered only the highest degree of education. The graduation date of the inventors is only considered by the graduation date of the latest degree for all the inventors.

We end up with 100 unique inventors. Some of them had a collaboration in more than one patent, therefore finally we reached 173 observations.

3.6 Methodology

3.6.1 Collaboration network graph

In this section, the procedure of building the co-inventorship networks of nanotechnology in Canada is explained and various properties of the network are evaluated.

The database of patents contains the list of patents and their authors together with the following information: the year of publication, patent ID, patent abstract, patent title, author information, etc.). In the first step, the data have been cleaned and duplicates have been removed.

The patents with at least one Canadian inventor are selected to create the collaboration network based on co-inventorship (if a patent has two or more inventors then these inventors have a co-inventorship relationship). The collaboration ties among inventors will thus be created if they collaborated on a patent. These collaboration ties lead to the exchange of knowledge and sharing of resources. These ties may last for various periods, but there is no accurate general estimation for the lifetime of these ties. Schilling and Phelps (2007) stated that this lifetime usually lasts for more than one year. Researchers used a different lifetime for collaboration ties in different contexts. For instance, Beaudry and Schiffauerova (2011) used 5-years for the lifetime of the ties in the nanotechnology collaboration network in Canada. In this study, we also used the five-year lifetime because we found it the most widely used approach (Baum 2003; Beaudry and Schiffauerova 2011; Eslami et al. 2013). To reach the corresponding patents, some queries have been run in MySQL for each five-year window from 1990 to 2015. The first window includes the co-inventorship from 1990 to 1995, the second from 1991 to 1996 and the last one is 2010 to 2015.

Each USPTO patent document has two different dates. One of them is the application date and the other one is the grant date. We decided to use the application date because the date when the patent application is submitted to the patent office the innovative activity is considered to have arrived at its end.

First, the data should be prepared in a special format so that it can act as an input of social network analysis software. In this study, Gephi software is used to analyze the network. It is specifically developed for the analysis of large networks. It is capable of analysis and visualization of networks with millions of nodes. The input of Gephi can be CSV, spreadsheet, etc. In this study, CSV files are used to import the edge list for each time window to the Gephi software.

Patents and inventors needed to get a proper ID before importing the data into a CSV file so that Gephi could identify them. The inventors and patents thus have been assigned suitable IDs starting from 1 and continuing up to the last. We encountered a problem in the inventors' IDs allocation due to the duplicate names (two different persons having the same name). To address this problem the IDs have been allocated based on the name, family name, and city of residence. If two inventors have the same name and family name and different cities of residence, we considered them as two separate inventors.

This approach results in 21 sub-networks which are all un-directed networks, which means the connecting links among nodes in the network are simple lines and not arrows, which is because we consider the co-inventorship of patents with no other considerations (such as the person who proposed the patent idea first). Multiple lines between two nodes (meaning that two inventors collaborated in more than one patent in the same sub-network) are not considered because we intend to consider the mere existence of the partnerships, whereas the intensity of the relationships is beyond the scope of this project. We end up with 1263 unique inventors from 657 patents in the whole 21 sub networks from 1990 to 2015.

After these networks are constructed, their structure is analyzed with the help of Gephi. The structural network properties including degree and betweenness centrality that are needed to be assessed were measured and recorded.

It should be noted that the collaboration network characteristics of inventors are calculated based on their position in the network in the last 5 years of the application date of their patents. For example, if an inventor had a patent in the year 1996, we considered the time interval between 1990 to 1995 to calculate the collaboration network characteristics of inventors.

3.6.2 Individual characteristics of inventors

In this section, the measurement process of individual characteristics of inventors including affiliation, firm size, education, and experience are introduced and explained in detail.

Affiliation: After the collection of data, the place of work for inventors is identified. We categorize the inventor’s affiliation based on the type of their employer. If an inventor works for a firm, inventors’ affiliation is considered as industry affiliation, whereas if he/she works for a university or any research institution, the inventor’s affiliation is considered to be an academic affiliation. We found only a small number of research institutes in our observations and we concluded that they have similar features with academic institutions such as focusing on research not the economic value of the invention, and coming from the public sector.

Firm size: The name of firms that the inventors work for is collected. The number of employees of the firms is found by searching the name of the firms in Google and LinkedIn. The firms are divided into three categories regarding the number of employees they have.

Large: firms with more than 500 employees.

Medium: firms with 100 to 500 employees.

Small: firms with less than 100 employees.

Education: The field of study was considered as an engineering education if the field of study in the latest degree contained the word 'Engineering' or 'Eng.'.

Experience: We consider the experience as the difference between the date of patent application and the graduation date of the inventors. In a few numbers of observations, the experience was less than 0 because the patent was initiated before the inventor graduated. All these observations are considered as 0-year experience.

3.7 Data analysis and visualization

In this section, the collaboration network and individual characteristics of inventors are analyzed. First, the collaboration network between inventors and its evolution over time will be described. In the second part of this chapter, the individual characteristics of inventors and their inventions' commercialization potential are analyzed in detail.

3.7.1 Collaboration network evolution and characteristics

Figure 1 shows the evolution of the nanotechnology collaboration network in Canada. The results showed a steady increase in both the number of patents and the number of inventors,

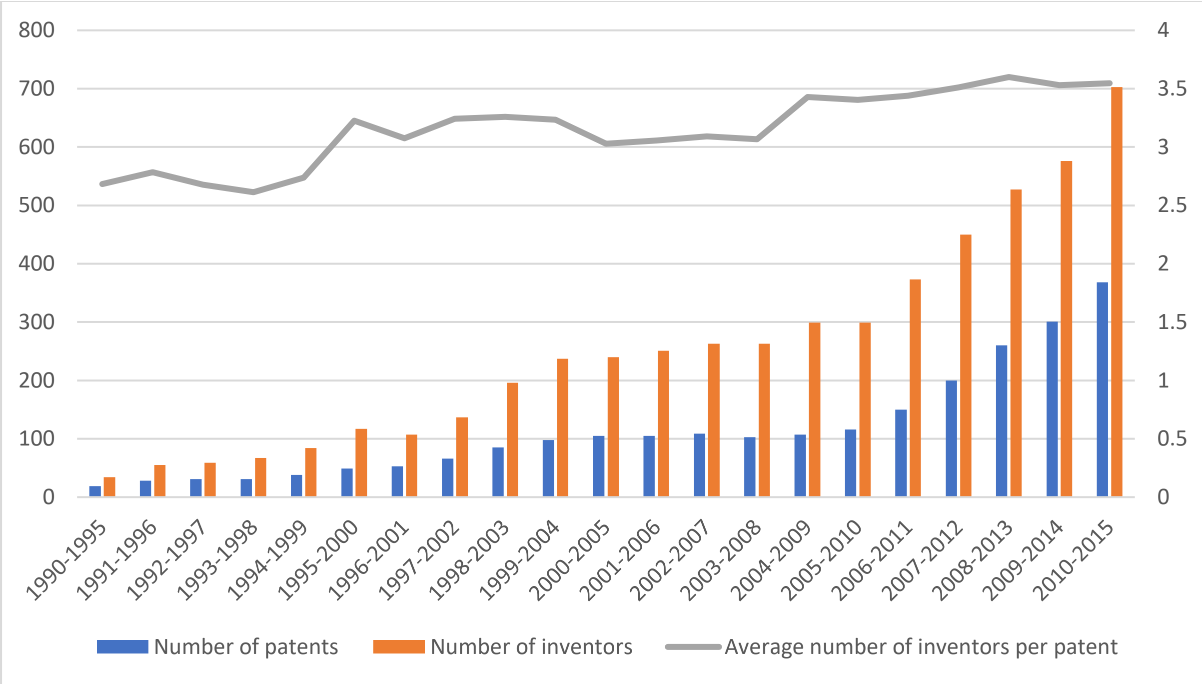

Figure 1 Network evolution statistics

while the average number of inventors per patent varies between less than 2.5 and 3.6. There is an almost steady increment in the average number of authors per patent each year, which shows the tendency of inventors to collaborate in a bigger team over time. Being a member of a bigger team helps inventors to share their knowledge and resources and it can be very helpful for them to increase the quantity and quality of their innovations.

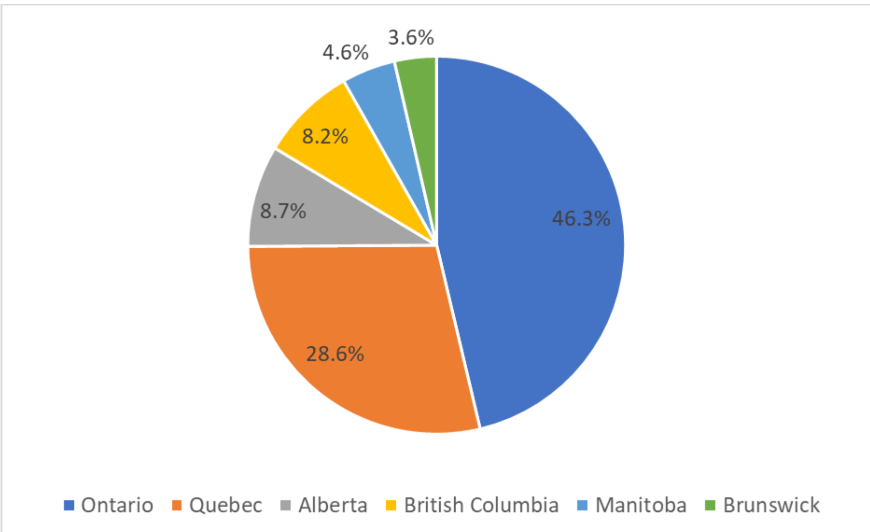

Figure 2 Distribution of inventors in provinces

Figure 2 shows the distribution of inventors in provinces of Canada with the highest numbers of patents. As you can see, nearly 75 percent of inventors are from Ontario and Quebec and about 17 percent of inventors are from Alberta and British Columbia and 8 percent of the total inventors are the residents of Manitoba and Brunswick. We assume that this result is a consequence of a higher number of universities and firms in Ontario and Quebec, the two biggest economies in Canada.

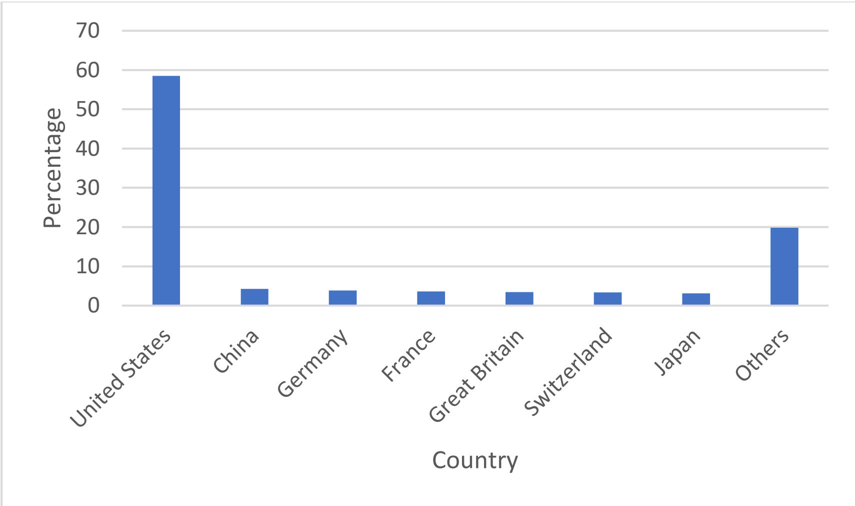

Figure 3 Countries with highest collaboration ties with Canadian inventors

Figure 3 shows the distribution of inventors' countries of residence who had a collaboration with Canadian inventors in the networks. As you can see the Canadian inventors collaborated with US inventors more than with any other country. This high amount of collaboration is expected because the US and Canada are neighbors and they enjoy a strong economic relationship and one of the biggest investment partnerships in the world. The United States had a $401 billion foreign direct investment (FDI) inventory in Canada as of 2018. 46 percent of Canada's overall investment is accounted by U.S. In the United States, Canada's FDI stock was $511 billion (United States government 2020). Moreover, since we extracted the patents from the USPTO database, the chance of finding patents with American inventors is expected to be higher than finding patents with inventors from other parts of the world.

3.7.2 Affiliation

Figure 4 shows that 67 percent of inventors in our sample have an industrial affiliation.

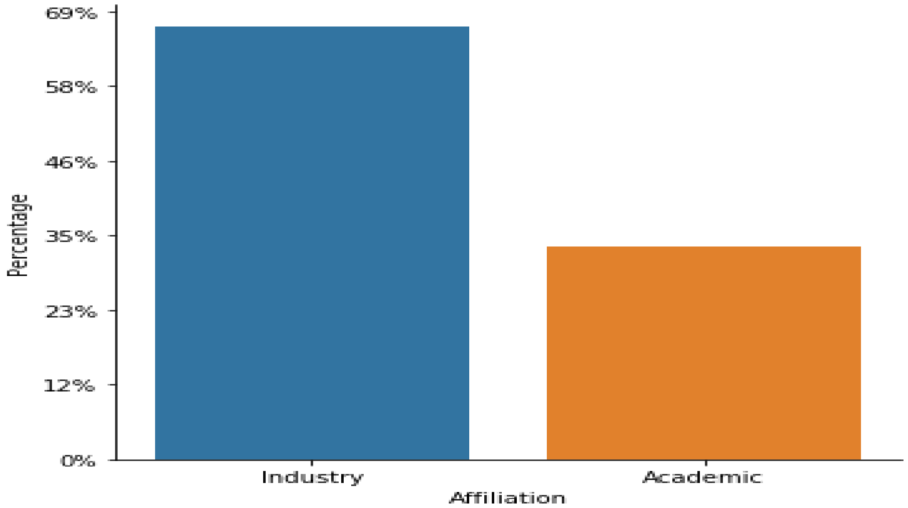

Figure 4 Inventors affiliation

3.7.3 Firm size

Figure 5 shows the number of inventors who work for large firms in our sample is about 3 times more than small and medium-sized firms. The number of small firms is slightly higher than the medium-size firms.

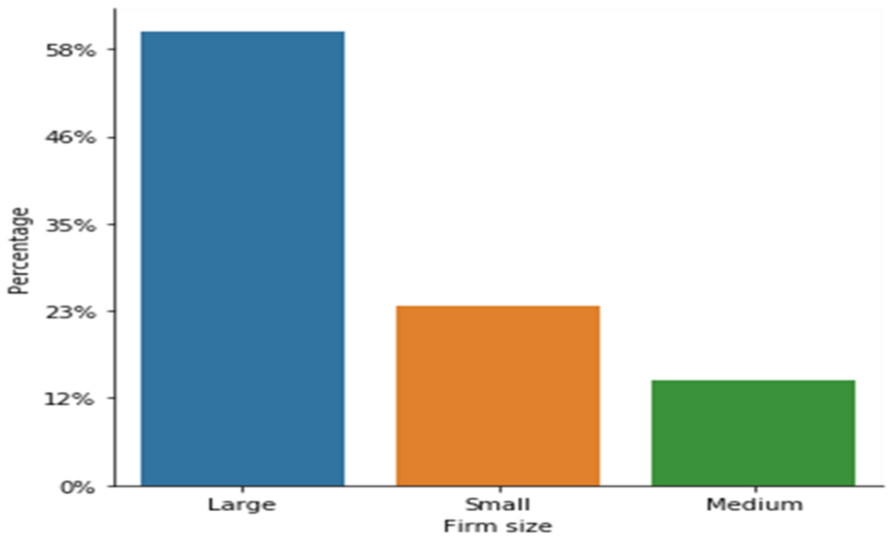

Figure 5 Distribution of inventors in different firm size (Large: firms with more than 500 employees, Medium: firms with 100 to 500 employees, Small: firms with less than 100 employees)

3.7.4 Education

Figure 6 shows the level of education among inventors. As you can see almost all the inventors in our sample have graduate education. The inventors in our sample would usually work in universities, research institutes, and R&D departments of the firms. In all these places it is essential and usually a requirement to have a graduate degree. Besides, a graduate degree can help inventors to be familiar with research from their education. Most graduate students must prepare a thesis or research paper to be graduated. These experiences can help inventors to be involved in innovation activities like a patent in the workplace.

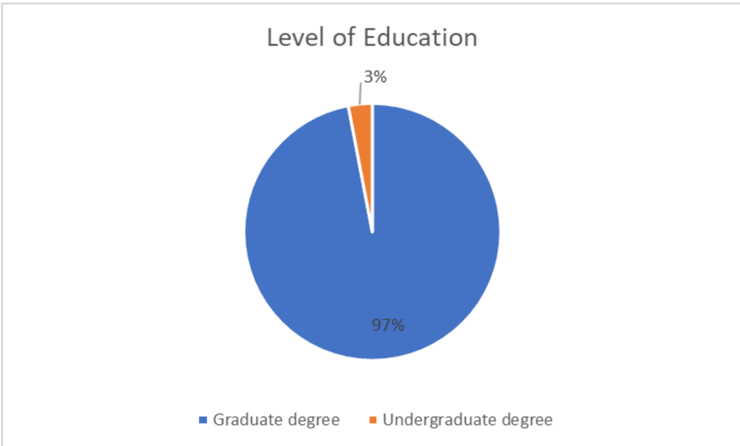

Figure 6 Level of education among inventors

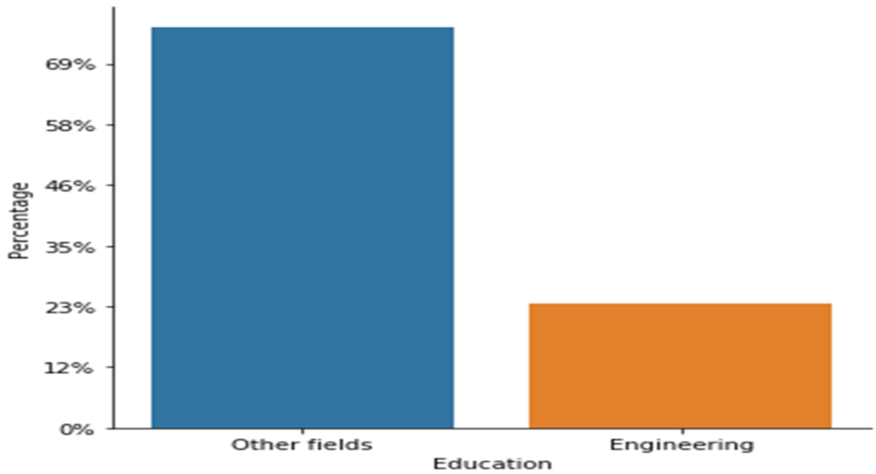

Figure 7 Fields of education among inventors

Figure 7 shows the inventors in our sample are educated more in other fields including chemistry, physics, organic chemistry, physical chemistry, and material chemistry rather than engineering fields.

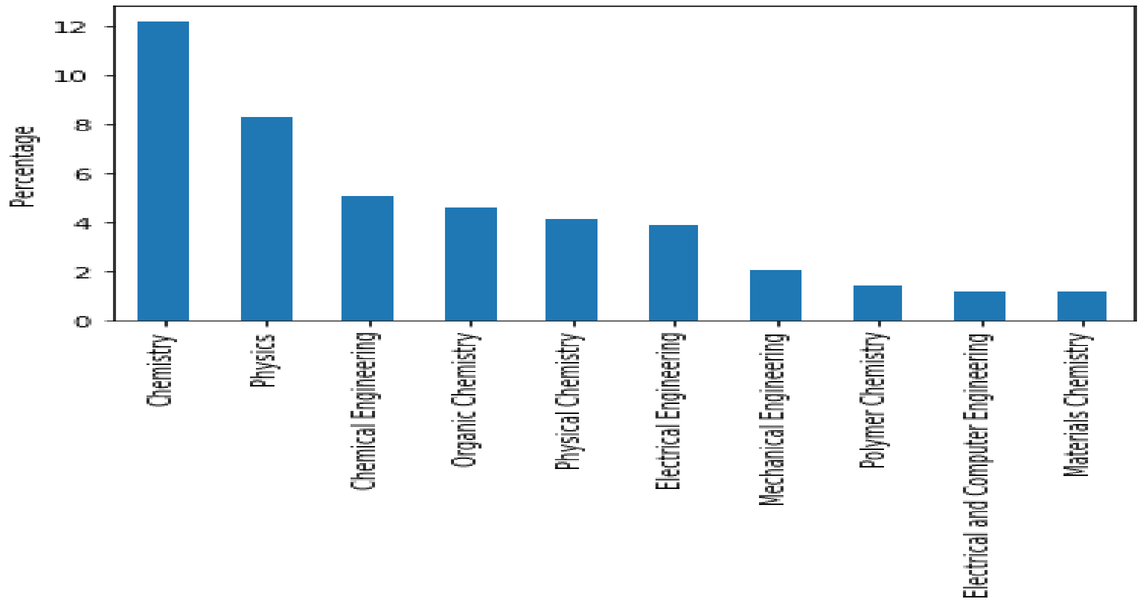

Figure 8 Fields of education of inventors

In Figure 8, we can see the frequency of various fields of education among inventors. The field of education is determined based on the latest degree. For example, if an inventor has a bachelor's degree in physics and a master's degree in physical chemistry, we considered his/her field of study to be physical chemistry. As you can see, chemistry and physics are the most frequent fields of study among inventors. The distribution involving various fields was expected because of the interdisciplinary nature of nanotechnology. One of the main aspects of the nano vision is that it is 'convergent,' in the sense that various sciences and technology are brought together in a single area (Porter and Youtie 2009).

3.7.5 Experience

Figure 9 shows the distribution of experience among inventors, where we can notice that the experience among inventors is highly distributed between 0 to 20 years. It means that the inventors whose experience is between 0 to 20 years are more involved in innovative activities than inventors with more experience. This result can be related to the fact that the nanotechnology industry is relatively new, and the inventors involved in it have less experience than they might have in older industries.

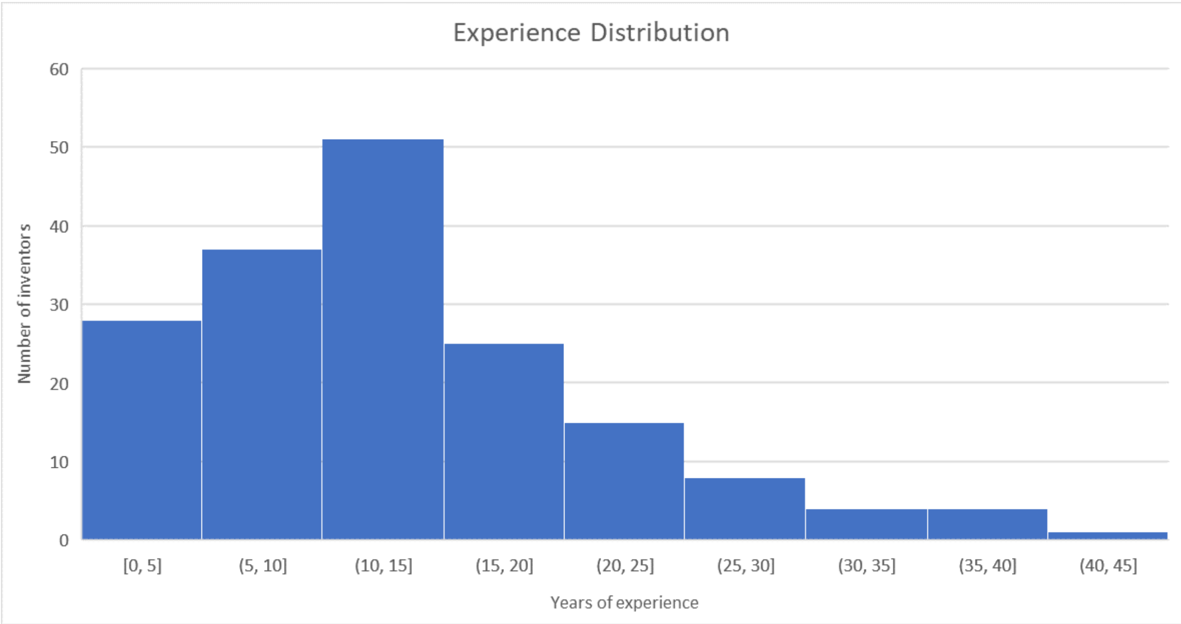

Figure 9 Distribution of experience among inventors (Experience=Patent application date-Year of graduation from latest degree)

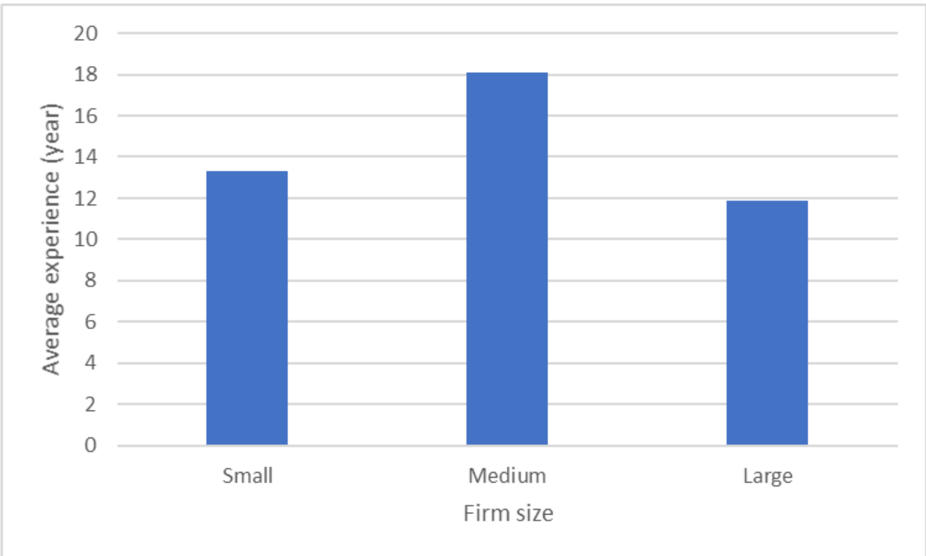

Figure 10 Average experience of inventors in the small, medium, and large firms

We can see the average experience of inventors in small, medium, and large firms in Figure 10. The average experience of inventors working for large firms is about 12 years. The average experience for medium and small firms is about 18 and 13 years respectively. According to the result, inventors may start their careers in smaller firms, and they can grow in the industry after a few years and move to medium and large firms.

In Figure 11, the Kernel Density Estimate (KDE) plot for the distribution of inventors' experience in different firm sizes is plotted. The distribution of inventors' experience in medium firms is more equally distributed in our observations than other firm sizes.

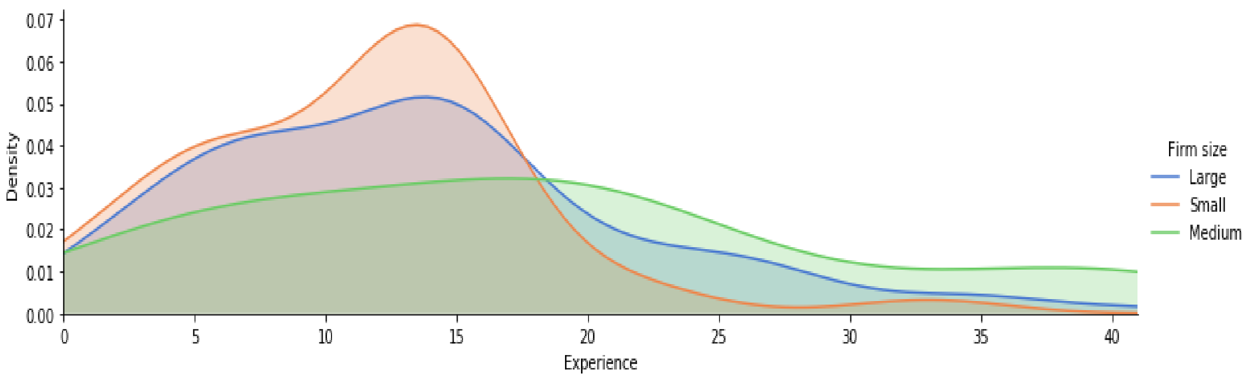

Figure 11 KDE plot of inventors' experience in the small, medium, and large firms

3.7.6 Betweenness centrality

As mentioned before, collaborators with high betweenness are more successful in productivity and quality of innovation (Beaudry and Schiffauerova 2011). In this study, we calculated betweenness centrality for each inventor in the 21 sub-networks.

We used the following formula to calculate the betweenness centrality for each node. For a given node u, and v and w as random nodes of the network, the formula to calculate betweenness centrality is as follows (Perez and Germon 2016):

$$B(u) = \sum_{u \neq v \neq w} \frac{\sigma_{v,w}(u)}{\sigma_{v,w}}$$

$\sigma_{v,w}$= all the shortest paths between v and w.

$\sigma_{v,w}(u)$= the shortest path between v and w include node u.

Figure 12 shows that most of the observations have betweenness centrality around 0. This means the number of inventors who have a high betweenness centrality and consequently important positions in the network is limited.

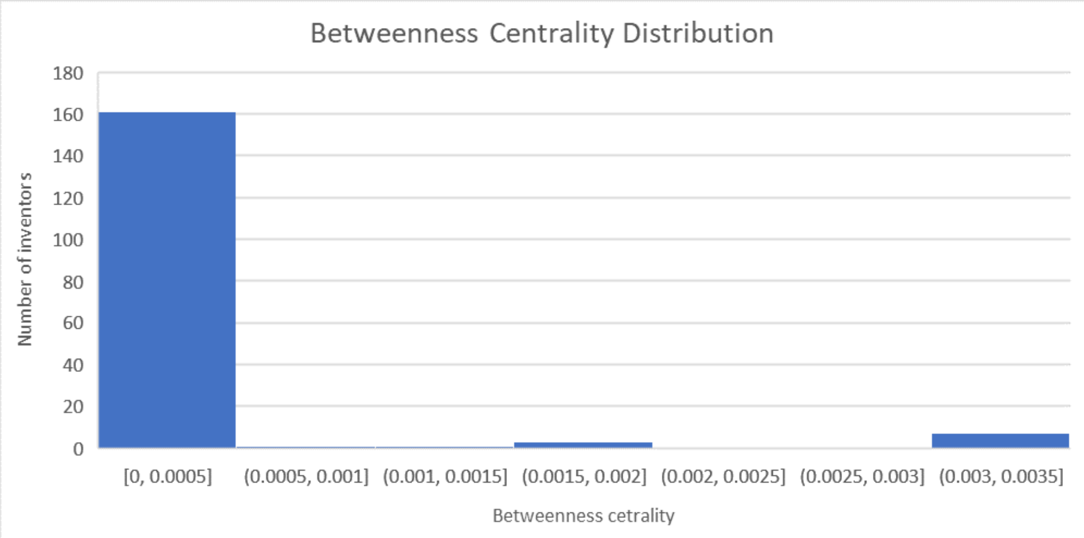

Figure 12 Betweenness centrality frequency distribution

3.7.7 Degree centrality

As mentioned before the inventors with a high degree centrality have a more central position in the network and many studies showed that the central position of an inventor can help it to be more productive and produce innovation with higher quality (Beaudry and Schiffauerova 2011; Eslami et al. 2013; Liang and Liu 2018). Figure 13 shows the amount of degree centrality for each inventor.

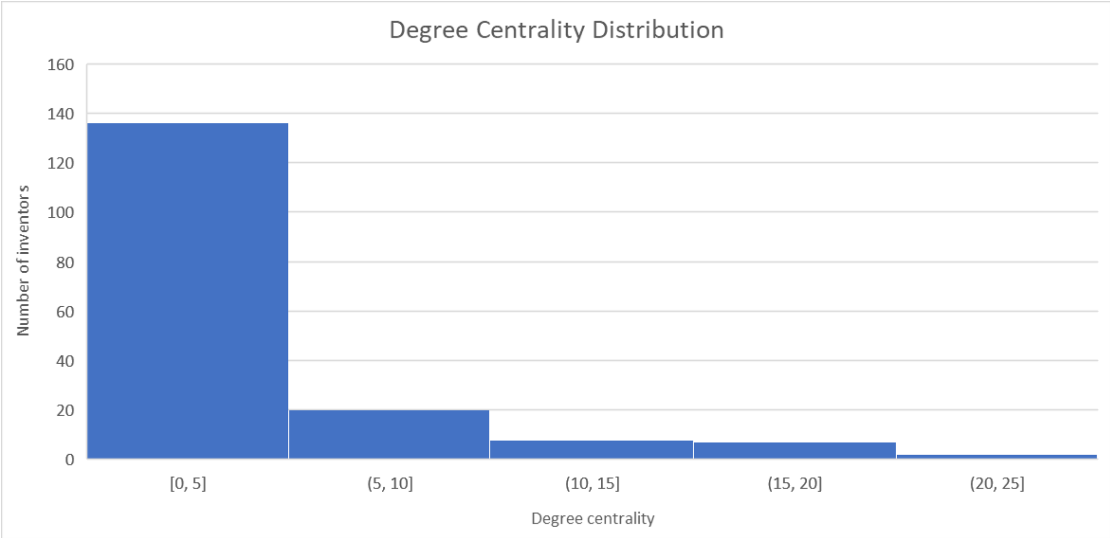

Figure 13 Degree centrality frequency distribution

3.7.8 Patent commercialization

As mentioned in the data collection section, we assume the patent is commercialized if any patent in the patent family ends up as a product or a license.

In Figure 14, we can see the commercialization potential of inventors' patents among provinces. We only considered the top four provinces with the highest number of patents in our database which are Ontario, Quebec, British Columbia, and Alberta. The ratio of inventors with commercialized versus un-commercialized patents in Ontario is 1.73. It means the commercialization potential of inventors' patents in Ontario is very high. This high commercialization potential can be related to the competitive environment for firms in this province. The commercialization rate in Alberta is 2.03. This rate of successful patents can be related to the high amount of investment in research and economic development of the Alberta provincial government in nanotechnology research and deployment ("Nanotechnology research in Canada" 2020). In the provinces of Quebec and British Columbia, the rate of commercialization is lower than 1. To conclude, Alberta and Ontario have outstanding performance in producing patents with high commercialization potential.

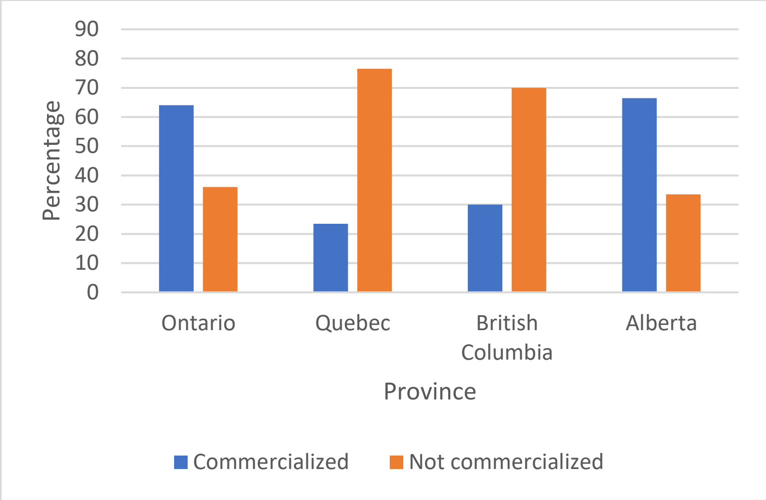

Figure 14 Commercialization potential of inventors' patents among provinces

As you can see in Figure 15, the distribution of inventors' experience among commercialized and not commercialized patents is similar. The high amount of experience is rare in both graphs, but it is scarcer in the distribution of inventors with commercialized patents.

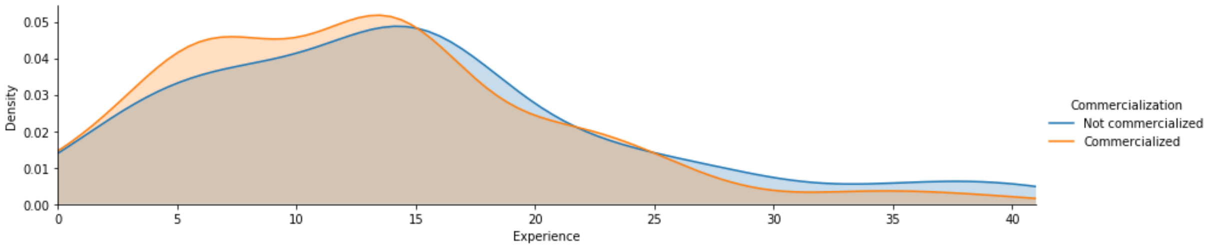

Figure 15 KDE plot for the distribution of experience in commercialized and uncommercialized patents

As you can see in Figure 16, the inventors with engineering education have patents with high commercialization potential than inventors with other fields of education. This result suggests a higher commercialization potential in nanotechnology in Canada.

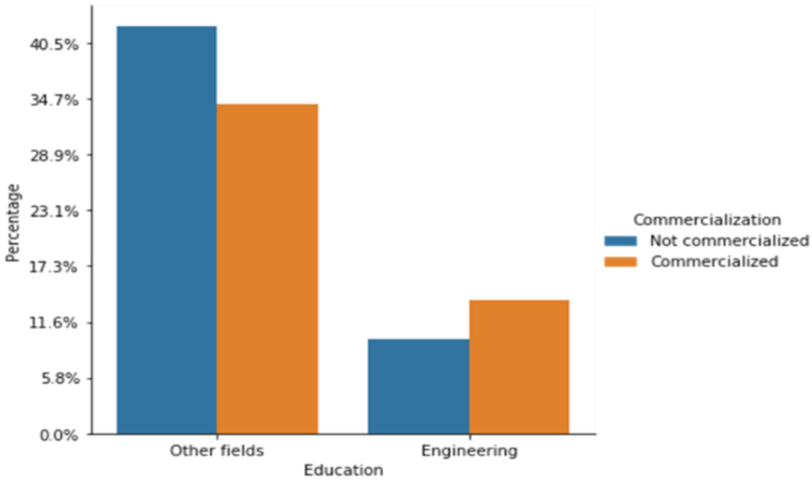

Figure 16 Commercialization potential of inventors' patents in different fields of education

In Figure 17, we can see the commercialization potential of the inventors' patents who work in each firm size group. According to the result, inventors who work for small firms have patents with higher commercialization potential than inventors working for medium and large firms.

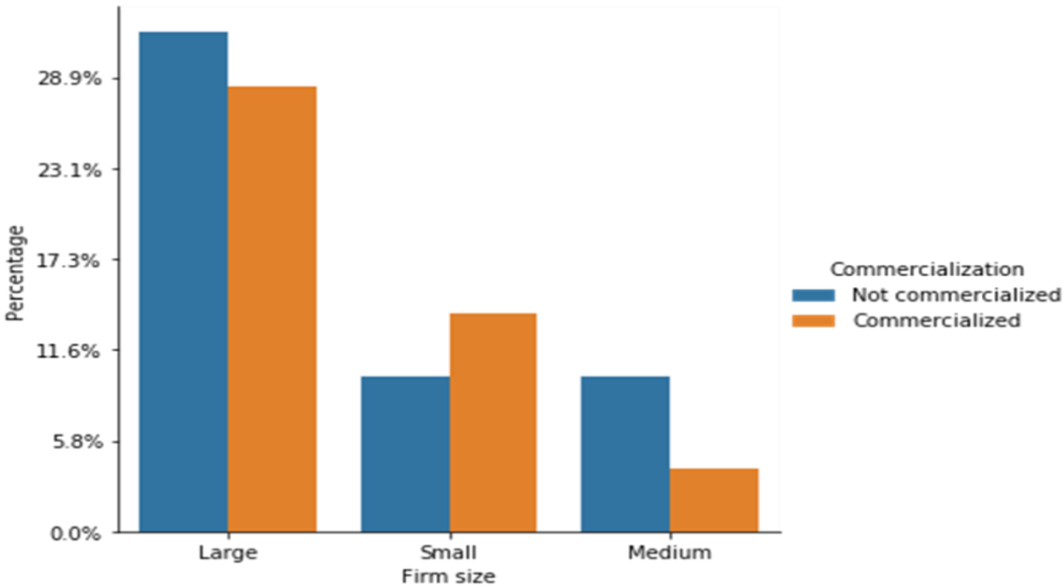

Figure 17 Commercialization potential of inventors' patents in small, medium, and large firms

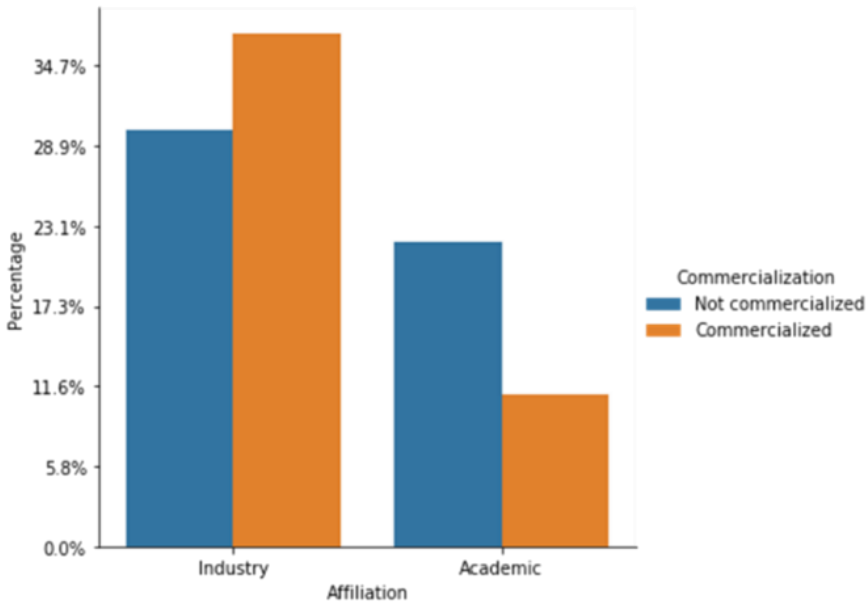

Figure 18 Commercialization potential of inventors' patents for academic and industrial affiliation

As you can see in Figure 18, the inventors who are working in industries have patents with higher commercialization potential. In the next chapter, we examine if the industrial affiliation of inventors has a significant effect on the commercialization potential of their patents.

Chapter 4 Statistical analysis

The main purpose of this research is to analyze the relationship between the commercialization potential of the inventors' inventions and the individual and collaboration network characteristics of inventors in the network. For this purpose, the regression technique is used to measure the significance of various independent variables including engineering education, experience, affiliation, firm size, degree centrality, and betweenness centrality on the patent commercialization potential. First, to show the relationship between variables, the correlation analysis is implemented. Then, the regression analysis is performed, and the results are explained for each of the independent variables.

4.1 Dependent and independent variables

The dependent variable in our models is the commercialization potential of the inventors' patents. The dependent variable is 1 if the inventors' patents end up with a product or license and 0 if they do not. The variable is named in the model as "**Status**".

The independent variables in our study are as follows:

Engineering: if the inventors' latest degree is in any engineering field then the variable is 1 and if not, the variable would be 0.

Experience: this variable shows the experience of the inventor at the time of the patent application date. The experience is defined as the number of years between the graduation date of the latest degree and the patent application date. This variable is normalized and used in the models.

Degree centrality this variable shows the amount of degree centrality of the inventors at the time of patent application. As mentioned in the methodology section, the degree and betweenness centrality of inventors are calculated based on the position of the inventors in the corresponding sub-network. This variable is normalized and used in the model.

Betweenness centrality: this variable shows the amount of betweenness centrality at the time of patent application. This variable is normalized and used in the model.

Affiliation: the affiliation of an inventor is 1 if the inventor works for a university or research organization and 0 otherwise.

Firm size: if the organization is non-academic and the number of employees is less than 100, this variable is 1 and 0 otherwise. We only considered if the firm size is small or not. By doing this, the number of variables in the models is reduced. In addition, the innovation process in medium and large firms are similar in different aspects but there is a huge difference in the processes and approaches in small firms (Rogers 2004).

Control variable:

Network Size: the number of nodes in the sub-network at the time of patten application. We considered the network size in the model as the control variable, because it affects the overall scientific and innovation performance in the network (Eslami et al. 2013).

4.2 Correlation analysis

To determine the relationship between the dependent and independent variables, a correlation analysis is implemented. The results of the correlations calculated with the SPSS 26 software are explained in Table 2.

The correlation analysis demonstrates positive and significant correlations for degree centrality, betweenness centrality, and commercialization potential. We expected this positive correlation because of the effect of being well connected to other inventors in the network on innovation performance (Eslami et al. 2013). The correlation between commercialization potential and academic affiliation is significant and negative. This negative correlation was expected based on the previous literature (Beaudry and Schiffauerova 2011). The correlation between commercialization potential and firm size is significant and positive. The relationship between firm size and commercialization is varied in different studies (Maffini Gomes et al. 2009; Rogers 2004). This relationship will be further explored in the regression analysis.

Betweenness centrality and degree centrality show the highest correlations (more than 0.6). This positive correlation between these variables was expected because if the degree centrality is high, the probability that the inventor is an important player in the network would be high too (Beaudry and Schiffauerova 2011; Eslami et al. 2013), but to find the effect of each of them on the commercialization we need to analyze the regression results. To avoid multicollinearity in our regression, the effect of these variables is examined in two separate models. The first regression considered the degree centrality, and in the second model, we replaced degree centrality with betweenness centrality to examine the effect of these variables on the commercialization potential of inventors' inventions.

Table 2 Correlation analysis

Correlations

		Engineering	Experience	Degree Centrality	Betweenness Centrality	Affiliation	Firm Size	Network Size	Status
Engineering	Pearson Correlation	1	.104	-.089	-.150*	.208**	-.077	.130	.182*
	Sig. (2-tailed)		.171	.244	.049	.006	.317	.089	.017
	N	173	173	173	173	173	173	173	173
Experience	Pearson Correlation	.104	1	.036	.001	.084	-.111	-.133	-.104
	Sig. (2-tailed)	.171		.641	.990	.272	.147	.081	.171
	N	173	173	173	173	173	173	173	173
Degree Centrality	Pearson Correlation	-.089	.036	1	.612**	-.046	.133	-.334**	.212**
	Sig. (2-tailed)	.244	.641		.000	.548	.081	.000	.005
	N	173	173	173	173	173	173	173	173
Betweenness Centrality	Pearson Correlation	-.150*	.001	.612**	1	-.050	.119	.024	.192*
	Sig. (2-tailed)	.049	.990	.000		.511	.120	.755	.011
	N	173	173	173	173	173	173	173	173
Affiliation	Pearson Correlation	.208**	.084	-.046	-.050	1	.487**	.212**	.328**
	Sig. (2-tailed)	.006	.272	.548	.511		.000	.005	.000
	N	173	173	173	173	173	173	173	173
Firm Size	Pearson Correlation	-.077	-.111	.133	.119	.487**	1	.091	.306**
	Sig. (2-tailed)	.317	.147	.081	.120	.000		.235	.000
	N	173	173	173	173	173	173	173	173
Network Size	Pearson Correlation	.130	-.133	-.334**	.024	.212**	.091	1	.164*
	Sig. (2-tailed)	.089	.081	.000	.755	.005	.235		.031
	N	173	173	173	173	173	173	173	173
Status	Pearson Correlation	.182*	-.104	.212**	.192*	.328**	.306**	.164*	1
	Sig. (2-tailed)	.017	.171	.005	.011	.000	.000	.031	
	N	173	173	173	173	173	173	173	173

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

4.3 Regression analysis

To investigate the association between the Canadian nanotechnology inventors' characteristics and the commercialization potential of their inventions, logistic regression analysis is implemented by using statsmodels.api[12] which is a Python library. Besides the correlation analysis which gives an insight into the relationships among pairs of variables in a simple binary term, i.e. whether a relationship exists or does not exist, the logistic regression analysis will also determine the power of each independent variable mathematically (Eslami et al. 2013). In contrast with linear regression and general linear models that are based on ordinary

[12] "statsmodels is a Python module that provides classes and functions for the estimation of many different statistical models, as well as for conducting statistical tests, and statistical data exploration. An extensive list of result statistics are available for each estimator. The results are tested against existing statistical packages to ensure that they are correct." (Seabold and Perktold 2010)

least square algorithms, logistic regression does not require many critical assumptions like normality, and homoscedasticity (Stoltzfus 2011).

The dependent variable in this study is the commercialization potential of patents and it is 1 if the patent is commercialized and 0 otherwise. In other words, we want to classify the commercialized and not commercialized patents by the model and logistic regression can helps to solve classification problems. The logistic regression can be used for more than one explanatory variable as an argument of the sigmoid function (Urso et al. 2019). Figure 19 shows the corresponding result of the sigmoid function is a value between 0 and 1. The middle output of the sigmoid function is 0.5 and it is considered as the threshold to determine if the output belongs to 1 or 0. If the output is more than 0.5 it is considered as 1 and if it is less than 0.5 then the output belongs to 0 (Urso et al. 2019).

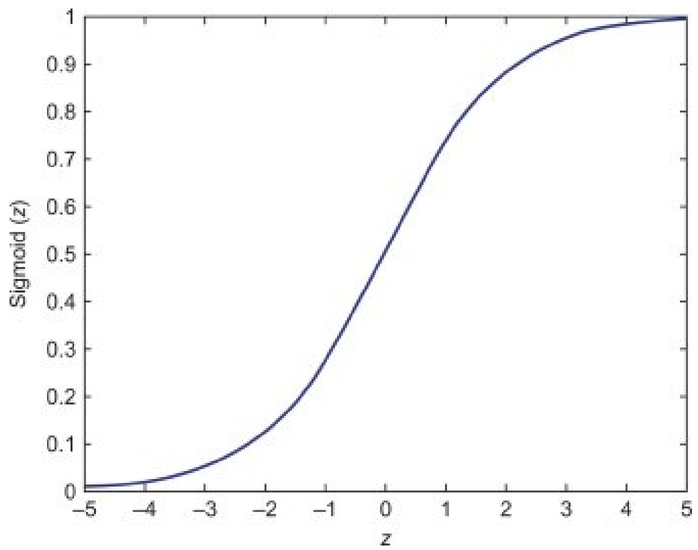

Figure 19 Sigmoid function diagram (Shin et al. 2016)

Logistic regression is a statistical tool like linear regression that can predict an outcome for a binary variable. In contrast with linear regression, the dependent variable can be categorical (DiGangi and Hefner 2013). This means logistic regression provides more freedom for the researcher to use this method for nonnormally distributed data or the samples with unequal covariance matrices (DiGangi and Hefner 2013). In this study our dependent variable and some of the independent variables are binary, hence logistic regression helps us to deal with the non-normality in our dataset.

To use logistic regression we need to check for the following assumptions (Stoltzfus 2011):

First, the dependent variable in binary logistic regression must be binary and in ordinal logistic regression, the dependent variable must be ordinal. The dependent variable in this study is the commercialization potential of patents that is a binary variable.

Second, the observations in logistic regression must be independent of each other. It means that the observations cannot come from a repeated measurement. In our dataset, we do not have any repeated observations.

Third, the independent variables should not be too highly correlated together. In other words, logistic regression requires no multicollinearity between the independent variables. The correlation analysis is implemented on our independent variable and except betweenness centrality and degree centrality, the correlations are low. To deal with the high correlation between degree and betweenness centrality we used them in the two separate models.

Fourth, logistic regression requires that the independent variables have a linear relationship with the log odds. But this method does not require a linear relationship between dependent and independent variables. The best way to avoid a non-linear relationship between the dependent variables and the log odds, is selecting the variables that logically should have a relationship with the dependent variable. To check this assumption, we need to check the p-values of the coefficients. If the p-values are small enough, then we have a linear relationship with the log odds. The p values of all independent variables in our models were less than 0.1 and it is acceptable.

Finally, for the minimum sample size, we need at least 20 observations per variable (van der Ploeg et al. 2014). In our model we have 6 variables, consequently, the minimum sample size is 120. We have 173 observations, therefore the number of observations we have is more than the minimum sample size for the logistic regression.

Concerning the above assumptions and the number of observations, two different logistic regression models are developed. This allows us to avoid the correlation problem among independent variables. Table 3 shows the dependent, independent, and control variables for each model.

Table 3 Logistic regression models variables

Model 1	**Model 2**
Dependent variable	
Commercialization potential	Commercialization potential
Independent variables	
Engineering	Engineering
Experience	Experience
Degree centrality	Betweenness centrality
Affiliation	Affiliation
Firm size	Firm size
Control variables	
Network size	Network size

The observation of the regression coefficients for the impact of individual and collaboration network characteristics of inventors in the nanotechnology industry in Canada on the commercialization potential of inventors' patents are presented in Table 4 and Table 5. Since the p-values reported for all the independent variables except Firm size are less than 0.05, they are considered as significant predictors of the commercialization potential.

Table 4 Logistic regression result for the first model

Logit Regression Results

Dep. Variable:	Status	No. Observations:	173
Model:	Logit	Df Residuals:	167
Method:	MLE	Df Model:	5
Date:	Tue, 08 Jun 2021	Pseudo R-squ.:	0.1186
Time:	22:48:40	Log-Likelihood:	-105.57
converged:	True	LL-Null:	-119.77
Covariance Type:	nonrobust	LLR p-value:	3.024e-05

	coef	std err	z	P>|z|	[0.025	0.975]
Experience	-0.0469	0.017	-2.680	0.007	-0.081	-0.013
Engineering	0.8705	0.405	2.150	0.032	0.077	1.664
Affiliation	-0.8793	0.346	-2.545	0.011	-1.556	-0.202
Degree Centrality	0.1082	0.043	2.517	0.012	0.024	0.192
Firm Size	0.7374	0.406	1.814	0.070	-0.059	1.534
Network Size	0.0003	0.001	0.373	0.709	-0.001	0.002

Table 5 Logistic regression for the second model

Logit Regression Results

Dep. Variable:	Status	No. Observations:	173
Model:	Logit	Df Residuals:	167
Method:	MLE	Df Model:	5
Date:	Tue, 08 Jun 2021	Pseudo R-squ.:	0.1136
Time:	22:48:32	Log-Likelihood:	-106.16
converged:	True	LL-Null:	-119.77
Covariance Type:	nonrobust	LLR p-value:	5.177e-05

	coef	std err	z	P>|z|	[0.025	0.975]
Experience	-1.6260	0.676	-2.406	0.016	-2.951	-0.301
Engineering	0.9211	0.401	2.297	0.022	0.135	1.707
Affiliation	-0.8985	0.344	-2.611	0.009	-1.573	-0.224
Betweenness Centrality	2.3603	1.163	2.029	0.042	0.081	4.640
Firm Size	0.8210	0.400	2.053	0.040	0.037	1.605
Network Size	0.3871	0.368	1.052	0.293	-0.334	1.109

The first predictor variable, the amount of experience of the inventor at the time of patent, has a negative influence on the commercialization potential. This result suggests that although the experience is a valuable asset for everyone but with increasing the experience the chance of creating inventions with high commercialization potential decreased. Denney (1995) found a negative relationship between critical thinking in adults and age. The decline of critical thinking can be a reason for the negative effect of experience on the commercialization potential of inventors' inventions because innovation is strongly related to the ability of critical thinking.

Career age can also affect the position of the inventor in the collaboration network. Ebadi and Schiffauerova (2015) found a negative effect of career age on betweenness centrality of the inventors. Therefore, with age increase, the importance of the position of the inventor in the network would be decreased. Consequently, the level of access to new ideas and power to control the flow of knowledge for the inventor in the network will be decreased.

According to the result, the experience diversity of inventors in a team who collaborate while working on an invention leading to a patent should be considered by the upper hand decision-makers to increase the commercialization potential of the inventions. The results suggest that a team with a high amount of experience does not necessarily create inventions with high commercialization potential.

The second predictor variable, the engineering education of the inventors, has a positive influence on the commercialization potential of the inventors' patents. As mentioned before, critical thinking is one of the most important players in innovative activities. Engineers have been educated to have critical thinking and solve the problem by combining a variety of fields of knowledge. Besides, the nature of nanotechnology is interdisciplinary and consists of a variety of knowledge such as physics, chemistry, material, etc. This interdisciplinary nature of nanotechnology requires a person to know a variety of fields and the ability to mix them to find an appropriate answer for the problems. As we expected, inventors with an engineering education produce inventions with higher commercialization potential in nanotechnology. The results suggest that the policymaker should be aware of the importance of engineers in the innovative team that works on an invention.

The third predictor variable, the industrial affiliation of inventors, has a positive influence on the commercialization potential of inventors' patents. This result shows that the inventors who work for an industrial organization can produce patents with higher commercialization potential. The inventors with industrial affiliation probably collaborate in patents with the industrial assignee (the patent owner) and according to previous literature, the industrial affiliation of the assignee had a positive effect on the innovation quality (Beaudry and Schiffauerova 2011). This positive relationship might be related to the different approaches used by the industrial sector. The commercialization of patents is very important for an industrial corporation because they fund a lot of research, and without commercialization they may note materialize any profits and will not able to continue funding the research and development, and the whole existence of the company may be endangered. On the other hand, academic patents are supported by the universities and are results of university research and thus not expected to make money, because of the consistent funding from public sector.

The fourth predictor variable, the firm size, has a positive influence on the commercialization potential of the inventors' patents with 90 percent confidence. For the firm size, the results show that the small firms have a positive and significant effect on the commercialization potential. Small-size firms can facilitate the process of innovation in many ways. First, in small-size firms, the process of developing and implementing new ideas takes less time and money in comparison to larger firms. In larger firms, everything about the new project is analyzed by many departments and the process of innovation slows down. Small companies are much more flexible. Second, small-size firms can temporarily allocate all their resources to execute new ideas. Consequently, all the employees be involved in the process of execution of new ideas.

The regression result shows that the degree centrality of inventors has a positive effect on the commercialization potential of their inventions. The result suggests that the inventors with a high number of collaborations with other inventors in the network produce inventions with higher commercialization potential.

The sixth predictor variable, betweenness centrality, has a positive influence on the commercialization potential of the inventors' patents. The regression results suggest that the existence of inventors with high betweenness centrality positions in the network may enhance the commercialization potential of the inventors' patents. This result can be explained by the following reason. Based on the definition of betweenness, a lot of information and knowledge will pass through the inventors with high degree centrality. Consequently, they not only have access to the variety of knowledge sources and ideas in the network but they also have the power to control the flow of knowledge by controlling the interaction between other inventors in the network. This provides a great opportunity for the inventor to be aware of what is going on in the network in terms of knowledge and new ideas in multiple areas.

Chapter 5: Conclusions, Limitations, and Future Study

This study explores the effect of characteristics of inventors in the nanotechnology network in Canada on the commercialization potential of their patents. The main objective of this study was to examine the impact of the collaboration pattern and individual characteristics of the inventors on the commercialization potential of the inventors' patents.

The first two sub-objectives of this study were to identify the effect of the collaboration patterns of the Canadian nanotechnology inventors on the commercialization potential of their inventions. To find the collaboration network characteristics of inventors, the collaboration network of Canadian nanotechnology inventors is developed, and the related parameters are measured to be examined in the models. The result shows that the inventors who collaborate with more other inventors in the network have patents with higher commercialization potential. The results also show that the inventors with a central position in the network and the power to control the flow of knowledge have patents with higher commercialization potential.

Another set of sub-objectives of this study are related to the relationship between the individual characteristics of inventors and the commercialization potential of their patents. The result shows that the inventors with engineering education produce patents with higher commercialization potential. This result can be explained by the stronger ability of critical thinking and combining a variety of knowledge to solve problems among engineers. The industrial affiliation of inventors has a positive influence on the commercialization potential of the inventors' patents. This result shows that the inventors who work for an industrial organization create patents with higher commercialization potential than academic inventors. For the firm size, the results suggest that working in small firms can be very helpful in increasing the commercialization potential because of the rapid decision-making process and reaction to new technologies in these kinds of firms. For the experience of inventors, the results suggest that inventors with a high amount of experience do not necessarily produce patents with high commercialization potential.

This study contributed to the literature from different aspects. As we know, this is the first study that investigated the effect of the collaboration patterns characteristics of inventors in the Canadian nanotechnology network on the commercialization potential of the inventors' patents. Besides, this study has explored the individual characteristics of inventors on their patent commercialization potential.

5.1 Limitations of this study

We were exposed to some limitations in our research which are explained in this section.

The first limitation we faced is that many important factors that can affect our dependent variables have not been considered in the models. Although we can identify any collaboration between inventors when they have a formal contribution to an innovation activity but there is a lot of collaboration between inventors that have not been recorded in any formal document. In our models, this kind of collaboration is completely neglected.

It should also be mentioned that some of the independent variables including firm size and affiliation are related to the recent time and we do not have the relevant information for the time of patent application. This is thus also considered as the limitation of this study. To deal with this limitation, we assumed that the inventors have the same affiliation and are working in a firm of the same size over time, which may not necessarily be true in reality.

The individual characteristics of inventors were collected by searching in Google and LinkedIn and we could not find any information for a large portion of inventors. Therefore, we missed a large amount of information about the individual characteristics of inventors. In addition, some of the individual characteristics of inventors are coming from a very recent time and we do not know anything about the affiliation and firm size at the time of patent application.

5.2 Future study

In this section of the thesis, some recommendations for future research are proposed. The first part of the suggestions is related to the possible solutions to the current limitations explained in the previous section. After that, some other theoretical and methodological recommendations are proposed.

As mentioned before, in this study, the collaboration among inventors is based on the collaboration in a patent. Developing a new collaboration network based on the collaboration in patents and research papers or any other publication can help to find more accurate and comprehensive information about the collaboration network characteristics of inventors.

In this study, we investigated patent commercialization and the factors that affect it. We can extend our scope in terms of location to have access to more patent commercialization data and consequently a more comprehensive and accurate model. For this purpose, we can extend the scope of the next study to the nanotechnology network in North America including Canada and the US.

Besides, it is highly recommended to investigate the collaboration patterns at the university level. In this study, we only considered the collaboration between inventors but if we consider the collaboration of universities, we can have a much better insight into the nanotechnology flow of knowledge and the effect of that on the commercialization potential. Analyzing both the network of inventors and universities together to bring further insight into the problem.

In the current study, the collaboration network characteristics of inventors are calculated based on 21 sub-networks with a 5-years time interval. Collecting the individual characteristics of inventors in each time window will help to get a more accurate result about the effect of individual characteristics of inventors on the commercialization potential of their inventions.

The strength of the relationship between inventors can also be considered in future studies. We did not consider multiple co-inventorship in our network and considered these multiple links as a single link instead. In the future study, any collaboration between inventors in a publication or invention can be collected and the effect of the strength of links between inventors on the commercialization potential of their inventions can be examined.

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