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ESSAYS ON THE RECOMBINATION AND DIFFUSION OF INNOVATIONS

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To those who draw new paths . . .

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RÉSUMÉ

La mondialisation a réorganisé l'activité productive sur notre planète. Alors que les pays industrialisés étaient initialement le centre de l'activité manufacturière, ils ont perdu leur position auprès de pays émergents qui offrent des coûts de production moins élevés. Compte tenu de la quantité apparemment inépuisable de main-d'œuvre bon marché disponible à l'échelle mondiale, ce déplacement progressif des opérations de production ne semble pas avoir de fin en vue. Faisant face à ce sombre tableau de la situation économique, l'innovation technologique est considérée comme la panacée pour résoudre le problème de la croissance de la productivité et de la baisse du niveau de vie dans les économies avancées. Quelques mots de mise en garde doivent être dits contre de tels vœux pieux.

Toutes les innovations technologiques n'ont pas le même impact économique et les récentes avancées technologiques ne semblent pas avoir le même impact que des innovations majeures du 19e siècle. De ce point de vue, le fait de ne pas contrôler le processus de production et de commercialisation des innovations qui ont une portée économique plus large semble être un obstacle pour ceux qui prêchent l'innovation comme une solution au problème de la stagnation économique.

Du point de vue des cycles économiques, la croissance économique est enracinée dans la production d'innovations de bases. Ces percées servent de base à des inventions ultérieures dans une multitude de disciplines technologiques. Pourtant, malgré leur immense importance d'un point de vue social, on en sait peu sur les conditions qui conduisent à leur création et des bénéfices privés qu'elles engendrent pour les innovateurs. En ce qui concerne la question de la création d'innovations de base, l'importance de l'exploration technologique par rapport à l'exploitation est une source de débat. Les entreprises devraient-elles concentrer leurs efforts de recherche à un ensemble restreint de disciplines ou doivent-elles combiner des technologies distantes ? En ce qui concerne la question sur les rendements privés sur l'innovation de base, le rôle des institutions publiques en tant que producteurs d'innovations de base est également un sujet controversé. L'objectif principal de cette thèse est de répondre à ces questions en identifiant 1) les conditions dans lesquelles la recombinaison de technologies distantes conduit à la propagation de l'invention résultante dans une multitude de disciplines, et 2) la manière dont les secteurs public et privé valorisent des innovations de base.

Pour répondre à ces questions, des analyses économétriques d'un échantillon de brevets canadiens dans l'industrie de la nanotechnologie sont effectuées. En ce qui concerne la première question, les résultats montrent que la recombinaison distante conduit généralement à des innovations de base. Toutefois, un ensemble de modérateurs ont un impact sur la recombinaison distante. Alors que les organisations privées sont moins susceptibles de produire des innovations de base, leur effort pour combiner des technologies distantes est plus susceptible de produire des innovations de base. En outre, des liens forts avec les sciences fondamentales ont un effet négatif sur la recombinaison distante.

En ce qui concerne la deuxième question de recherche, les résultats montrent que les innovations de base sont généralement associées à une perception des rendements privés plus importants sous conditions de dynamisme industriel et de régimes d'appropriation forts. Toutefois, en ce qui concerne les secteurs public et privé, les perceptions dépendent de la diffusion actuelle d'une technologie ainsi que sa diffusion future perçue. Les entreprises privées perçoivent des rendements plus élevés sur les inventions qui se sont déjà propagées dans plusieurs disciplines, tandis que celles qui seront propagées dans l'avenir sont perçues comme étant moins précieuses.

ABSTRACT

Globalization has reorganized productive activity in our planet. While industrialized countries where initially the center of manufacturing activity, they have lost their title to emerging economies who offer cheaper production costs. Given the seemingly endless supply of cheap labor available at a global level, this gradual shift of production operations does not appear to have an end in sight. In such a bleak economic picture, technological innovation is seen as the panacea for solving the problem of productivity growth, and thus the issue of decreasing standards of living in advanced economies. A few words of caution need to be said against such wishful thinking.

All technological innovations do not have the same economic impact and recent technological advances do not appears to have the same impact as major innovations of the 19th century. From this perspective, the failure to control the process of producing and commercializing innovations that have broad economic impact appears to be an obstacle for those who preach innovation as a solution to the economic stagnation problem.

From a business cycles perspective, economic growth is rooted in the production of basic innovations. These breakthroughs serve as the basis for subsequent inventions in a multitude of technological disciplines. Yet, despite their immense importance from a social point of view, little is known about the conditions that lead to their creation and the private benefits that they engender to innovators. Regarding the question about the creation of basic innovations, the importance of technological exploration versus exploitation is a major source of debate. When aiming for innovation impact, should firms focus their search effort to a focused set of disciplines or should they combine technologies from distant ones? Concerning the question about private returns to basic innovations, the role of public institutions as producers of basic innovations is also a controversial subject. The main purpose of this thesis is to answer these questions by identifying 1) the conditions under which distant technology recombination leads to the spread of the resulting invention across disciplines, and 2) how the private and public sectors value basic innovations.

To answer these questions, econometric analyses of patenting activity in the Canadian nanotechnology industry are performed. Regarding the first question, the results show that distant recombination generally leads to basic innovations. However, a set of moderators have a negative impact on distant recombination. While private organizations are less likely

to produce basic innovations, their effort to combine distant technologies is more likely to produce basic innovations. Also, strong linkage with basic science has a negative effect on distant recombination.

Concerning the second research question, results show that basic innovations are generally associated with higher perceived private returns under conditions of industry dynamism and strong appropriability regimes. However, regarding private and public sectors, perceptions depend on the present spread of a technology and its future perceived spread. Firms perceives greater returns in inventions that have already spread across disciplines, while those that will subsequently spread in the future are perceived as less valuable.

CONDENSÉ EN FRANCAIS

La mondialisation a réorganisé l'activité productive sur notre planète. Alors que les pays industrialisés étaient initialement le centre de l'activité manufacturière, ils ont perdu leur position auprès de pays émergents qui offrent des coûts de production moins élevés. Compte tenu de la quantité apparemment inépuisable de main-d'œuvre bon marché disponible à l'échelle mondiale, ce déplacement progressif des opérations de production ne semble pas avoir de fin en vue. Faisant face à ce sombre tableau de la situation économique, l'innovation technologique est considérée comme la panacée pour résoudre le problème de la croissance de la productivité et de la baisse du niveau de vie dans les économies avancées. Quelques mots de mise en garde doivent être dites contre de tels vœux pieux.

Toutes les innovations technologiques n'ont pas le même impact économique et les récentes avancées technologiques ne semble pas avoir le même impact que des innovations majeures du 19^e^ siècle (Gordon, 2000). Ainsi, si le cycle actuel de croissance faible de la productivité continue, la croissance explosive que nous avons pu observer dans les pays industrialisés pourrait s'avérer être un épisode unique dans l'histoire mondiale (Gordon, 1999, 2012). Du point de vue des cycles économiques (Schumpeter, 1939), la croissance économique est intrinsèquement reliée à la production des innovations de bases (Mensch, 1979).

Les économies passent par des cycles de changement radical suivi de périodes d'améliorations incrémentales qui mènent éventuellement à la stagnation (Schumpeter, 1939; Abernathy and Utterback, 1978; Nelson and Winter, 1982; Klepper, 1996). La période d'amélioration incrémentale mène à la stagnation parce que toute percée technologique a une limite inhérente qui ne peut être surmontée à travers des améliorations incrémentales. Une fois que ces limites sont atteintes, de nouvelles percées doivent être introduites pour qu'il y ait un nouveau cycle de croissance (Mensch, 1979). De ce point de vue, les innovations de bases ont un impact économique plus large puisqu'elles servent de pilier à de nombreuses innovations incrémentales (Mokyr, 1990; Rosenberg, 1994; Mowery and Rosenberg, 1999; Arthur, 2007). De ce point de vue, le fait de ne pas contrôler le processus de production et de commercialisation des innovations qui ont un large impact économique semble être un obstacle pour ceux qui prêchent l'innovation comme une solution au problème de la stagnation économique.

Pourtant, malgré leur immense importance d'un point de vue social, on en sait peu sur les conditions qui conduisent à leur création (Fleming, 2007) et des bénéfices privés qu'elles engendrent pour les innovateurs (Arrow, 1962). En ce qui concerne la question de la création d'innovations de base, l'importance de l'exploration par rapport à l'exploitation technologique est une source de débat (Fleming, 2001; Rosenkopf and Nerkar, 2001; Kim et al., 2012). Les entreprises devraient-elles concentrer leurs efforts de recherche à un ensemble restreint de disciplines ou doivent-elles combiner des technologies distantes ? En ce qui concerne la question sur les rendements privés sur l'innovation de base, le rôle des institutions publiques en tant que producteurs d'innovations de base est également un sujet controversé (Henderson et al., 1998; Mowery and Ziedonis, 2002). L'objectif principal de cette thèse est de répondre à ces questions en identifiant 1) les conditions dans lesquelles la recombinaison de technologies distantes conduit à la propagation de l'invention résultante dans une multitude de disciplines, et 2) la manière dont les secteurs public et privé valorisent des innovations de base.

Cette thèse tente de répondre à ces questions à travers deux ensembles d'hypothèses. Le premier ensemble d'hypothèses va répondre à l'objectif de recherche portant sur la création d'innovations de bases. La littérature semble associer l'exploration technologique à la création d'innovations radicales et l'exploration technologique à la création d'innovation incrémentales (Fleming, 2001; Kim et al., 2012). Ainsi, l'hypothèse suivante peut être émise :

H1.1. Les innovations de bases seront plus probablement le résultat de recombinaison de technologies distantes.

Alors que la prouesse technologique est importante, les habiletés complémentaires en marketing sont aussi importantes pour qu'il y ait diffusion technologique (Slater and Narver, 1995). À ce chapitre, une différence majeure existe entre les institutions publiques et les entreprises privées. Ces dernières sont régies par les lois du marché et ne peuvent se contenter de jouer exclusivement un rôle de créateurs de connaissances. Elles doivent donc nécessairement développer leurs habiletés en marketing pour survivre. Ces habiletés leur permettent de pourvoir trouver des solutions qui sont proches des besoins du marché, ce qui donnera lieu à une diffusion plus importante de leurs inventions (Sainio et al., 2012). On peut donc supposer que :

H1.2. La recombinaison distante par le secteur privé donne un plus haut taux d'innovations de bases.

Les inventions qui sont proches des sciences de bases sont plus complexes et donc plus difficile à absorber (Cohen and Levinthal, 1990; Nooteboom et al., 2007). Cela signifie que les innovations qui ont de forts liens avec des sciences de bases auront une diffusion plus difficile sur les marché. Une troisième hypothèse peut alors être émise :

H1.3. La recombinaison distante est négativement modérée par des liens forts avec les sciences des bases.

Le stade du cycle de vie dans lequel l'industrie se retrouve a aussi des répercussions sur la recombinaison de technologies distantes. En effet, les innovations de bases sont plus souvent associées aux industries compétitives (Klepper, 1997; Malerba and Orsenigo, 1997). Lorsqu'une industrie est dominée par quelques joueurs, la plupart des innovations qui seront adoptées auront une nature cumulative, ce qui signifie qu'ils consistent principalement en des innovations incrémentales. Ainsi, l'hypothèse suivante peut être émise :

H1.4. La recombinaison distante est positivement reliée aux innovations de bases dans les environnements compétitifs.

Le deuxième ensemble d'hypothèses répondra à l'objectif de recherche portant sur les différences entre les secteurs privés et publics dans la valorisation d'innovations de bases. Les innovateurs ont des incitatifs à faire de la recherche lorsque les régimes d'appropriation des retours sont efficaces (Arrow, 1962; Levin et al., 1987). Lorsque cette condition est remplie, l'incitatif de conduire un type de recherche en particulier (exploitation ou exploration), dépend de la structure de l'industrie. Tel que stipulé plus haut, les innovations de bases sont associées aux industries dynamiques. Ainsi, dans les environnements marqués par des régimes d'appropriation forts et de dynamisme industriel, on peut supposer que :

H2.1. Les innovations de base sont associées à une plus grande valeur privée perçue.

Toutefois, les conditions externes ne sont pas suffisantes pour assurer l'appropriation des retours sur l'innovation. L'innovateur doit posséder des atouts complémentaires pour y arriver (Teece, 1986). Encore une fois, le secteur privé est mieux équipé puisque ses activités journalières consistent à développer les ressources nécessaires pour capturer les bénéfices des connaissances que l'entreprise a acquises. Ainsi, même sous condition de dynamisme industriel et de régimes d'appropriabilité forts :

H2.2. Les institutions privées seront plus aptes que les institutions publiques à s'approprier les retours sur les innovations qui ont démontré leur application dans plusieurs disciplines technologiques.

Les routines développées au sein des entreprises privées sont toutefois concentrées sur le développement de marchés spécifiques avec lequel l'entreprise est familière (Levinthal and March, 1993; Ahuja and Lampert, 2001). À l'inverse, les routines auprès des institutions publiques sont développées autour de la génération de connaissances ayant une portée large sur la société. Ainsi, les institutions publiques peuvent se démarquer des institutions privées en misant sur des technologies qui auront un impact plus diversifié dans le futur. On peut alors supposer que :

H2.3. Les institutions publiques allouent plus de ressources à des innovations qui seront diffusées, dans le futur, auprès de différentes disciplines technologiques.

Pour répondre à ces questions, des analyses économétriques d'un échantillon de brevets canadiens dans l'industrie de la nanotechnologie sont effectuées. La littérature utilise de manière exhaustive les données bibliométriques sur les brevets afin de mesurer l'activité innovante (Pavitt, 1985; Narin, 1994; Narin and Hamilton, 1996). Toutefois, quoique l'utilisation de ces données est attrayante pour le cas des industries émergentes, leur utilisation pour évaluer l'activité commerciale n'est pas aisée car les brevets ne génèrent pas tous des revenus (Allison et al., 2004; Moore, 2005). De plus, ils ne sont pas toujours conçus pour des fins de production et peuvent être l'objet de différentes considérations stratégiques (Hall and Ziedonis, 2001; Gallini, 2002; Moore, 2005; Reitzig et al., 2007). De tels pratiques sont, toutefois, moins répandues dans les technologies discrètes telles que l'industrie chimique, pharmaceutique et les biotechnologies (Cohen et al., 2000; Hall and Ziedonis, 2001). Dans ces industries, les brevets représentent un régime d'appropriation fort et sont donc de meilleurs indicateurs d'activité innovante (Levin et al., 1987; Merges and Nelson, 1990). Ainsi, pour répondre aux questions posées ci-dessus, il importe de classifier les brevets selon leur industrie.

Ce besoin de discriminer entre les brevets de différentes classes technologiques pose un problème méthodologique. Par définition, les disciplines émergentes sont continuellement en croissance et sont redéfinies par ce que les *communautés de pratiques* (Wenger, 1999) croient être les applications prometteuses. Cela devient difficile pour des observateurs tels que l'USPTO à mettre en place une classification standard des brevets en nanotechnologie. En effet, la classe 977, réservée par l'USPTO pour les nanotechnologies, ne contient que 4,193 brevets, alors que la requête de Porter et al. (2008) retourne plus de 50,000 brevets pour la période 1990 à 2005.

Puisque les brevets doivent faire référence à l'état antérieur de la technique, les citations de brevets peuvent, en théorie, être utilisés pour monter des réseaux où les communautés de co-citations représentent les principaux domaines de développement technologique. Trouver ces communautés revient à identifier les zones d'inter-citations denses. Parmi les techniques d'apprentissages non-supervisées, l'analyse de groupement (*cluster analysis*) peut être effectué pour trouver ces zones (Girvan and Newman, 2002). Une telle méthode reposerait sur le principe que la co-citation est un indicateur de similarité entre des documents (Small, 1973). Toutefois, puisque les citations de brevets peuvent être ajoutés stratégiquement par les déposants (Sampat, 2010) et par erreur par les examinateurs Cockburn et al. (2002), cette méthode ne peut pas être automatiquement appliquée aux brevets.

Toutefois, les citations peuvent être interprétées comme indicateurs de proximité technologiques entre les brevets puisqu'ils sont issus du processus de classification des brevets (Lerner, 1994). Une contribution supplémentaire de cette thèse, est donc de valider si les citations peuvent être utilisés pour mesurer la proximité technologique entre les brevets.

Plusieurs indicateurs peuvent être utilisés à cette fin. Plus les citations sont loin d'être le résultat d'un processus contrôlé, plus les réseaux de co-citations auront une topologie proches de celle des réseaux aléatoires. D'un autre côté, si le processus d'assignation de citations est contrôlé, alors les réseaux résultant auront les caractéristiques des petit-mondes (Watts and Strogatz, 1998). De plus, une fois les communautés trouvées, l'information sur les cessionnaires de brevets peut être utilisée pour valider cette méthode. Puisque les organisations sont plus souvent portées à se spécialiser dans un ou quelques domaines technologiques, ils ne devraient pas être distribués de manière uniforme dans les communautés. Plutôt, chaque communauté devra être dominée par quelques firmes. Il faut noter que la domination de tous les partitions par une seule organisation peut aussi indiquer que la détection de communautés basée sur les citations de brevets n'est pas fonctionnelle, car cela pourrait signifier que le groupement automatique ne fait que regrouper les brevets de la même organisation.

Les résultats de l'analyse de groupement des réseaux de co-citations montre que les brevets peuvent être utilisés pour grouper des brevets qui sont technologiquement similaires. Même si des citations non-pertinentes peuvent être ajoutées par les examinateurs ou les déposants, les réseaux de co-citations ne sont pas des graphes aléatoires. De plus, les technologies de différentes classes possédées par de larges entreprises sont identifiées dans des grappes différentes. De plus, l'analyse de tendances pour différents domaines d'expertises, tels que le nombre de citations, les revendications et les références à des articles scientifiques peuvent être utilisés pour mesurer le stade de développement d'une industrie émergente. L'analyse de ces tendances pour les brevets canadiens des nanotechnologies montre que l'activité l'innovante est concentrée dans trois industries : les nanobiotechnologies, les technologies d'affichage et l'optique. La première industrie est dynamique et paraît être au début de son cycle de vie. Les deux autres industries sont toutefois dominés pas quelques firmes, et quoique l'utilisation de la nanotechnologie semble être nouvelle, peu de nouveaux entrants font surface dans ces industries.

Cette validation de l'utilisation des brevets pour l'analyse de l'industrie multidisciplinaire et émergente des nanotechnologie nous permet de tester l'ensemble des hypothèses se rapportant à nos objectifs de recherche qui étaient d'identifier les conditions dans lesquels les innovations de bases sont créées et leurs retours peuvent être appropriés.

En ce qui concerne le premier objectif, les résultats montrent que la recombinaison distante conduit généralement à des innovations de base. Toutefois, un ensemble de modérateurs ont un impact négatif sur la recombinaison distante. Alors que les organisations privées sont moins susceptibles de produire des innovations de base, leur effort pour combiner des technologies distantes est plus susceptible de produire des innovations de base. En outre, des liens forts avec les sciences fondamentales ont un effet négatif sur la recombinaison distante.

En ce qui concerne le deuxième objectif de recherche, les résultats montrent que les innovations de base sont généralement associées à une meilleure perception des rendements privés sous conditions de dynamisme de l'industrie et de régimes d'appropriabilité forts. Toutefois, en ce qui concerne les secteurs public et privé, les perceptions dépendent de la propagation actuelle d'une technologie ainsi que de sa diffusion future perçue. Les entreprises perçoivent des rendements plus élevés sur les inventions qui se sont déjà propagées dans plusieurs les disciplines, tandis que celles qui seront propagées dans l'avenir sont perçues comme étant moins précieuses.

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LIST OF SIGNS AND ABBREVIATIONS

IP	Intellectual Property
M&A	Merger and Acquisition
NPR	Non-Patent References
R&D	Research and Development
SIC	Standard Industrial Classification
USPTO	United States Patent and Trademark Office
VC	Venture Capitalist

INTRODUCTION

Globalization has reorganized production activities in our planet. While industrialized countries where initially the center of manufacturing activity, they have lost their position to emerging economies who offer cheaper production costs. Given the seemingly endless supply of cheap labor available at a global level, this gradual shift of production operations does not appear to have an end in sight. In such a bleak economic picture, technological innovation and entrepreneurship have been seen as the panacea for solving the problem of productivity growth, and thus the issue of decreasing standards of living in advanced economies. A few words of caution need to be said against such wishful thinkings.

Indeed, all technological innovations do not have the same economic impact and the impact of recent technological advances compared to that of major innovations of the 19th century is questionable (Gordon, 2000). If the cycle of productivity slowdown continues, the explosive growth that was witnessed in industrialized countries could well be a unique episode in world history (Gordon, 1999, 2012). From a Schumpeterian business cycles perspective, the question of economic growth is tightly connected to the creation of radical innovations (Schumpeter, 1939; Mensch, 1979).

Economies go through cycles of radical change followed by periods of incremental improvements which eventually lead to stagnation (Schumpeter, 1939; Abernathy and Utterback, 1978; Nelson and Winter, 1982; Klepper, 1996). The period of incremental improvement leads to stagnation because breakthroughs have inherent limits which incremental improvements cannot surmount. Once these boundaries are reached, new breakthroughs must be introduced and adopted for another cycle of growth to reoccur (Mensch, 1979). From this perspective, basic innovations have a wider economic impact since they serve as the basis of many subsequent incremental innovations (Mokyr, 1990; Rosenberg, 1994; Mowery and Rosenberg, 1999; Arthur, 2007). Thus, the ability to create and bring about radical - as opposed to incremental - change is an area of concern for advanced economies that need to play the leading role in the global knowledge creation network if they hope to attract capital investments.

Concerning basic innovations, two questions are investigated in the literature. The first is concerned with the impact of explorative versus exploitative search on innovative capabilities. Various studies associate radical innovation with the exploration of technologies from a multitude of disciplines while they associate incremental innovations with the exploitation of technologies within a narrow set of disciplines (Fleming, 2001; Rosenkopf and Nerkar, 2001; Kim et al., 2012). However, technology exploration, while capable of producing breakthroughs, also leads to many failures because their complexity also means that their diffusion is slower and represents greater risks (Fleming, 2001; Nooteboom et al., 2007; Nemet and Johnson, 2012). The second source of discussion is concerned with the private returns that basic innovations will engender for innovators (Arrow, 1962). University-industry linkage can be viewed as an effective way to explore new knowledge that can have broad impact (Rosenberg, 1994; Narin et al., 1997; Etzkowitz et al., 2000; Cohen et al., 2002), but it can also change the nature of research performed by universities (Henderson et al., 1998).

The main purpose of this thesis is to answer these questions by identifying 1) the conditions under which distant technology recombination leads to the spread of the resulting invention across disciplines, and 2) how the private and public sectors value basic innovations. As such, this thesis does not intent to study directly broad subjects such as globalization, economic cycles or growth. Instead, it is interested in the study of innovative activity which falls within these broad subjects of discussion. To answer these questions, econometric analyses of patenting activity in the Canadian nanotechnology industry are performed. Regarding the first question, the results show that distant recombination generally leads to basic innovations. However, a set of moderators have a negative impact on distant recombination. While private organizations are less likely to produce basic innovations, their effort to combine distant technologies is more likely to produce basic innovations. Also, strong linkage with basic science has a negative effect on distant recombination.

Concerning the second research question, results show that basic innovations are generally associated with higher perceived private returns under conditions of industry dynamism and strong appropriability regimes. However, regarding private and public sectors, perceptions depend on the present spread of a technology and its future perceived spread. Firms perceives greater returns in inventions that have already spread across disciplines, while those that will subsequently spread in the future are perceived as less valuable.

The rest of the thesis is structured as follows: Chapter 1 reviews the literature concerning innovation management; Chapter 2 presents the research objectives, hypotheses and the methodology employed; Chapters 3 and 4 validate the use of the methodology; Chapters 5 and 6 answer our main research questions; and Chapter 7 discusses the findings. The document will then conclude with a synthesis and the limitations of this work.

CHAPTER 1

LITERATURE REVIEW

Management literature is one in which many theoretical concepts are intertwined. This section intends to group this literature in three large subsections. The first section (1.1) poses the foundation of innovation studies: it discusses various aspects of the economics of knowledge and poses some basic definitions in the literature. Here, a distinction is made between information and knowledge with the latter concept being of more interest to the study of innovation (subsection 1.1.1); various aspects of knowledge which make it a public good are discussed (subsection 1.1.2); literature distinguishing between science and technology is reviewed (subsection 1.1.3); the distinction between the notions of invention and innovation is made (subsection 1.1.4). The second section (1.2) reviews literature about three interconnected concept in the production of knowledge: subsections 1.2.1, 1.2.2 and 1.2.3 review literature regarding how new knowledge is absorbed, created and is subsequently disseminated in an economic setting. This interconnectedness between knowledge assimilation, creation and diffusion leads to the acknowledgment that innovation happens in a social context. The third section (1.3) thus further discusses the collective aspects of innovation. The notion that learning and innovating is a collective phenomenon opens the door to the study of performing search in a context of complexity: subsections 1.4.1 and 1.4.2 reviews literature regarding two search strategies that can be adopted by innovators.

1.1 Economics of knowledge

The contemporary economy is often referred to as being one based on knowledge and sometimes called the *learning economy* (Lundvall and Johnson, 1994; David and Foray, 2002; Powell and Snellman, 2004). The latter nomination suggests that knowledge creation and learning are very similar activities. It also suggests that firms are increasingly valued by their capacity to learn. The importance of knowledge is felt even in low-tech industries where firms must learn to innovate on day-to-day operations in order to stay competitive. Therefore, knowledge plays such a central role in today's economy that few products are really low-tech. Even traditional sectors, such as the food industry, incorporate a great amount of technology during the development and in the products. In this new context, firms are increasingly switching from a cost reduction paradigm to activities that have to do with knowledge creation. The implication for this change in perspective is that knowledge is no longer seen as a pure market good. The economics of knowledge are no longer linked to transaction costs minimization. Rather, managers are increasingly aware that the nature of knowledge differs from that of traditional goods. In today's global economy, concepts such as knowledge creation, innovation, and learning are central concepts in firms' competitive strategic planning.

Knowledge, its economic importance and its management have been studied from three main perspectives Amin and Cohendet (2004):

- **Strategic management approach**: in this line of thought, managers are the only members of the organization with cognitive role: they are the one doing all the thinking. They take strategic decisions about the optimal structure and competence building paths of the organizations. Concepts such as core competences assessment and building and the resource-based view of the firm are often used as theoretical tools for decision making. The manager's task here is to build the structure that helps learning that reinforces those core competences. Lower layers within the organization merely carry the tasks that they have been assigned to by managers and give little feedback to the system.

- **Evolutionary-economics approach**: in this approach, organizations are repositories of routines that represent the knowledge of that organization. These routines arm the organizations with the dynamic capabilities that allows for readjustment of the routines and competences to external changes. As opposed to the core competence approach where managers try to get better at what they do best, the evolutionary approach allows for change in competences and routines. Organizations can therefore recreate themselves through a process of readjusting to a changing environment.

- **Social-learning approach**: according to Bogenrieder and Nooteboom (2004) knowledge can be seen as the understanding and interpretation of the world according to mental categories. To become knowledge, information needs to be interpreted in a cognitive framework. Learning is achieved through practice that is bound to a sense of identity in a certain social setting. In this perspective, knowledge is formed and shared in a process of social interaction where action and learning feed each other. Here, learning is not exclusive to individual contribution but depends on the social dynamics of communities and the mechanisms of organizational learning.

1.1.1 Information and knowledge

According to Cowan et al. (2000), scientific activity produces two types of knowledge. The first type, which is called tacit knowledge, is difficult to articulate and is normally transmitted through face-to-face meetings and interactive conversations. The second type, called codified knowledge, is knowledge formalized through a set of statements or messages using an appropriate language. These definitions bring distinction between two terms that are often used interchangeably: knowledge and information.

Information is "a message containing structured data, the receipt of which causes action by the recipient" and "knowledge is simply the label affixed to the state of the agent's entire cognitive context" (Cowan et al., 2000, p. 216). These two economic products have distinctive characteristics. Information is super additive and has low marginal cost of transmission making it similar to other public goods, while tacit knowledge is sticky data and its benefits can only be achieved within idiosyncratic communities (Cowan and Foray, 1997).

Codification requires the definition and utilization of a language which defines the proper syntax and semantic for the conceptualization of tacit knowledge. Since the definition and implementation of a language is an extremely costly operation, we do not dispose of a language tailored for the codification of all instances of tacit knowledge. As a result, a person that holds tacit knowledge will always keep a certain quantity of it if only because of a lack of codification capabilities (Cowan and Foray, 1997).

Cowan et al. (2000) state that for emerging disciplines, knowledge arises from within communities of idiosyncratic individuals. In this regard, these individuals embody the larger part of knowledge that is in its tacit form. The codification process begins when community size increases, physical artifacts are created and articles are published. At this point, discussions and conflicts emerge over the standard messages to be used. When these conflicts are settled, research activities happen around these new concepts and ideas that are codified but that are not necessarily referred to anymore. Knowledge reaches a state where it is latent-codified. As a result of this process, basic research is always in a state of tacitness, incomplete codification and latent-codification. Cohen and Levinthal (1990) observe that knowledge is never perfectly transferred between people inside scientific and technical communities, supporting the idea that tacit knowledge exists and that it plays a central role in the economy of knowledge.

Nonaka and Takeuchi (1995) have defined a similar model for knowledge and information. In their socialization, externalization, combination and internalization (SECI) model, they distinguish between tacit and explicit knowledge. The latter is a knowledge that has been articulated, that has been stored in a media and that can be easily transmitted to other people. According to the authors, tacit knowledge is obtained during the internalization process where people make sense out of explicit knowledge which itself is the result of internalization of the former.

1.1.2 Knowledge as a public good

Marshall (1890) viewed knowledge as a non-material personal good which is non-transferable. Here, knowledge is seen as part of a person's wealth that cannot be shared or sold in any form of exchange. This view was somehow brought into question by seminal econometric studies endeavored by Griliches (1958, 1979) that have shown that there are economic spillovers associated to research and development activities. The fact that individual firms invest in R&D creates an aggregate stock of knowledge on which each can rely on to further advance their work.

In a similar way, studies conducted on the economics of innovation show that firms have great difficulty in appropriating full value from their research effort (Arrow, 1962). Somehow, knowledge flows from the producer to other economic agents without the former being able to make any profit from the transfer. From there, knowledge is seen as a non-rival public good: it can be possessed by many and that its access cannot be easily restricted to others (Dasgupta and David, 1994).

1.1.2.1 Knowledge spillovers

Spillovers happen when knowledge created by one person can be used by another person without compensation to the former. Spillovers are an intrinsic phenomenon associated with the low appropriability of knowledge. Jaffe (1989) asks the question of whether knowledge spillovers are stronger for informal communication mechanisms or if they are due to the diffusion of knowledge through academic publications. Patent data are used to find if industrial labs are more productive when they are concentrated in the same state than university. The study shows that university R&D affects industrial R&D at the aggregate level but that local spillovers were more important in certain fields than in others. More importantly, the author shows that industrial R&D elasticity is strongly linked to university research, i.e. a change in public research output will lead to greater change in private research output. Industrial R&D is therefore very dependent upon basic research (Cohen et al., 2002). Finally, university research is found to have an important effect on patent elasticity relative to its size compared to industrial R&D. In fact, public research produces a great amount of patents given its small size compared to private research.

Among notable empirical studies supporting knowledge spillovers, Narin et al. (1997) have found evidence of strong linkage between public and private research. Their study shows that patents, which are the result of private research, tend to cite academic papers from their respective fields. Patents cite more often papers that have been published recently and this dependence on basic research seems to be a phenomenon on the rise as references to academic papers are increasing over the years.

1.1.2.2 Knowledge exchange

Knowledge can be seen as both and input and an output of production activity. Scientific and innovative effort use accumulated knowledge as an input during a process of recombination which leads to the creation of value. This effort, in turn, creates new knowledge that is localized, path-dependant, interactive and cumulative (Rosenberg, 1994). However, knowledge cannot be seen as a traditional input-output good because of *a priori* uncertain value and costs of acquiring of knowledge, but also because of the difficulties in appropriating total returns from created knowledge (Arrow, 1962). Therefore, a few changes in perspective regarding the trade of knowledge are necessary in order to have a better understanding of its economics (Amin and Cohendet, 2004).

Codification. According to Amin and Cohendet (2004), one of the myths surrounding knowledge is that if it cannot be exchanged, it can nevertheless be transformed into messages that can be exchanged following market rules. These messages are instances or expressions of knowledge that can be transferred through different means between individuals. Therefore, information technology can revolutionize knowledge management and lead to significant economic growth because it minimizes the transaction costs of diffusing messages. A closer study of language shows, however, that not every kind of knowledge can be translated into messages since language or codebook does not always exist for them. Since there are important costs associated with the development and acceptance of language, many forms of knowledge that result from human activity will be left without a proper language for its transfer. Also, from a *constructivist* point of view, the codification and internalization of knowledge depends on the cognitive context of agents involved in the knowledge creation and diffusion processes. Since prior knowledge as well as information internalization are required for the codification of knowledge, the same message can be interpreted in different ways by heterogeneous agents. The fact that not all forms of knowledge are codifiable has deep impacts on the economics and management of knowledge, such as the presence of localized spillovers.

Transaction costs. Transaction costs economics relies on the hypothesis that the actions of economic agents are shaped by rational thinking that is bound to their cognitive limitations. Because of these information asymmetries, institutions must be designed in order to define incentives that will coordinate and govern the actions of agents. These coordinated actions must be performed in a way that will minimize the transaction costs associated with the exchange of knowledge, knowing that all agents seek to maximize self-interests and that cooperation is not always the best option seen from individual perspectives.

From a social perspective, however, learning involves weak levels of rationality where the practice of social norms is more important in guiding behavior. This perspective states that the value of knowledge is difficult to assess prior its transfer, that it has little meaning outside the social settings where it was created and cooperative behavior leads to better results than self-interested action. The open source movement is one example of such communities where collective action is not driven by pure economic incentives and where knowledge is created by cooperating agents.

Individuals and collective knowledge. While it seems hard to contest that knowledge resides within the individual, the recognition that routines are established, shared and practiced within the boundaries of an organization leads to the concept of collective knowledge (Amin and Cohendet, 2004). Routines are part of an organization's knowledge in that they direct collective action and guarantee regularity and predictability in individual behavior. Routines therefore play the role of an organization's memory in dealing with problems. Routines will also lead to the economy of scarce resources when dealing with issues that are difficult to face from a top-down approach to problem solving, by minimizing the number of agents involved in problem solving activities.

In the same way where knowledge is attached to the cognitive state of an individual, routines are context-dependent and involve all the organization's settings such as its equipment, work environment and location. These settings will influence the organization's experimenting paths and their interpretations of reality. As new solutions are found to daily problems, new routines emerge and get adopted and old routines are forgotten in a process analog to natural selection. Therefore, knowledge has a social dimension where action and practice inside communities plays an important part in the creation of knowledge.

1.1.2.3 Research policies

It goes without saying that firms will create knowledge only under the condition that they can appropriate returns from this knowledge (Arrow, 1962; Levin et al., 1987). With R&D having a high social impact and being difficult to appropriate privately, it would seem justified for governments to implement policies that encourage more spending in this area especially when we know that markets fail to do so because they cannot cash in all the value they that they have created (David et al., 2000). Given the importance of R&D and the systematic failure of markets to invest in projects with lower private returns, Jaffe (1998) surveys methods that public initiatives can use to invest in technology projects that have better spillover potential but that would not attract private investment. David et al. (2000) conduct a literature survey about the effectiveness of tax credits in encouraging R&D. They found that tax incentives do not always help in encouraging firms to invest in projects that have a higher social return. However, tax incentives have an effect on R&D performance when seen as a way of decreasing user cost of R&D.

David et al. (2000) have conducted a literature survey concerning the question of whether public funding has an impact on private funding of R&D. While public funding might seem to be the boost needed for firms to invest in projects that have high social but low private returns, it could also have the perverse effect of displacing marginal cost of capital in a way that will actually discourage private investment in the project. This negative effect has been observed by many articles reviewed by the authors. However, the phenomenon of public grants substituting private funds seems to be more accentuated at firm and business unit level rather than at industry or country level. Also, firm-level substitution seems to happen more often in the US than in Europe, perhaps suggesting that policies can be defined in ways to favor complementarity between public and private R&D.

Arora et al. (1998) study the effect of public funds at research unit level. Their econometric analysis based on the elaboration of a resource allocation and research output models shows that scientific affairs have a 'star' system structure where a few scientists produce most of the output. Research output is very dependent on grants, indicating the cumulative nature of scientific knowledge stocks: those who have received funding earlier will produce more knowledge and will more likely receive future funding.

1.1.3 Science and technology

The Compact Oxford English Dictionary (2010) defines science as "the intellectual and practical activity encompassing the systematic study of the structure and behavior of the physical and natural world through observation and experiment", but also "a systematically organized body of knowledge on any subject". Technology is defined as "the application of scientific knowledge for practical purposes" or "the branch of knowledge concerned with applied sciences".

Cowan et al. (2000) states that science and technology can be differentiated by the level of tacit knowledge and the degree with which standard activities – called codebooks – are referred to by the community. Normal science is a space where knowledge is partially codified but where codebook reference is latent and often alluded to. The authors' claim is that common knowledge supplants references to what is known as authority source of codified knowledge. Engineering and applied R&D, on the other hand, are situated in the area where knowledge is uncodified but where standards are explicitly referred to. This is mostly the case for proprietary research groups who perform based on uncodified skills and experience-based expertise but who often refer to procedures that have proven to be successful in the past. The authors call this area the no disagreement zone where sticky data and local jargons are methods used by a community for knowledge appropriation.

Another way of defining science and technology is to associate them with public and private research respectively (Dasgupta and David, 1994; Cohen et al., 2002). Here, norms in terms of knowledge disclosure and reward system distinguish the former from the latter (Dasgupta and David, 1994; Murray, 2002). Knowledge that is generated for profit making purposes and that is kept as propriety is classified as technology. On the other hand, knowledge that is financed through general taxation and that is allowed to be used for free can be recognized as science. Narin et al. (1997) differentiate basic from applied science by associating the former to articles that are the product of public research and the second to patents which are produced by private research. Balconi et al. (2004) distinguish science and technology with the level of openness of knowledge. In science, knowledge is open, meaning that it is available to dissemination and discussion for all within the scientific community. Technology on the other hand is closed and proprietary, meaning that it isn't shared outside the boundaries of the firm. From this perspective, scientists and inventors are distinguished by that the former communicate knowledge in an open way characterized by extensive and rapid codification in the form of publications, while the latter is more concerned about secrecy, implementation of intellectual protection mechanisms and delays in codification.

Seen from the knowledge-based view of the firm, the distinction between science and technology is blurred since a firm's knowledge is in reality appropriated by its employees and that it can therefore evaporate with turnover (Grant, 1996). It is also observed that while firms dispose of legal mechanisms to protect their intellectual property, they are seldom sufficiently compensated for their effort in innovating because these mechanisms are neither efficient nor sufficient for appropriating the returns on created knowledge (Schotchmer, 1996; Dasgupta and David, 1994).

1.1.3.1 Distinguishing scientists from inventors

The behaviors of those who are involved in the innovative activity are very much shaped based on the reward system that is imposed on them. Public scientists who are involved in research funded by private firms will have to readjust their behavior to the incentive structure of the program. They might not own all the intellectual property resulting from the research effort, and will have to collaborate on the application intellectual property mechanisms that will grant the exclusive right of the research findings to the funding firm. Inversely, private researchers that collaborate with universities often find it easy to publish their work that will often be co-authored with university researchers (Balconi et al., 2004; Furukawa and Goto, 2006; Breschi and Catalini, 2010).

Scientists and inventors differ also in the type of knowledge they produce and work with. Scientists are involved in the development of basic research, while inventors are interested in the development of technology which can be seen as the application of basic research to a real-world problem (Furman and MacGarvie, 2007). Following this line of thought, scientists are generally thought of having a broader impact on future technological than inventors do.

From a network topology point of view, reward systems have an impact on network density and the size of main component (Balconi et al., 2004; Breschi and Catalini, 2010). Studies of scientific and inventor communities seem to find that scientific networks usually enjoy a large main component and more dense connections. This is primarily due to the open nature of scientific communications that encourages frequent interactions and exchanges. With the exception of industries that have high staff mobility (Breschi and Catalini, 2010), inventor networks are more fragmented and less dense because closed development models dominate the invention scene. Ejermo and Karlsson (2006) also find that there is strong relationship between patenting performance and self-reliance for a region that is densely populated. While smaller regions are willing to work with more populous regions, it is not often the same for the latter who are content with the level of expertise they find in their own population.

1.1.3.2 Linking scientists to inventors

The literature offers a wide range of studies that show how scientists and innovators are linked together. For instance, Audretsch and Feldman (1996) show that scientists play a central role in transferring knowledge to firms and giving guidance to the future scientific directions of firms. Zucker et al. (1998) show that firms benefit from formal ties to star scientists in that they are able to develop new products and have more products on the market.

Murray (2002) point out that even if science and technology can be seen as separate entities, they seem to co-evolve as science is advanced through technological progress and *vice-versa*. This is obvious when one admits that knowledge spillovers lead to one agent being able to profit from the findings of another agent. The study of patent-paper overlaps through cross-citations shows that there is minimal overlap between the scientists and innovators networks.

However, a social network analysis of co-authorship and co-invention in the laser, biotechnology and semiconductor industries performed by Breschi and Catalini (2010) shows that there is considerable connectedness among the scientific and inventor communities. Their findings were in line with previous studies that indicated a strong dependence on scientific research from the private technology spheres. As it will be discussed later, this connectivity is mostly assumed by a few scientist-inventors who are active in both the scientific and invention networks.

Owen-Smith and Powell (2004) conduct a study on knowledge transfer channels in the Boston biotechnology community. They find that firm ties to university research have a positive impact on innovation. Especially during the early stages of the industry life-cycle, universities are often the anchor points of the innovation networks. In this regard, they act as gatekeepers as they are often in central network positions and are the more active members in the knowledge transfer process. While their role gradually declines as the industry matures and shifts to the production of closed knowledge in the form of patents, scientists' collaboration with inventors has nevertheless an important effect on the industry during initial stages marked by high uncertainty.

Furukawa and Goto (2006) have researched about the role of corporate scientists in the invention process. Corporate scientists here are defined as those scientists who are employed by firms. These researchers perform basic research which's findings are going to be published. Corporate researchers usually enjoy a good reputation in the scientific community as they are often more productive in terms of both the number of papers and citations received. The study shows that corporate scientists are not productive in terms of patents. While it might appear that their links with firm inventors are quite weak, it was found that scientists who co-authored papers with corporate scientists do produce more patents than other inventors.

1.1.3.3 The case of scientists-inventors and scientists-entrepreneurs

According to Zucker et al. (1998), star scientists can play a major role in the invention and entrepreneurship process because of the high excludability that is involved when they contractually agree on developing technology in exchange of its ownership. While patents are often assigned to private companies, star scientists are often offered equity by firms who are interested in the basic knowledge required for patenting and product development. When the application of their basic findings does not immediately fit a firm's expertise, they can manage in raising capital and get involved in the startup of spin-offs. In fact, scientists affiliated or linked with firms patent more often than those that are not. Furthermore, scientists who have registered for patents are more often cited than others.

Network analysis of a patent-paper pair by Murray (2002) also underlines the role played by some key scientists who were found to be active in both scientific and invention spheres. Even if the study finds little overlap between science and technology, the importance of scientists involved in invention has to be considered given their role in building inter-institutional relationships.

In an attempt to measure the impact of public inventors in the Italian patent network, Balconi et al. (2004) found that academic inventors contribute significantly to patenting in electronics, instrumentation and industrial engineering. In most of the cases, patents are owned by firms supporting the idea that public inventors have strong contribution in the technological sphere. These academic inventors patent as much as other inventors and a considerable fraction of them are star inventors who hold much more patents than average. Academic inventors play a more central role and are less isolated than others in the invention network. Academic inventors also seem to be less isolated than regular inventors as most of them enjoy many network connections. Since public inventors often work with larger teams, they develop more relationships and are active for longer periods. Academic inventors have stronger brokerage connectivity and will more often be present in larger network components.

Breschi and Catalini (2010) show that scientist-inventors act as gatekeepers and brokers between the scientific and technological worlds. They play a central position in the scientific community and improve the reachability of isolated individuals in an otherwise low density and fragmented network of inventors. Scientist-inventors also play a strategic position and are influential within both communities.

Most studies covered in this section find that scientists-inventors represent only a smaller fraction of the scientific and invention communities. Many empirical studies find that Lotka's distribution of publishing and patenting performance holds for star scientists (Zucker et al., 1998), corporate scientists (Furukawa and Goto, 2006) and scientists-inventors (Balconi et al., 2004; Breschi and Catalini, 2010). Scientists-inventors are among those few who are as much successful in science as they are successful in inventing. They are rather the exception than the rule in the scientific and invention communities.

1.1.3.4 Private returns

Most quantitative studies concerning return on investment for R&D activities use total factor productivity to measure innovation. According to Hall (1999), doing so has the disadvantage of always missing some of the returns due to the fact that a) there are always time lags between when effort in research are expended and when productivity grows, and b) the difficulties in controlling for other factors that increase (or decrease) productivity in the time-frame of the study. An alternative method is proposed where a firm's financial market valuation is compared against its intangible assets created by R&D and other innovative activities. The advantage of this method is that it can be used as an indication of the appreciation of the market for a firm's knowledge asset. Nevertheless, separating market gains that are due to the taste of investors for the firm's knowledge from the market gains that are due to the other more tangible assets of the firm is still a difficulty that has to be dealt with. Therefore, other financial indicators such as firm book value, P/E ratio, dividend yield, etc. must be controlled for in order to isolate gains resulting from innovative activity. Hall (1999)'s review of studies that link R&D activity to firm value show that they are valued by financial market. However, the intensity of this appreciation is not stable over time, suggesting that market changes its perception towards the value of R&D activity when changes external to the firm happen. However, studies that link stock value to firm patent show that market perception towards patents is more stable over time. Furthermore, patents weighted by the number of citations enjoy significantly more important attention from the market.

Deng et al. (1999) have further studied the impact of patent citations as a measure of quality and importance of an invention. Citations can first be viewed as an indication of the social gains associated by an invention. Therefore, the number of citations received by a firm's patents can be viewed as an indication of the value of the firm's science and technology. In an attempt two view how the market reacts to signals sent by public firms through their R&D and patenting effort, the study measures the impact of the number of patents, the number of citations received by patents, the degree with which patents are linked to science and the technological cycle of patents on the market-to-book ratio and stock return of the firm. While both dependent variables where positively influenced by patent quality indicators, the importance of these indicators where less obvious in timely manner through stock returns. Stock returns are more influenced by immediate information conveyed by firm R&D expenditure rather than ex post information provided by patent citations. Nevertheless, patent-based measures provide relevant information for investment analysis of a firms science and technology.

Chan et al. (2001) also argue that accepted accounting methods do a poor job in valuating firms' intangible assets such as R&D. The fact that R&D activity has a long term return timespan further complicates the task. Therefore, firms who adventure in the path towards innovation may seem to be more leveraged as they face a higher cost of capital due their R&D spending. On the other hand, historical data suggest that non-R&D-intensive firms show the same rate of stock price growth as R&D intensive firms. In other words, markets are generally efficient in properly valuating R&D intensive and non-R&D intensive firms stock prices. However, markets fail by undervaluing R&D intensive firms that have low book-to-market ratio but who still heavily invests in R&D. These firms have a weak record of R&D success but whose managers are still optimistic about their R&D programs. These firms invest heavily in R&D despite poor track record.

1.1.4 Invention and innovation

All inventions do not enjoy the same kind of commercial success. In an attempt to distinguish between invention and innovation, innovation is defined as an invention that has known a certain level of commercial success (Schumpeter, 1934). Patents for instance are the formulation of an invention, but statistics show that not all patents generate the same level of commercial success (Harhoff et al., 1999). In fact, only a few patents end up being used and even a smaller number represent much greater commercial gains than the majority. Basberg (1987) also states that patents are not used uniformly across firms and industries as they are known to be less efficient in protecting process innovations than in protecting drugs for instance. Firms dispose of other forms of intellectual property protection, such as the industrial secrecy, meaning that innovation is not only measured through patenting activity. Finally, all patents are not filed with the intention of using it for commercial purposes. Often, competing firms develop patents that could prevent each other from developing and commercializing products, but implicit agreements exists where none of the firms take legal actions to protect their patented technology.

Nevertheless, patent statistics have been used as indicators of technological change, of diffusion of knowledge between countries and as a variable correlated to productivity (Basberg, 1987). The distance between invention and innovation is further reduced by the increasing role that universities play in developing commercial applications. There seems to be a relationship with patenting and increasing revenue. For example, universities were able to cash in on their research effort by implementing technology transfer offices (Mowery et al., 2001).

(Christensen, 1997) defines disruptive technologies as inventions that improve a product or service in a way that was not initially expected. These technologies aren't usually competitive with established technologies, but can nevertheless answer the needs of a niche. Firms who introduce these disruptive technologies will gradually improve their performance in a way that it will eventually answer needs of more performance-sensitive market niches, thus displacing incumbent technologies that were previously serving those niches. At the same time, Marketing myopia leads incumbent firms to invest heavily on incremental improvements of their bread and butter products and miss the opportunities brought by those disruptive technologies.

In their popular article about architectural innovations, Henderson and Clark (1990), claim that innovations are the result of the integration of core concepts and peripheral components. A firm that introduces an innovation can either change or improve upon the core concept, but also keep or change the peripheral components. Radical innovations are those in which both core concepts and components are overturned. Incremental innovations, on the other hand, are those in which core concepts are reinforced while components are unchanged.

It is worthwhile mentioning that commercial success does not always imply technological superiority. In fact, network externalities that are often the result of trivial circumstances can play in favor of competing technologies and lead to an inferior technology being selected by the market (Arthur, 1989). David (1985) studies the case of the QWERTY keyboard which enjoys widespread market adoption even if it is a less efficient alternative to its competitor, the AZERTY keyboard. Since patent success cannot be predicted a priori, firms often take part in patent gambling hoping that a percentage become successful commercially (Lemley and Shapiro, 2005). Patents are only a link in the overall chain of activities that lead to innovation and productivity growth. Because of the appropriability issues inherent to knowledge, patents

– on their own – do not guarantee that a firm will be able to make use of an invention since part of the knowledge necessary for this purpose is within people (Dasgupta and David, 1994).

1.2 The recombination and diffusion of knowledge

From the perspective of evolutionary economics, innovation consists in combining resources and components in new ways (Schumpeter, 1939; Nelson and Winter, 1982; Kogut and Zander, 1992). The recombination of existing knowledge components requires capacity to assimilate the said components. As such, the concept of learning, combining and disseminating knowledge are inter-related.

1.2.1 Absorptive capacity

Firms that invest in R&D gain what Cohen and Levinthal (1990) call absorptive capacity or the ability to use outside knowledge. An organization's absorptive capacity is a function of that of its employees, but also of the routines and procedures that are used on a daily basis. An organization can learn new things that are similar to the kind of knowledge that its employees already have. Organizations can also adopt new routines that are similar in fashion to those that are already in use by the personnel. In this perspective, the innovative capacity or the capacity of a firm to produce new knowledge depends on how much a firm can learn from its environment. Innovating is therefore similar to imitating as studies suggest that both functions require more or less the same cognitive capabilities.

The concept of absorptive capacity also account for the cumulative nature of knowledge, meaning that the more an organization has learned in the past, the more it can learn new things in the future. Also, learning is a process that is path-dependant, meaning that the understanding and interpretation of future phenomena is function of the stock of knowledge that was previously held by the organization or individual. Cohen and Levinthal (1990) also mention that diversity must not be neglected when managing the knowledge-base of an organization. Developing resources and competences that are too close in terms of knowledge can be detrimental to the firm's capacity to learn new things. For instance, if a firm invests most of its resources in one technology, it will be increasingly difficult to adopt other technologies as the kind of knowledge required to employ them is too different from that of the initial technology. This is often called the competency trap or the lock-in situation where organizations are incapable of getting rid of old cognitive state. In these cases, the dexterity that an organization develops in one technological are renders the development of dexterity in other areas too expensive and unattractive in terms of effort investment.

1.2.2 Knowledge creation

Levitt and March (1988) state that organizations are guided by routines which are a set of rules, procedures, beliefs and codes external to the individuals that compose the organization. When organizations perform new experiences, they adopt new routines when these experiences are perceived collectively to have positive outcomes. This process is labeled learning by doing and emphasizes the importance of experimenting for creating knowledge. Exploring new possibilities is associated with terms such as "search, variation, risk taking, experimentation, play, flexibility, discovery, innovation" (March, 1991). When an organization is committing resources in the search for new knowledge, the speed with which it can get better at older knowledge (called 'exploitation') is naturally reduced. Since the returns from exploration are less certain and more remote in time, it can appear less attractive in the short run perspective (March, 1991). While the internal characteristics of an organization are important in shaping its decision of exploring or exploiting, factors external to the organization can have an impact also. For instance, firms who evolve in the military or pharmaceutical sectors are more inclined in investing in basic research because of the market structure (Rosenberg, 1990).

Knowledge creation can also be impeded by knowledge codification because it implies that a path has been previously explored and that a codebook is defined and manifest for it: future explorations will be building along these explored paths and result in lock-in situations (Cowan et al., 2000). Greater codification means greater path-dependence and reliance on past experiences when it comes to creating new knowledge. March (1991) believes that mutual learning inside organizations leads to convergence between organizational and individual beliefs. Turnover combined to slow socialization of new organization members is a remedy to this problem because it brings about diversification inside an organization and increases the likelihood of exploring new venues. In the same line of thinking, the reputation of researchers having great impact on their receiving grants (Arora et al., 1998) can be a moderator for creativity because it will result in previous experiences being reinforced at the expenses of new experiences.

Intellectual property rights also have a negative impact on creativity because they impose a cost on innovators who need to use protected knowledge and thus depreciate the value that might be appropriated otherwise (Murray and Stern, 2007).

1.2.3 Knowledge diffusion

According to Levitt and March (1988), the process of knowledge diffusion means learning from the experience of others. Organizations learn from others by imitating their behavior. In fact, the larger body of innovations comes from borrowing from others rather than inventing and the acts of creating new knowledge and learning new knowledge are very similar and involve the same cognitive capabilities. Therefore, knowledge growth comes from interactions inside scientific communities. Interactions between individuals result in the diffusion of knowledge which is perceived through an exponential increase in publications.

Geroski (2000) is a review of different models that explain for the S-curve diffusion of technology. According to the epidemic model, users will not adopt a technology until they obtain enough information about it. The information diffusion is dependent on two factors: the rate of transmission from a central source and the rate of transmission through word-of-mouth. The density dependant growth model is similar to the epidemic model, but where the two diffusion forces are legitimation which accelerates diffusion and competition which tends towards an asymptote. The probit model differentiates people by features that lead to them adopting or not a technology. Firm size, its suppliers, technology life-cycle, learning costs, opportunity costs and exchange costs are all factor that impact the probability with which a firm will adopt a technology. The information cascade model states that first adopters will influence next adopters by generating information. Network effects will lead to the technology information being exponentially more available. This model explains how technological lock-ins or excessive inertia, where users hesitate in being initial users, can occur.

Cohen et al. (2002) show that public research has an important impact on industrial R&D. In fact, research publications are recognized to be the most important source of knowledge for firm R&D. While applied research has a broad impact on the industry, basic research tends to be very influential in specific industries. For instance biology and chemistry are the most important fields where knowledge emerges for pharmaceuticals. Similarly, physics is the dominant field for the semiconductor industry. Knowledge availability for a certain technology has an impact on its diffusion and adoption (Stonemann and Diederen, 1994). Intellectual property protection, while not efficient for the protection of innovator has, paradoxically, a perverse effect on knowledge diffusion (Mowery, 1998).

Mowery et al. (2001) study the effects of Bayh-Dole act of 1980 to find out if it caused a shift from basic to applied research within universities and if it was the main cause in the rise of university patenting practices of after the 80's. The act was mainly designed with the intention of protecting the results of publicly funded research in order to receive commercial benefits from them. By studying patenting practices from three leading American universities, the authors haven't found any link between the increase of university patenting and the Bayh-Dole act. Instead, the rise seems to be linked with the emergence of the microbiology and software fields. Also, the policy did not have a significant impact on shifting university effort from basic to applied research. The main effect of the act was to change university behavior in regards to the dissemination of their findings: what used to be communicated through open channels such as journal publications was now patented which might have a perverse effect on knowledge diffusion thus resulting in lower social returns.

Concerning the question about whether Bayh-Dole act helps or hinders the transfer of knowledge, Colyvas et al. (2002) have analyzed the case of 11 patented inventions in order to see if intellectual property rights have an effect in bringing inventions into practice. Their findings show that 'embryonic' inventions that result from university research generally receive more attention from firms if there are possibilities to obtain exclusive licenses. However, exclusive licensing introduces the issue of choosing the right licensee for these inventions because firms who receive exclusive licenses but are not able to develop a product might lose interest in the invention. The authors have also founds that ready-to-use inventions did not need intellectual property protection to get into practice from the industry.

1.2.3.1 Organization and knowledge transfer

Organizations that get involved in knowledge transfer innovate and perform more than others (Van Wijk et al., 2008). Knowledge transfer is a process that involves both internal and external knowledge of the organization. From inside the firm, strategic units come with different technological perspectives and are able to complement each other in a way that the firm can adopt emerging technologies and processes. Different functional departments also have their own understandings of what can be done for developing innovative products and services. Marketing, management and technology teams all look at the firm's environment with different perspectives and are therefore able to grasp different opportunities. Of course, every department has a relative importance depending on the characteristics of the sectors in which the organization evolves (Sammarra and Biggiero, 2008). For instance, mature industrial sectors do not introduce technological innovations as much as they introduce process or market innovations. In this regard, department activities need to be integrated in order to take advantage of different views erupting from within the organization. Put simply, diversity and complementarities inside an organization are essential in dealing with the complexities of today's hypercompetitive markets.

However, firms will seldom succeed in accumulating enough knowledge to answer all their needs. Since there is so much more knowledge on the outside than inside the organization, not taking part in knowledge transfer can be a fatal mistake. Therefore, organizations are forced to look outside their borders and absorb knowledge that can be used for developing innovative solutions (Van Wijk et al., 2008). These external sources of knowledge can be suppliers, customers, universities, government labs, competitors and other nations (Chesbrough, 2006). Each of these agents can be helpful in providing a certain type of knowledge which will each require appropriate skills in terms of relation building. For example, customers and universities differ greatly in the type of knowledge they can provide. Also, firms cannot manage their relationships with suppliers and competitors in the same way as power structures are different in each case.

Kang and Kang (2009) have identified three main methods for sourcing external knowledge: informal networks, R&D collaboration and technology acquisition. Informal networks are weak ties for which organizational interactions are not required. These informal exchanges usually happen during conferences, fairs, exhibitions, customer contact, professional associations' gatherings and other types of meeting where people share their experience about new products, emerging topics and latest technological trends. In these settings, there are no directives set by management as how to interact among members of the network. Rather, these informal networks are often the result of initiative taken by professionals that are active in their fields, and this, independently of the will of the firms that employ them. Informal networks are often thought of having inverted U-shaped relation with innovation performance because of an increasing cost involved in searching and maintaining these informal ties, although progress in information and search technologies can help reduce some of that burden. In fact, progress in the adoption of electronic databases and bibliometric and data mining techniques (Porter et al., 2008; Huang et al., 2003) can be beneficial in exploring technological landscapes with little search effort. In fact, Kang and Kang (2009) find a positive link between the number of informal networks and the success of knowledge transfer.

R&D collaboration networks differ from informal networks in that they are the result of a strategic intent from organizations. These are strong ties leading to formal network structures. The great number of interactions required for relationship building makes this form of knowledge transfer to be a very costly one. In these settings, several issues related to opportunistic behavior and unwanted knowledge leakage are common worries for all parties involved. Because of the excessive cost of building strong ties and the mentioned risks in collaborating, this method of knowledge sourcing is believed to have some negative impacts on performance and lead to an inverted U-shape curve on innovation performance. In fact, the study from Kang and Kang (2009) shows that firms who overinvest in R&D collaboration might find themselves in situations where they cannot support commercialization or proper internal R&D because too many resources have been invested in this expensive path. As a result, much of the collaboration effort is lost in vain because no concrete project emerges out of it.

The third method for sourcing, technology acquisition, is also a formal method but that involves weak ties because it does not require organizational interaction. This method can be seen from the open innovation (Chesbrough, 2006) perspective where the acquisition is one way of relying on knowledge that was created outside the organization. As a method for knowledge transfer, this method has received mixed reviews from the literature where there are as many success stories as failures in knowledge transfer from acquisitions. However, this view is not shared by Kang and Kang (2009) who find a significant positive impact on knowledge transfer coming for technology acquisition.

Easterby-Smith et al. (2008) enumerate franchising, co-production agreements, licensing and joint ventures among the most used methods for knowledge exchange. Again, these methods must be assessed from an open innovation perspective. Licensing can be seen for the selling firm as one way to expand its business model. For the buying firm, it is one way of using knowledge that was developed by another firm. Joint ventures are formal agreements that tackle a relatively uncertain technological path by sharing failure risks and minimizing the lack of knowledge from both sides. Finally, soft transfer mechanisms can be used to get inter-firm communities of practice jointly develop a document, a process in which both sides learn from each other while taking part in shared development activities.

Chiaroni et al. (2008) studies the consulting of technical and scientific services (TSS) as another method for knowledge sourcing. These knowledge intensive business services are widely recognized as playing a knowledge-bridging role in the economic development of industrial countries. These services foster knowledge transfer because they can understand complex data, and ensure the efficient and effective adsorption of knowledge by recipient firms and into the recipient's innovation process. TSS firms often play the role of gathering and recombine information from different sources and provide this knowledge to their traditional companies that enter an industry in early stage of its lifecycle. Later on, when the industry grows and reaches maturity, the role of these TSS firms becomes one of specialization and personalization of knowledge for a few clients and applications.

1.2.3.2 Choosing the right method

Although the above mentioned methods are positively linked to knowledge transfer, a review of other studies shows that the choice of the proper method depends on factors such as the type and characteristics of the knowledge that is coveted, the organizational characteristics of recipient and donor firms, network characteristics and the industrial sector's characteristics.

Types and characteristics of knowledge exchanged. Sammarra and Biggiero (2008) inquiry about the exchange of marketing, managerial and technological knowledge among firms and the way in which each of these types of knowledge is exchanged within a network of localized Italian firms evolving in the aerospace industry. Like many knowledge intensive industries, innovation in the aerospace sectors is not only about adopting or creating new technologies, but also about understanding market trends (marketing innovation) and improvement of organizational processes (managerial innovation). The study shows that most companies are involved in alliances for sharing all three types of knowledge. This shows the importance that companies are according to diverse and complementary knowledge. Even if the technology sharing network is more important in size and intensity than market and managerial networks, network topologies for each type of knowledge shows that different players are involved differently for each type of knowledge. This is due to the fact that every firm builds relationships according to the kind of knowledge they need and that they can bring on the table. Since firms come with different backgrounds and expertise, it is natural that complementary knowledge is absorbed if firms get involved in different exchange networks.

Also, knowledge characteristics such as its tacitness, specificity and complexity have an impact on how easily it can be transferred through market transactions, leading to the preference of either formal or informal relationships and the occurrence of certain network structures. Sammarra and Biggiero (2008) find that when knowledge is more tacit and complex, informal meetings are better fit for exchange of heterogeneous knowledge. Since management has little control over what is exchanged between members of an informal network, partitioning of tasks and physical separation of experts can be used as a way of protecting proprietary knowledge. A meta-analysis conducted by Van Wijk et al. (2008) nevertheless shows that ambiguous knowledge, i.e. one that is simultaneously tacit, specific and complex, is more difficult to transfer, which can be one way of avoiding unwanted leakage. Also, tacit knowledge is more effective in hampering knowledge acquisition more than it knowledge exchange. Ambiguous knowledge is also easier to transfer inside the firm than between firms. In the light of these findings, organizations that want to proceed with the transfer of strategic knowledge are better off relying on informal networks because these are more effective channels of communication for complex knowledge and because their complexity minimizes the possibility of unwanted leakage and opportunistic behavior outside the informal network.

Organizational characteristics. Partner-specific variables such as absorptive capacity, prior experience and cultural and geographical distance have an impact on knowledge transfer (Sammarra and Biggiero, 2008; Van Wijk et al., 2008; Easterby-Smith et al., 2008). Absorptive capacity shows how much firms can access diverse and complementary knowledge and are able to combine and integrate this heterogeneous knowledge into innovative products and services. Sammarra and Biggiero (2008) state that mere technological know-how is not enough to be able to transfer knowledge with success. Organizational capabilities, strategic networking capabilities and market knowledge are also important to be able to search for the right alliances as well as to monitor and maintain them. Therefore, the degree of heterogeneity of individuals and groups involved in knowledge exchange is important in facilitating effective exchange. This is true for firms willing to exchange knowledge with other firms, but also for firms willing to create internal knowledge transfer (Van Wijk et al., 2008).

Van Wijk et al. (2008) also find that organization size, age and hierarchical structure of decision makings have an impact on how knowledge is going to be transferred within and between organizations. Larger firms have more resources to devote to knowledge transfer and chances are that those resources come with diverse backgrounds. With a broader knowledge-base, larger firms can assimilate external knowledge more easily. Older units have more difficulty in being involved in knowledge transfer inside their own firms because they have learned to be self-supporting. The older a unit, the higher is the chance that it is living out of a few key and matured technologies. These units usually engage in exploitation activities by deepening their experiences with those technologies. This means that the unit has done little exploring and broadening of new technological venues. These firms have little diversity in their activities and are specialized in certain fields, which could mean lower absorptive capacity. Decentralized organizations also have trouble in transferring knowledge at inter-organizational level. The main reason behind this is that decisions about building strategic alliances are usually taken at corporate level, even though units are structured in a network for daily operations.

Easterby-Smith et al. (2008) claim that firms that are disposed to take risks are more often involved in knowledge sharing, but only with firms that have a strong collaborative reputation. Here, reputation within networks of peers is crucial in building trustful relations that can lead to open atmospheres of knowledge exchange. Along with a risk taking profile come the motivation and intent from both the recipient and donor to engage in knowledge exchange activities. Firms that are committed to learning will align their resources to knowledge sharing activities, thus avoiding opportunistic behavior. Firms who are willing to take risks and are motivated to learn will therefore be more open towards building formal collaboration ties such as R&D collaboration, joint ventures and acquisitions.

Easterby-Smith et al. (2008) also underline that the learning capacity of organizations will dictate the cooperative/competitive nature of the knowledge exchange relationship. Recipient firms who learn faster will dominate their relationship with the donor because they absorb more knowledge in a shorter time frame, leading to power asymmetries and a shift towards competitive or opportunistic behavior. Here, building strong and formal ties can be detrimental and counterproductive and often lead to dead-end situations where the donor could stop cooperating if feeling threatened, or the recipient could default from its knowledge sharing commitments when it has absorbed a satisfactory quantity of knowledge. Difference in corporate culture has a tendency to distort meaning and diminish the perceived usefulness of knowledge. Cultural distance therefore hinders knowledge transfer especially at intra-organizational level (Van Wijk et al., 2008). Corporations need to deal with cultural distance by getting collaborating members from both sides to socialize and to know each other better in order to lower cultural barriers.

Network characteristics. Geographical proximity helps in the transfer of knowledge (Sammarra and Biggiero, 2008). Easterby-Smith et al. (2008) also believe that space between firms can become a barrier to knowledge transfer. One major drawback of spatial distance is that it renders very difficult the creation and maintenance of strong informal ties. Strong ties require trust and time consuming commitment in the relationship, things that are difficult to achieve when distance is imposed upon relationships. Similarly, informal networks involve frequent face-to-face interactions which require members to be physically close to each other.

Van Wijk et al. (2008) report that the number of network relations, tie strength, shared vision and systems and centralized position are network characteristics linked to knowledge transfer. These characteristics have different impacts on knowledge transfer when analyzed at inter-organizational and intra-organizational levels. Strong ties, the number of relations and the centralized position have a positive impact on inter-organizational knowledge transfer, but this impact is less obvious for units inside the organization. Trust, on the other hand, has a significant positive impact on knowledge transfer both inside than between organizations.

Even if it seems less intuitive, this finding supports the idea that units inside a firm can also compete for resources. Therefore, a trustful relationship among them is important for efficient knowledge flows inside the organization.

Industrial sectors characteristics. All industrial sectors are not involved in knowledge transfer in the same way. For instance, Sammarra and Biggiero (2008) find that SMEs in a sample of aerospace companies were very active in terms of networking and knowledge transfer. Indeed, SMEs in high technology need to have more diversified capabilities than in other sectors. They cannot act as mere passive suppliers but must also be involved in market or managerial innovations in their sector. In mature or low-technology industrial sectors on the other hand, vertical relationships are the norm. Decision making in terms of technological path exploration and exploitation are taken hierarchically. The type of dense, horizontal network relationships found in Sammarra and Biggiero (2008) does not hold anymore. Knowledge exchange is more directed and of formal nature. Other sectors, such as the defense industry, also differ in that they are characterized by secrecy as well as formal vertical relationships with suppliers. Here, distributed knowledge is not frequent and large-centralized firms tend to dominate the technological landscape.

1.3 Collective knowledge

The central idea behind learning in communities is that collective action leads to greater performance than that of individuals. The mystery is finding how collective action performed by individuals that come with diverse cognitive backgrounds can be coordinated in a way that leads to the creation of knowledge that transcends those individual contributions.

According to Bowles and Gintis (2002), when markets fail because of information asymmetries and when governments fail because of their incapacity to coordinate self-interested individuals, communities can be the answer by relying on insider-outsider concepts. By providing a sense of identity that leads to cooperative effort from members, communities are complements to markets and states.

One example of how communities and collective action can give superior results is the performance difference between the Silicon Valley and Route 128 (Saxenian, 1996). From its inception, Route 128 was influenced by a spirit of formality through MIT's strong ties to Washington and heavy orientation towards large established producers, while Stanford relied on collaborative relationships among small firms.

While MIT built strong ties with large technology producers and governments invested heavily in large military R&D projects that benefited local universities and industry, technology developments triggered a circle of industrial development with a strong orientation towards ceremony and formalities. Silicon Valley on the other started with a few small companies building new electronics technologies with very little investment (including HP). Unlike Route 128, universities and firms had an interactive relationship. This example shows how one historical setting that had formality and rational thinking in its core for generation behaved and performed compared to another where open exchange mentality dominated initial developments.

1.3.1 Communities of practices

Traditional schools of thinking viewed learning and working as distinct things. Learning was mainly seen as the transmission of abstract knowledge from one person to another and where the setting in which learning happens does not matter. Learning was abstracted from practice. In the same way, operations inside firms were designed with the intention of separating practice from procedures. Canonical procedures where the expression of what management believes should be done for a certain task. Those who were assigned to perform the tasks were supposed to execute those canonical procedures word for word and their performance was assessed based on how well they've followed procedures. These views did not recognize that abstractions detached from practice distort the details of that practice and that procedures can never contain enough detail as to describe complex tasks such as that require problem solving.

Andriessen et al. (2004) class these attempts under codification strategies that consist of information storage, retrieval and exchange. Because the tacit nature of knowledge, its distinction from information and the fact that it loses personal and contextual meaning have been ignored by believing so, knowledge management efforts usually fail. Furthermore, the implementation of these systems ignores the psychological barriers of sharing knowledge, an important good that gives power and leverage to its holder.

Brown and Duguid (1991) point out that what dictates the success of a firm is how procedures are performed and not how they are defined. In other words, what actually matters is the practice of procedures and not the canonical procedures. Because of the divergence between canonical procedures and what is actually being practiced, workers develop non-canonical practices to overcome the insufficiency of canonical procedures.

These noncanonical procedures are exchanged inside the community of practice through a process of storytelling. Workers talk about their personal encounters of the same problem, with each worker having a significantly different version. Through story-sharing process, new stories are created and passed around inside the community. Storytelling therefore reflects the complexities of the work environment that is not described by canonical procedures and that is hided from management. From here, learning is no more the act of memorizing and executing canonical procedures, but understanding 'workarounds' to canonical procedures.

It is through this constant change of circumstances and membership in this ongoing process of practicing that communities of practice become places for innovation. Communities of practice become a platform for the exchange of explicit and implicit knowledge. They provide grounds for developing situated learning where social interaction is critical. These communities develop a procedural knowledge around their practice that is available to all members in the form of a shared repository of wisdom (Andriessen et al., 2004).

1.3.1.1 Learning

In this legitimate peripheral participation model, learning involves becoming an insider of a community of practice. Learners, or newcomers, learn to function in the community by learning to speak its language and acquiring its subjective vision by first being connected to its peripherals in a process that is called enculturation. The point is to become a practitioner and not to learn abstract ideas about the practice. Learning involves things that are not explicable or explicit and must be developed in a communal context to be grasped.

This new approach to learning has three main features. First, narration helps diagnose issues and acts as a repository of accumulated wisdom. Second, learning happens by collaboration because individual learning is inseparable from collective learning in situations where difficult problems are solved in groups of individuals who share their past experiences. Third, social construction is a process where community members build a shared understanding out of conflicting and confusing data and where they build their own identity as members of the community.

Learning can be fostered by giving access to practitioners, while restricting access to knowledge for those who are at the periphery slows it down. Periphery needs to be empowered because it is not only a site for learning but also innovating since the interaction of newcomers with the environment brings fresh perspective and interpretation to the work context.

1.3.1.2 Innovating

Innovation is the result of dynamic learning where alternative views and interpretation of spontaneously occurring experiments leads to new understanding. Discovering organizations learn to respond to changes in the environment and enacting organizations create the conditions to which they must respond. Here, the process of innovating involves "actively constructing a conceptual framework, imposing it on the environment and reflecting on their interactions".

Andriessen et al. (2004) also state that personalization strategies have been more successful in sharing knowledge and fostering innovation. These are methods of learning based on participation and informal socialization inside communities of practice. Downskilling, on the other hand, can be detrimental to innovation because it diminishes that role of communities of practice (Brown and Duguid, 1991).

1.3.2 Epistemic communities

Adler and Haas (1992) report that world politics have long been viewed from a neorealist perspective where national security and interests predominate over ideas and social constructions. This line of thought is very similar to that of the rational choice theory where information supremacy leads to optimal decision making. However, we can see that in our complex world, there is not enough transparency for the conditions to leads to an informed and rational decision in terms of national interests. Under these conditions, policy coordination is based on consent and mutual expectations that come from interpretive processes rooted in political and cultural structures.

Different epistemic communities will bring about methodological pluralism and offer different descriptions of the world. As epistemic communities exert influence in their nation-states, those policies and values, in turn, be represented and promoted at international levels. Epistemic communities have therefore the possibility to have a say in world affairs. If we know the dominant epistemic community, we can deduce the likely policies available for political selection.

1.3.2.1 Leading change

The first role of epistemic communities is in bringing policy innovation. They do so by identifying the nature and context of an issue. When society is face with a certain problem, epistemic communities interpret that problem from their own perspective. Based on the prescribed policies in their respective line of thought, they define state interests and set norms and standards to tackle the issue.

Epistemic communities are always active in diffusing their ideas among political groups in their own nations, but also at transnational levels in scientific communities and international organizations. Internal diffusion has a direct impact on national politics, while international diffusion helps reach common understanding and coordinate behavior at the global level. However, in the case of hegemony, influence becomes undirected as epistemic communities from the dominant state exert indirect influence on policies of other subordinate nations.

Epistemic communities are also active in the process of policy selection. When there are no existing policies, when policy makers are not familiar with an issue, and when no institution tackling the issue exist yet, epistemic communities can easily exert influence. However, developed habits and inertia perpetuates the influence of an epistemic community at the expense of others. Often, the epistemic community that is closer to the mainstream political factions has an advantage for being selected. For the sake of being selected, coalitions can build coalitions to gaining influence among decision makers. Also integrative ideas that can generate broader coalition can influence the selection process. Timing is another important factor for policy selection.

Policy persistence occurs through a process of socialization, where ideas become institutionalized, and then they become orthodoxy. This is precisely how policy inertia occurs and how political leaders develop cognitive habits that will shape future interpretation of events. Also, ideas that can reach consensus among community members have a longer lifetime. In fact, even if knowledge cannot be objective, positivism is still possible among different epistemic communities. Successful ideas and epistemic communities that have proven to be right also last longer.

1.3.2.2 Empowering epistemic communities

Competition among ideas between epistemic communities depends on the absorptive capacity and motivation to understand diverse alternatives to single issues. Absorptive capacity in turn is shaped by past experiences and theories that people already have in mind have. New technologies can help in organizing and dealing with the increasing complexity and technical natures of issues, creating a hospitable environment for epistemic communities. The process of exchanging ideas has a great deal of impact on how epistemic communities will perceive and interpret new concepts. It is by interacting, therefore, that epistemic communities can shift the debate from state interest to shared understanding. Studying epistemic communities will help understanding expectations, thus leading to cooperation.

1.3.3 Communities of creation

Sawnhey and Prandelli (2000) account for communities of creation that are the main force behind innovation in a world market by rapid change and constant transformation. Traditionally, innovation was an internal affair for the firm and was managed through hierarchical governance mechanisms. These closed firms have decreased in their capacity to innovate. On the other end of the spectrum, lie open movements that apply minimal secrecy and structure to their activities. However, these communities lack governance and coordination mechanisms which lead to inefficient allocation of resources and rewards. The communities of creation are somewhere in between the closed and the open model by offering a compromise between too much structure and complete chaos. Communities have specific rules for membership and need a sponsor as well as a system for managing intellectual property rights.

1.3.3.1 Creation and sharing

Knowledge can be defined as something that is spread socially and influenced by social settings. It is a social construction based on the interaction of several meanings shared by agents who process information through cultural processes. These interactions lead to the creation of new meanings that transcends individual contributions. New knowledge is the output of synergistic interplay between individual contributions and social interactions. It is therefore shared among organizational members and is developed through participation. Therefore, knowledge cannot be owned by individuals but is rather distributed among community members. Networks are therefore a place for creating and sharing knowledge by freely interacting with others. This process of continuous interaction leads to continuous change in the cognitive setting of the community members and of the social settings in which they evolve.

1.3.3.2 Distributed innovation

According to the transaction costs analysis school of thought, hierarchies will reduce transaction costs when there is uncertainty, rationality and opportunism. From a community of creation perspective, there is a need to shift from minimizing transaction costs, to maximizing transaction value from networks of firms. The main question for knowledge creation in communities of creation is about how to coordinate actions to take into account that knowledge is contained in more than one mind.

One thing that helps the recognition of such possibility is the fact that knowledge is increased in value when it is exchanged thanks to incremental development and diffusion. Also, giving away knowledge does not deprive the donor from it. Therefore, the question is not how to defend itself from leakage of knowledge to other network members, but how to get them involved in the process of knowledge creation.

Knowledge socialization and collective learning is based on relationships of meaning building and sharing. These relationships are governed by informal structures of strong intensity built as members transform into a community. In this sense, the theory of legitimate peripheral learning is met here where periphery becomes a relevant place where new meaning joins the community.

The role of leadership is to help self-organization by promoting organizational identity, create sufficient destabilization in the organization, and nurture relationships in the organization. Firms also have to shift their view of intellectual property from one of possession to one of participation. After all, most innovation being the result of joint efforts, it is difficult to measure the contribution of individual members. Firms should not care about for the distribution of existing knowledge but for favoring production of new knowledge.

1.3.4 Communities and formal structure

Generally speaking, community learning is based on Weickian constructivist and loose coupling perspective on decision-making (Ferrary and Pesqueux, 2006). Organizational enacting and sensemaking are dynamic processes that transcend structural boundaries. Organizations must be better suited for organic development in fast moving environments, rather than developing rigidities in their structure. In other words, organizations must take the shape of their members and their networks rather than imposing their own structure on others. Imposing formality in phenomena that require free flow of ideas can be detrimental to the learning process.

1.3.4.1 Formal boundaries

Brown and Duguid (1991) provide a few notes on how communities of practice fit with formal structures. Communities often cross the boundaries of the organization and get knowledge that comes from outside the organization. Therefore, reorganizing of the workplace into canonical groups can disrupt these communities since members are not always willing to share knowledge outside the community. Communities must be able to interact with each other in an autonomous way and information must travel freely inside the community. Organizations must recognize the existence of communities of practice and foster peripheral learning and large atypical organization that do so have a strong innovative capability.

The study of Silicon Valley region (Saxenian, 1996) also shows how blurring the firm's boundaries are beneficial for the development of communities. In the Valley, large firms were gradually opening themselves by building local alliances and subcontracting relationships, while firms on Route 128 kept a self-centered approach. HP (the main player in the Valley) started a transition towards open systems while DEC (Route 128) stayed with a proprietary model. The openness to external knowledge allowed big Valley firms to understand changing trends in the market while close-minded corps of Route 128 where in denial of the emerging market opportunities. When (often late) decisions were made to enter new markets, the obvious decision was also to internalize production at the expense of (often late) market entry.

In the Valley, when companies reach a certain size, they split into independent divisions that are designed to 'bring the market inside the company'. This network-centered point of view also led to a complex interrelation of specialized customers and suppliers which naturally favored smaller and more agile firms. As a result, firms where loosely coupled and more freedom of designs and changes were available. Firms however, understood that each other's success was very interrelated and went often as far as sharing strategic information for the sake of better synchronization of efforts. In this context, firms often learned from each other but also together by joining their respective complementary knowledge.

1.3.4.2 Geography and structure

Spatial proximity is often thought of a place where innovative ideas emerge at fast pace. From a social learning point of view, geography plays a particular role in the process of enacting and sensemaking. Saxenian (1996) provides Silicon Valley and Route 128 as two examples of regional industrial success stories where one region was able to keep on growing while another slowly lost its dominant position as an innovating region. The Valley had a network-based system that encouraged collective learning, while Route 128 consisted of a few highly integrated firms that internalized a wide range of productive activities.

Regional systems have 3 dimensions which are closely interrelated: 1) local institutions and culture such as universities, business associations, local government and professional associations; 2) industrial structure or the division of labor between competitors, customers and suppliers; 3) internal organization includes the degree of hierarchy, centralization, and specialization. The way these three dimensions are manifested in a regional system will dictate how the region will be able to respond to changes in the industry. If these dimensions are all aligned with open perspectives of innovation, then spatial proximity can become a factor that helps cooperation and coordination. However, if hierarchy, formality and verticality dominate the structure of firms, institutions and industry, then geographical proximity will make little difference on how firms will perform.

In the Valley, the interactive tendency of network-based firms contrasted with the vertical approach of route 128. Firms who were open to their environment profited from the interactions and flows of information that happen between firms, that is the knowledge that is outside the corporation. On the other hand closed firms were unable to readjust to the fast pace at which change occurred in their industry and could only rely on their limited know-how to innovate.

1.3.4.3 Community governance

Bowles and Gintis (2002) have studied governance mechanisms in communities. Governance is mainly done through peer monitoring. Community members can share income, costs, information and training resulting in higher level of work commitments and better total factor productivity. Insiders have a sense of identity which leads to trust and cooperative behavior among peers. Since communities are not governed by self-interests, they can help overcome market failures. The main issue then rests on how to provide incentives that can lead to community cohesion.

Inside communities, incentives can take different shapes. For instance, people who interact today will probably interact in the future. Also, frequent interactions indicate how future interactions will go and will therefore lower transaction costs. Inside communities, opportunistic behavior can be punished by members more effectively than in markets where the number of possible interactions prohibits peer monitoring. Punishment, in turn, has a positive impact on member involvement and cooperative behavior as it gives a sense of justice to deal with free-rider issues. Finally, studies showing that most people are strong reciprocators suggest that incentives are not always needed to exhibit cooperative behavior.

Fostering community governance. The main weaknesses of communities reside in a natural tendency towards homogeneity and the possibility of an insider definition that can set boundaries that are discriminatory. Communities have therefore a natural tendency to lead to cognitive lock-ins. To help overcome those weaknesses, a number of measures must be taken. Members should be able to cash in on community success and own part of the returns. Also, policies that increase peer action and transparency inside the community will foster cooperative behavior. Advocating for a fair and equitable treatment of community members and anti-discriminatory practices helps reaching the proper level of diversity in the community. Legal and government structures should be designed to favor community functioning. Market and states can hinder proper community governance. For instance, certain configurations of property rights lead to a stronger sense of identity for communities. Policies that enhance income equality also increased identity and loyalty to the community.

Cooperation in the Valley. Some parallels about how trust and identity leads to community governance can be drawn from Saxenian (1996)'s study of the Silicon Valley. Most people in the Valley were from technical background and were very risk averse. They often frequented the same places and exchange ideas in informal ways. These informal exchanges happened between quite often between competitors in contrast to Route 128 where communication with competitors were mostly prohibited. Relationships, in the Valley, depended a lot on trust and reputation, were open and had little hierarchy. Employees were often given stock options which created a corporate community and a sense of owning the company's success. Formal mechanisms of control weren't often present.

The culture of self-reliant big corporation was so deeply rooted in the corporate culture of Route 128 that small firms and startups were trying to look like large companies. Often, experienced managers from big corporations were hired to grow startups into big corporations. These managers were obviously going to implement formal structures in those startups once in their place. Personnel rarely got involved in community activities or chambers of commerce. Secrecy was an obsession and firms were trying everything to avoid information leaks. Networking, therefore, happened only inside a firm while vertical integration was de facto development model for firms.

1.3.4.4 Institutions as coordination facilitators

Institutions are traditionally seen as entities capable of reducing transaction costs. However, the organization of economic activities by hierarchy leads to opportunism especially in the case of information asymmetries, such as reported by the theory of vertical complementary assets. Firms who do not have all the skills necessary can fall prey to firms who own those resources and who can use them as leverage tools for imposing their will on the former.

From a community's perspective, where trust is involved, the risk of opportunism is significantly lower. According to Lynn et al. (1996), the role of institutions within innovation communities must be that of catalyzing coordination and fostering an environment of trust. Innovation community is composed of a substructure, i.e. organizations that produce innovations or complementary technology for the introduction of innovations, and of a superstructure, i.e. organizations often play the role of coordinators and information diffusion. Superstructures can vary in the number of power centers, orientation towards cooperative problem-solving. Superstructures specialized in certain areas will be better able to foster incremental innovations, while encompassing superstructures will help the diffusion of radical innovation.

Coordination can simply mean efficient flow of information. Institutions such as professional societies, trade associations, various forms of industry consortia and university-industry relationships can help the diffusion of information, coordinate investments and provide infrastructural support inside the community.

Institutions in the Valley. In the case of the Silicon Valley (Saxenian, 1996), associations helped coordinate the decentralized set of firms evolving in the region. Trade shows were used to get known on the market but also exchange ideas. Networking was also a way for job searching with turnover at very high levels giving place to high mobility of workforce. As a result, people were moving from one industry to another.

VCs also had a cooperative vision and were sometimes exchanging information about possible deals and collaborated on jointly building new companies. As new firms were being developed and other were installing in the region, a greater pool of talent was available to all the firms. Diversity and specialization existed at the same time: a firm's difficulties could not threaten a whole industry; an industry's failure could not threaten the region.

On the other side of the spectrum, Massachusetts had a traditionalist culture with people having a long family history in place. Leaders in Route 128 were more introvert, self-reliant, did not have a public presence or a sense of community. Stability and loyalty were valued over experimentation and risk-taking. This attitude toward risks hindered the entrepreneurial culture of Route 128 to the point where the kind of people who were capable of dealing with the operational issues of a startup just wasn't available in the region. At the same time, VCs were very careful in their startup selection process less where they didn't invest unless someone had proven himself before. University-industry relations weren't designed for easy interaction as strong formal ceremonies were required for the simplest of collaborations to happen.

1.3.4.5 Firms as places for identity

Kogut and Zander (1996) state that firms are places that solve the coordination issues between people by providing a sense of community by which discourse, coordination and learning are structured by identity. The main question in employee coordination is about how self-interested people can come to cooperate. In other words, the main question is: how a system of incentive can be designed in order to align individual behavior towards a common goal? This is in a context where the division of labor leads to people being more specialized and therefore less aware of what others are doing in the organization.

The identity to a group leads to members being loyal to each other. In groups, people develop a sense of justice and good behavior that shared by all. This leads to a feeling of expected cooperative behavior among firm members. Therefore, coordination inside firms is achieved through convergent expectations that are the result of everyone's perception of what is good and just behavior for the group. Discourse is about finding a way to communicate specialized knowledge to a wide pool of people. This is a necessity imposed by the division of labor. Here again, identity helps in creating a system of dialog in which information and solutions are discovered and shared by people inside the firm. Learning is done through social interaction where it is a matter of imitating others members' behavior. Since learning is situated in an identity it is very difficult to unlearn (interpretation is based on identity).

1.3.5 Open innovation

Traditionally, firms saw internal research and development as the only way to create new knowledge that could lead to the development of innovative products and services. Strategic decisions had to be taken internally by senior manager, and directives about how to perform research activities are transferred hierarchically to the relevant units and suppliers. In this traditional vertical integration model, firms perform R&D internally and then distribute the product to clients. Because a tremendous amount of effort is spent on innovative activity, firms work hard at protecting their knowledge from leaking out and being used by others. This is mostly an inward looking paradigm to knowledge creation.

According to Chesbrough (2006), open innovation on the other hand puts emphasis on external as much as internal knowledge. The main idea behind the open innovation paradigm is that knowledge is widely distributed and that firms must identify, connect and use external knowledge to innovate. This is a whole new perspective that has deep impact on how organizations see their relationships with their suppliers, customers, competitors and public research institutions. The supplier's role is no longer limited to provisioning goods that must be tied to rigid specifications defined by the client firm. Since they often hold valuable knowledge, they can shape the client firm's products or processes in an interactive way. Customers are no longer mere consumers but are also integrated in the product and service development process. This new perspective of co-creation of knowledge is central to the open innovation model. Knowledge sharing among competitors becomes an accepted practice. Even competitors can become partners in knowledge sourcing, especially when it comes to exploring risky technological paths.

In the open innovation paradigm, knowledge does not merely take a technological definition. Innovation also means that firms must explore external paths to market. Relying on its distribution channels that have been traditionally subordinate to the firm is no longer the only option. The rise of intermediate markets is also associated with wider acceptance of the open innovation model. Here, value-adding activities can be part of the firm's market entry strategy. These firms are also part of a whole new set of nodes in the networked structure of industrial sectors. This new perspective introduces a sustainability view of the firm who must redefine its position in the industry's value chain over time.

1.3.5.1 Shift towards open innovation

Early reasons to invest in R&D were motivated by the unique nature of activities undertaken by a firm. In this line of thought, firms were different from each other in that they had know-how that was difficult to imitate and that was kept secret from the rest of the economy. Market innovation was motivated by the will to benefit from economies of scope as well as to put barriers to entry for competitors through economies of scale. Commercialization was the way to exploit benefits from R&D activities. By mass producing, firms guaranteed themselves and blocked others from entering the technological domain in which they had invested so much R&D in. This configuration of the firm and of the industry led to an increasing verticalization of the market with firms seeking little contact with the competitor and one-way relations with its subordinate firms.

However, an imminent problem was recognized and raised by managers who were increasingly aware of the low appropriability of knowledge. Managers were confronted with the anomaly of other firms benefiting from their own R&D effort even when all the precautions were taken to block knowledge flows. It was soon recognized that attempt to secrecy were in vain and that knowledge leakage is something that is impossible to avoid. Gradually, even if knowledge spillovers were initially unwanted, a shift occurred in knowledge management perspective when managers tried to take advantage of it. The main idea was for firms to learn to focus their effort on long-term returns instead of worrying about knowledge leakage. This aspect will be discussed further.

Later on, external sources of knowledge were identified in suppliers, customers, universities, governments and private labs, competitors and other nations. Gradually, the need to encapsulate the firm from the outside world shifted to the need to build strategic alliances and to benefit from other firm's knowledge. Geographical clusters were also recognized as places where innovation happens because, it was thought, knowledge spillovers have a strong spatial dimension. This was mostly true for the high technology sector where change was happening at a fast pace and where firms needed to be aware of the latest development with only few resource at disposition.

From here, management's focus was on developing models explaining how knowledge can be acquired from external sources of knowledge. R&D activities no longer needed to be staffed exclusively inside the company. This idea opened the door for the outsourcing of strategic knowledge intensive activities to technical and scientific services consultants (Chiaroni et al., 2008). Lead users were recognized as valuable sources for innovating ideas. Network characteristics and positions were studied to find out about the best way to form alliances. With this new perspective about knowledge creation, the focus of management was no longer confined to the development of internal innovative capabilities but shifted to the development of the firm's networking and strategic partnership building capabilities.

Knowledge spillovers and collaboration. Spillovers were initially seen as the cost of being creative and not being able to appropriate value from it. In the new paradigm, spillovers are an opportunity to expand a company's business model. Creating knowledge that can be used by other firms has the advantage of creating new opportunities that were not initially considered by management. While managers initially designed and adopted sophisticated project assessment methods to avoid investing in projects that had little chances of commercial success, they also dismissed projects that could have been successful, would it be that management held a piece of puzzle that could prove the feasibility of the project. By deliberately sharing their knowledge, firms can now receive feedback from other players and find new ways of having returns from that knowledge. Disclosing knowledge will also place it in a position where other economic agents might want to make use of it. This need for the new knowledge wouldn't have manifested itself if the firm had a purely hermetic view about knowledge sourcing.

However, this way of dealing with knowledge implies that firms must embrace a long term view of R&D. It implies that firms have to be patient for knowledge to disseminate inside communities and return to them in a transformed state. Firms that embrace the open innovation perspective, redirect their effort from controlling and preventing knowledge leakage towards interactive learning with other firms.

Intellectual property. Intellectual protection policies were of defensive nature in the traditional paradigm. They were intended at protecting the firm's work, allowing further internal development of a technology and avoiding the risks of being blocked by intellectual property protection (IPP) mechanisms from external companies. For example, patenting was the manifestation of a strategic intent to take a particular technological path. From there, it was essential for the firm to own all the rights to that technology, but also to block competitors from entering that technological path.

With the open innovation paradigm, intellectual property is an extension to the firm's business model. In the same way where knowledge spillovers can be deliberately embraced for collaboration and joint ventures, IPP mechanisms can be used to better position the firm in the collaboration network or draw additional revenue through licensing. Firms can also view IPP mechanisms as transaction opportunities in intermediate markets.

1.3.5.2 Impacts on knowledge management practice

The most important impact of the open innovation perspective on knowledge management practices was the widespread adoption of outward looking methods for knowledge creation (Kang and Kang, 2009). Managers have since spent considerable effort on building the porosity or absorptive capacity of the firm. Firms have switched from a hierarchical and vertical integration model for knowledge management to one of horizontal-network-based collaboration and exchange. The goal is no more to protect the results of research and development activities, but to be part of the knowledge flow process. These changes in perspective have mainly affected three aspects of knowledge management: networking, acquisitions and product development processes.

Networking. When knowledge resides outside of the firm, it is natural that networking capabilities become an integral part of the innovative capabilities of the firm. Firms no longer promote a policy of secrecy but one of network centrality and maximum reachability. Firms seek to develop strong ties and trustful relationships with other agents in the economy. The more a company is in contact with other players in their industry, the more knowledge is transferred, and the more the company innovates and performs well (Kang and Kang, 2009).

Therefore, being able to network efficiently is almost the same thing as being able to innovate. Great attention has been given to factors that enhance an organization's networking capability, centrality and reputation. Working on joint ventures, collaborating in R&D projects and being strongly involved in informal networks are among those activities performed to boost a firm's networking capabilities. It should be noted however, that larger firms can more easily enjoy a central network position since they dispose of greater resources to build deeper and broader network relations.

Acquisitions. In technological fields marked with high uncertainty, firms minimize risks by acquiring technology. Here, the goal is not to directly boost sales or grow in size, but rather to learn through the acquisition process. In fact, global giants often buy out smaller firms that are innovative and that are capable of solving problems that weren't solved internally (Kang and Kang, 2009). These acquisitions will most represent little increases in sales or personnel size, but they will make a difference in the dynamics of knowledge exchange inside the firm.

Of course, technological acquisition has the advantage of broadening the firm's business model and offering new possibilities in terms of alliance building. For example, firms who do not hold a certain technological know-how could lose certain partnership opportunities. By acquiring those technologies, a firm will be able to build the coveted partnerships and profit from the results of those joint activities. In other words, technological acquisition must be seen as one way to increase a firm's absorptive capacity.

Product development. Firms are more conscious of the benefits of the open innovation perspective in the area of product development. Firms often do a transition between open exploration phases and closed exploitation phases for product development (Easterby-Smith et al., 2008). This is a result of firms acknowledging that it is not possible to be self-sufficient if one wants to innovate. Here, firms broaden and widen their knowledge by sharing their most fundamental experiences. Then, each firm adapts this newly acquired knowledge to the needs of its industry and customers in a hermetic knowledge deepening process. It is important here to take into account that open innovation does not always mean blindly throwing knowledge outside of the firm's boundaries. Rather, frequent interactions with the external world happen for exploration purposes. When it comes to product development and specific technological exploitation, firm porosity can be controlled.

1.4 The search process

Prior to combining existing knowledge in novel ways, firms must *search* (March and Simon, 1958). This selection process is not *blind*, if one takes the biological analogy (Nelson and Winter, 1982), but depends on the firm's *absorptive capacity* (Cohen and Levinthal, 1990).

When searching for existing knowledge in a complex world, firms can either *exploit* known technological paths or *explore* new ones (March, 1991). Knowledge exploitation involves *local search*, i.e. searching for solutions in the immediate periphery of dominant routines. It involves the improvement of current procedures and an ever increasing specialization in a few fields of expertise. Technological exploration in contrast involves searching or experimenting in ways that break away from dominant routines. It requires learning radically different ways to solve encountered problems. This can be referred to as *distant search*.

1.4.1 Proximity

Proximity is needed for knowledge to be transferred from one person to another. However, there is serious disagreement between what 'closeness' is and how much of it is needed (Gertler, 2003). In fact, there are many kinds of proximities and it is difficult to ascertain which one is more beneficial to knowledge diffusion (Boschma, 2005).

1.4.1.1 Geographical proximity

A strong argument for the geographical clustering of firms in high demand regions is that increasing returns meet lower transportation costs for regions that see a rise in 'pecuniary' externalities (Krugman, 1991). Seen from this point of view, economic growth is the result of agglomerated effort from different actors attracted by sudden rise in supply or demand of goods in a given region. The supply side benefits associated to agglomeration forces are the access to a larger pool of labor, localized knowledge spillovers and access to specialized inputs (Baptista and Swann, 1998). The demand side benefits of agglomeration forces are easier access to the customer, better flow of information as well as an easier appropriation of market shares. Bresnahan et al. (2001) stipulate that cluster benefits go beyond that of entities being helpful to each other. In fact, the whole economy of a region is augmented because of activity happening around the cluster.

Certain studies associated with the benefits of agglomeration economies have put aside the benefits of cost reduction associated with proximity and have studies the phenomenon of localized knowledge spillovers (Jaffe, 1989; Jaffe et al., 1993; Jaffe, 1998; Audretsch and Feldman, 1996; Audretsch, 1998; Baptista and Swann, 1998; Narin et al., 1997). For instance, it is observed that inventors tend to cite papers from researchers of the same country. Studies support the positive effects of research and development activities on regional innovative capabilities. Academia also seems to agree that universities are the center of gravity for industrial clusters where knowledge and innovation plays a central role or for emerging technological sectors where a large body of knowledge is tacit. These clusters are an amalgam of researchers, qualified professionals, universities, firms and research centers that are geographically gathered. Informal meetings, knowledge exchange networks, conferences, and hiring of university graduates and qualified workers are some of the most recognized channels of knowledge sourcing for firms.

The importance of geography and knowledge spillovers is very linked to that of tacit knowledge. Since qualified resources hold a great amount of tacit knowledge, physical proximity seems to be an important factor in helping knowledge diffusion because it gives the occasion for face-to-face and interactive communication. Malmberg and Maskell (2002) believe that interactive learning is the main cause for innovation when studying cluster success stories such as the Silicon Valley. Interactive learning happens at horizontal level when firms learn by observing local competitors and vertical level when suppliers and clients share complementary knowledge. Industrial clusters are efficient because those who are located near the cluster can benefit from knowledge spillovers. As a result, it is beneficial for all actors in a technological sector to gather around the same area. However, Jaffe et al. (1993) find that in the earlier years following publication, article citations from patents will more likely come from inventors that are in the same state of the publication authors. However, this phenomenon dissipates with time as information travels through codification.

Jaffe (1998) study the impacts of workers' mobility on innovation output. They have shown the importance of individuals and their actions in the local markets in which they operate. The article shows that engineers leave trail of their knowledge when they move from one location to another. One reason for this observation can be given in that knowledge is held tacitly by those engineers. Since its transfer is more efficient through local interactive exchanges, knowledge moves with those engineers and diffuses to new locations.

Finally, Zucker et al. (1998) study the role of star scientists in the innovation process and the way in which they are involved in knowledge spillovers in the biotechnology industry. Star scientists are associated with the birth, growth and location of the biotechnology industry. Enrolling star scientists will give excludability advantage to the firm, meaning that other organizations are not going to be the fortunate recipients of the star's knowledge. This is in contrast to widely diffused knowledge which will only have normal returns because everyone disposes of it and is able to use it for improving its productivity and innovative output. Firms will therefore try to enroll star scientists, especially when the nature of the knowledge that is looked for is of complex and tacit nature. The study also contains discussions with linked scientists who indicate that knowledge spillovers are the result of deliberate market exchanges between firms and scientists and not a byproduct of R&D activity. These formal contracts mean that star scientists receive technology ownership or equity in the company. It is in the framework of such market transactions that star scientists have been linked to performance indicators such as the number of products in development, the number products on the market, and growth in employment.

1.4.1.2 Social proximity

Newman (2003) studied networks of scientific collaboration that spawn geographical locations. His findings show that scientific collaboration is not bound to geographical distance and that scientists are interconnected in a social network that depends more on mutual scientific interests. Furthermore, geographical proximity seems to have a smaller effect on knowledge flow once the existence of collaboration ties between nodes is taken into account. Different simulations of knowledge diffusion within social networks have also linked social network structure and dynamics to overall network knowledge levels (Cowan and Jonard, 2003, 2004; Morone and Taylor, 2004).

Schilling and Phelps (2005) have found positive effects from industry-level alliances on firm innovation. Powell et al. (1996) also show that collaboration networks are beneficial to the innovation capabilities of the firm. In fact, firms rarely hold enough knowledge to be able to innovate at an acceptable rate in a competitive environment. These alliances with other firms are somehow necessary for the continuation of innovative activity for the firm. Their view is that network centrality is the most important factor for a firm's innovative productivity. According to Wink (2008), even a firm's immediate geographical area does not contains enough sources of knowledge to answer all it's needs. In order to overcome this local search trap, firms must create alliances with other firms and encourage inventor mobility to access and acquire new knowledge.

In a critical review of localized knowledge spillovers, Breschi and Lissoni (2003) state that social networks of people from similar backgrounds are the main and most productive knowledge diffusion channels. They claim that researcher's mobility establishes network ties that are also beneficial to innovation. The importance of social over physical proximity is illustrated by Agrawal et al. (2006) who show that an inventor's previous presence in a location is beneficial for future researches even after he is gone from that location. Therefore, knowledge flows do not happen exclusively at the geographical level, but also at social levels. These social ties are relationships that are based on mutual trust between two partners. Knowing the nature of knowledge as a public good that is difficult to appropriate, trust seems to be an important factor for successful exchange and communication of it. Social proximity encourage an open attitude of communication by eliminating the risk of opportunistic and calculative behaviors.

1.4.1.3 Technological proximity

Cohen and Levinthal (1990) stress that learning is cumulative meaning that we are able to learn new things more easily when we have already learned similar things in the past. In a literature review about proximity Boschma (2005) shows that firms can learn by imitating external sources of knowledge when they have cognitive proximity with those sources. Studies about the effect of relative absorptive capacity between firms have shown that partners' similarities in knowledge bases have a positive impact on inter-organizational learning. By analyzing patent citation data from 224 firms in chemical, electronic and electrical and computer industries, Fung and Chow (2002) show that a great part of knowledge spillovers come from within an industry and technological overlap between firms inside an industry favors knowledge flow. From another point of view, the uncertain nature of innovation is just another factor that incites firms to search for new knowledge that is close to their existing knowledge base (Boschma, 2005).

Empirical evidence from Cantner and Graf (2006) is in support of this claim as firms would naturally be attracted towards creating alliances with other firms with whom they have technological overlap rather than building alliances with firms with which they have worked in the past. Their study of a network of innovators shows that what permanent members do in reality is increase their technological overlap with other permanent members over time. They mainly engage in exploring and exploiting activities of technologies that are similar to what they have accumulated so far. As a result, technological proximity can be seen as something than brings firms closer together and opens the door for more cooperation. In this line of thought, scientific or engineer mobility takes a special meaning. Mobility leads to future cooperation because it can be a substitute for trust. Even if firms have not worked together previously, mobility can compensate for alliance uncertainty and risks associated with the lack of previous relationships because the mobile worker comes with knowledge and expectations about how the alliance will probably turn. As shown by Jaffe (1998), staff mobility will also lead in technological proximity since knowledge moves with workers as they change positions from one firm to another.

Podolny et al. (1996) introduce the concept of the technological niche which is the set of technological developments that have resulted from the firm's research and development effort. In line with the cumulative nature of knowledge creation, the authors show that firms that have similar technological niches tend to produce future technologies that are related to their past niches. Also, a firm's reputation in a technological niche is important in shaping future technological direction taken by other firms. Once a technology is chosen by the community, a new technological landscape is expected to take form with many firms building knowledge on those technological paths that were initially taken by the leading firm.

The concept of technological proximity has also received attention from the merger and acquisition literature. For instance, Ahuja and Katila (2001) show that firms tend to acquire technologies with which they are familiar with and that these acquisitions have a positive impact in their innovative output.

1.4.1.4 Alliances and private returns

Besides generating knowledge, alliances create value for the shareholders of the partnering firms. Alliances are defined as incomplete contracts, implying that a semi-formal agreement has been reached by two parties Anand and Khanna (2000). In fact, the complex and ambiguous nature of knowledge means that all the details surrounding resource sharing and transfer process in a project cannot be described formally in a contract. Nevertheless, alliances can have benefits in that both parties reach minimize risks and uncertainties linked to R&D activities.

Chan et al. (1997) show that strategic relationships create significant value for shareholders in the form of abnormal stock returns around the day of its announcement. These gains are especially higher when alliances involve two firms that are categorized in the same three-digit

SIC class. This finding could mean that partnering with firms from the same industry is more beneficial to shareholders. Also, data from this study show that technological alliances exhibit significantly higher returns that marketing alliances. In fact, markets believe that alliances will be beneficial to both firms when there is an intention to share complementary technical skills.

Similarly, Das et al. (1998) have studied the impact of strategic alliance announcements on stock returns. The study shows that markets are in general indifferent towards alliance announcements. However, data suggests that there are abnormal stock returns for a small time window before and after the announcement of technological announcements. Abnormal stock returns are measured by comparing average stock value for a 200-day period before with a 6-day period after the announcement. This phenomenon can be explained by the fact that technological alliances can signal future market gains and profits for the partners. On the other hand, alliances seem to have negative return for the more profitable firm. This is because stockholders perceive certain costs associated with the agency problem were managers can have interests that diverge with that of shareholders and the hold up problem where the smaller firm will have a stronger position after the alliance. Here, the hold up problem implies that bigger firms are willing to enter into alliance with a smaller firm when the latter is innovative and has know-how that the former perceives as being of significant importance.

Anand and Khanna (2000) measure the impact of firm experience in managing strategic alliances on abnormal stock returns. The study shows that firms enjoy an increasing abnormal stock returns as they accumulate experience in joint venturing. Research joint ventures are also more productive than marketing joint ventures. Also, grouping of firms based on the number of alliances shows that financial performance is more important in the groups that have higher numbers of alliances. Alliance or relational capabilities are therefore one of the characteristics of the firm that impacts how markets perceive its initiative in engaging in joint ventures.

Kale et al. (2002) compare stock returns with management assessment of an alliance. By doing so, they pose the question of whether market are efficient in predicting if an alliance is going to be successful in creating value for both firms. The main assumption in this study is that alliance experience, while important, is not a sufficient success factor. Rather, the dedicated alliance function is a better explanation for successful partnering. The dedicated alliance function plays the role of a central unit that makes sure that the organization acquires and diffuses the information that it accumulate as a result of ongoing alliances. In fact, data shows that while experience has a positive impact on abnormal stock returns, the dedicated alliance function has a greater effect. Markets also seem to be efficient in predicting winning alliances as abnormal stock returns were more often associated with alliances that ended up being successful from the firm managers' perspective.

1.4.2 Distance

According to Baptista and Swann (1998), an obvious disadvantage associated with geographical proximity is in the congestion and competition effect. These can be viewed as negative externalities where too many players in the same network can lead to transaction inefficiencies. In the case of geographical congestion, transportation and search costs are among the most recognized forms of negative externalities. The agglomeration of competitors in a location can also lead to price wars that will erode profit margins and impede investments in innovative capabilities.

Boschma (2005) states that the main argument against cognitive as well as geographic proximity is that it can lead to lock-ins scenarios. Spatial proximity can have a perverse effect on innovative capabilities because clustered firms tend to develop blind spots, i.e. they accumulate knowledge that is too similar which inhibits their capacity to respond to certain stimuli coming from their environment.

Concerning cognitive proximity, Boschma (2005) claims that too much of it can be detrimental to innovation capabilities. Cognitive proximity can lead to competency trap where the firm cannot get rid of old and obsolete routines. It can also lead to involuntary knowledge leakage. This phenomenon is due to the low appropriablity of knowledge and the inefficiencies of diffusion barriers in having a completely nonporous organization. The more cognitive distance is small between firms, the easier knowledge can leak to other organizations. Since geographical proximity will only amplify this phenomenon, competing firms will often avoid co-location of their core activities when there are technological overlaps among each other.

Boschma and ter Wal (2007) also found that proximity does not always lead to strong local knowledge transfers. They found that innovative output was as much impacted by local than nonlocal relationships. The main argument for this observation is that an exclusive adherence to local network relationships can lead to building a set of relationships that are similar in their content. Boschma (2005) supports the idea that distance players can still be effective in sharing tacit knowledge when they have other forms of proximity such as technological or cultural proximities. This means that exclusive adherence to local relationships for learning can be costly under certain circumstances.

Goerzen (2007) studies the effect of equity-based repeated partnership on firm performance. Data shows that repeated partnership between two firms has a negative impact on both firm's performance. The author argues that while repeated partnerships can lead to transaction costs efficiency, there is still a net negative economic outcome because both partners have access to the same redundant knowledge assets. This effect is even more pronounced in highly uncertain technological environments where having access to complementary assets is more relevant than transferring knowledge in more efficient ways.

1.4.2.1 Weak ties

According to Granovetter (1973), strength of an interpersonal tie is proportional to the amount of time, emotional intensity, intimacy and reciprocal services invested in it. Strong involvement in an interpersonal relationship, however, can only happen between individuals that are similar. As a result, two people who have a strong tie together will most probably share friends with whom they also have strong ties. These strong ties will form a clique of friends who happen to be very similar to each other. However, there are cases where a tie exists between two individuals that are not so similar to each other and that therefore do not involve sharing of friends. Granovetter (1973) believes that these weak ties are at least as important as strong ties because they serve as bridges connecting two cliques inside a network.

Granovetter (1973) thinks that weak ties have an important role to play in knowledge diffusion and creation. First, diffusion is directly proportional to the number of strong ties and inversely proportional to the path length between nodes. Therefore, removing a strong tie from a network would not be so disastrous since that strong tie is most likely inside a clique who already has many strong ties and thus a short path length between nodes. However, removing weak ties could mean that two network components are no longer connected or that the path length is too long for diffusion to occur effectively. From a knowledge creation point of view, Granovetter (1973) believes that individuals with more weak ties are more inclined to adopt 'deviant' or 'risky' behavior since a smaller clique or a smaller part of the network will be affected by the negative effects of that behavior.

Hansen (1999) argues that the importance of weak ties for knowledge transfer is relative to the kind of knowledge that needs to be transferred. He distinguishes two forms of knowledge:

simple information that is highly codified and rich forms of knowledge that are tacit in nature. By studying project completion inside a big multiunit firm, the author finds that weak ties are more effective in the diffusion of non-complex knowledge. This finding indicates that codified knowledge is more easily searched and transferred when ties are less constraining. However, the study also shows that weak ties seem to impede transfer between units when knowledge is complex. This result shows that strong ties are more beneficial for executing complex tasks because they guaranty the level of interaction that is required for the transfer of tacit knowledge.

1.4.2.2 Structural holes

Burt (1992) believes network efficiency is achieved by minimizing the number of redundant ties. The absence of connection between two network nodes is called a structural hole if an indirect connection can be offered by a broker. These open social structures are beneficial to brokers since they have a distinctive advantage of combining knowledge obtained from cliques who are disconnected from each other. While still effective in diffusing knowledge, indirect ties dismiss disconnected firms from the burden of maintaining a strong tie. Burt (1992, p.27) believes that "weak ties and structural holes describe the same phenomenon" since both play the role of connecting network components that would otherwise be disconnected.

In contrast, other studies maintain that network centrality is an important factor in firm's innovative output because technological breakthrough is a too complex business to be handled by a firm alone (Powell et al., 1996). Linking with other firms is therefore a necessity through which knowledge is obtained and accessed. By analyzing patent data from the chemical industry, Ahuja (2000) found no evidence of positive effect on output for firms that spanned structural holes. However, the study shows that indirect ties do have an effect on network effectiveness. These results might indicate that structural holes could increase the likelihood of a firm taking a bad decision that could be avoided by having direct contact with firms that have the right knowledge. Also, structural holes can be bad from a resource-sharing point of view. Firms who do not have direct contact cannot benefit from the trust levels that are necessary for sharing knowledge and combining skills.

Burt (2001) answers to skepticism toward the benefits of brokerage by integrating the concepts of structural holes with network closure. While the argument about trust in a closely tied network can be strong, empirical evidence shows inverse relationships between network closure and manager performance evaluation, promotions and compensation. The integrated model states that network closure inside a group's member can be high but that connections outside the group are non-redundant. In this case, the group performance is expected to be at its best since a cohesive team can quickly react to good ideas coming from outside. This assumption is partly supported by a study that shows that better output were achieved from teams composed of scientists from diverse background but in which communication networks were very close (Reagans and Zuckerman, 2001).

Burgelman et al. (2008) links brokerage to 'good ideas' in the case of supply chain managers in a large electronics company. Managers who were not involved in highly dense clusters of contacts were more likely going to find ideas that were going to be more appreciated by higher management. Taking advantage of structural holes means that firms recognize the value and integrate external knowledge in order to find new solutions to their own problems. By analyzing the evolution of patent-to-paper networks, Chen and Hicks (2004) have found 'bridging' papers that connect two major scientific fields to receive increasing attention over time. These papers act as cradles for new scientific and technological fields.

1.4.2.3 Small-world

Given n nodes connected through m edges, different network structures can be obtained by random configuration of edges with probability p. Since m edges will connect n nodes, trying different values of p in $[0, 1]$ will result in a range of structures that are between the regular network ($p = 0$) and the random network ($p = 1$).

For any given p, the average path length L(p) is the average shortest path separating two nodes in the network and the average clustering coefficient C(p) represents the average degree with which each node's neighborhood is close to be a clique. Small-worlds are characterized by average path length almost as small as random networks but an average clustering coefficient much higher than random networks.

The small-world is therefore a type of network in which most nodes are not connected to each other, but that most of them can be reached through a small number of leaps (Watts and Strogatz, 1998). Decentralization is an important aspect in small-world networks. Decentralization is imposed by the fact that maintaining close associations with large number of people is impossible. However, huge populations are still able to connect through a small degree of separation because of the existence of network 'shortcuts' who connect cliques together and thus decrease path length between any given nodes in those cliques. In this regard, a network edge that connects two nodes that are not part of the same clique has a great impact on the average path length , whereas the connection of two nodes that are part of the same clique has only a small impact on the cohesion level of that clique and the average path length.

Many empirical graphs exhibit structures that qualify them as small-worlds and that these types of networks have the characteristics of rapid propagation of whatever can be propagated between nodes (Watts and Strogatz, 1998). Scientific networks also exhibit characteristics of small-world networks where paper authors are connected to each other through a very small number of vertice (Newman, 2003). Cowan and Jonard (2004) have applied the small-world model to the diffusion of tacit knowledge. Their simulations have shown that knowledge diffusion is faster and lasts longer in small-worlds and that it leads to the highest network-wide knowledge levels. Li et al. (2007a) have compared network topologies for patent citation networks for the nanotechnology sector and found that countrywide as well as institutional citation networks exhibit small-world networks characteristics. However, technological and patent networks did not quite resemble to that of small-worlds, indicating that knowledge diffusion is more efficient at country and institutional level.

1.4.2.4 Diversification

As Cohen and Levinthal (1990) state, diversified knowledge inside firms means better absorptive capacity. Diversity of knowledge means that there are resources inside the organization who can translate outside knowledge into meaningful messages for other resources inside the organization. In a survey about the effects of diversity in workgroup performance, Jehn et al. (1999) find that informational diversity increases performance when tasks are complex. When tasks are simple, there is no need for debate about how best to execute them. On the other hand, procedures need to be discussed and debated when tasks are complex. In fact, breakthroughs require such a diverse set of skills that it is impossible for one person or organization to hold (Powell et al., 1996). From this perspective, diversity is both required and beneficial when it comes to achieve difficult tasks. It should also be noted that Jehn et al. (1999) have found that social diversity and value diversity moderate the effects of informational diversity on performance.

This phenomenon has been empirically observed at city level and authors have stressed the importance of diversification in regional innovation capabilities. According to the theory, cities tend to diversify as they become larger because of a need for various kinds of non-tradable goods (Duranton and Puga, 2000). This diversification in the production of non-tradable goods and services is generally known to favor innovation. In fact, new or relocating plants seem to prefer locating in larger cities which also happen to be more diversified than smaller ones. Diversification forces were more influential for young high-technology industries. These sectors also happen to find birth in larger multidisciplinary cities where a diverse pool of talent and important stocks of accumulated knowledge can support the innovation process (Beaudry and Breschi, 2003; Beaudry and Schiffauerova, 2008). When it come to new product development, diversification helps the innovation process once the new product has reached maturity (Beaudry and Schiffauerova, 2009). Other researches have shown that diversification is associated to innovation in the service sector.

1.4.2.5 Heterogeneity and gatekeepers

In their study of innovator networks in Jena, Cantner and Graf (2006) find that there is an increasing concentration of actors involved together in building the core competencies of the network. These are usually permanent and long term members of the innovation network. They enjoy the higher number of network ties but also the most important rate of innovation. Firms who see their rate of innovation decrease are increasingly pushed towards the peripheries of the network and eventually exit the network. New entrants on the other hand try to connect with permanent players in order to have access to new knowledge and introduce innovations on their own. They also have ties with other peripheral players in that they often exchange complementary know-how that can also lead to the creation of new knowledge. In this model, both entrants and permanents try to concentrate on developing the core competency of the network. What seems to work well in this model is that new entrants come with fresh perspective that can be used by other peripheral players as well as permanent member.

Heterogeneity and distance must be balanced in order to avoid dead-ends. Heterogeneity is also a regional matter as pointed out by Steiner and Ploder (2008). By performing a social network analysis of the industrial region of Styria, the study shows that network positions differ depending on the type of interactions between firms. Network density is found to be higher when exchanges involve different forms of knowledge. Here, firms within a region are more often involved in exchanges with other firms who come with complementary knowledge. In other words, cognitive distance within a region can be one way of dealing with the perverse effects of regional lock-in.

According to Wink (2008), this balance is often taken in charge by gatekeepers who have a role of integrating knowledge that is developed in one region into the knowledge that is developed in another region. Their role goes beyond the integration of regional knowledge. In fact, their knowledge-base spans across many technological fields which precisely allows them to integrate knowledge from different industries. Boschma and ter Wal (2007) also come to similar findings in their study of Italian footwear district where large firms with both central network positions and non-local connections where much more innovative than other firms that played more peripheral role and were more connected to local networks.

Gatekeepers are able to profit from brokerage opportunities that are provided by building ties with different network clusters. By studying the effects of structural holes on innovative performance, Burt (2004) shows that having connections outside one's own immediate clique of network connections can be beneficial in finding 'good' ideas. Those that look outside their immediate surroundings can have access to interactions that are of different nature to what they are most often exposed to in their own cliques.

Morrison (2008) conducts a research on the mechanisms with which gatekeepers are involved in the regional innovation process. For this purpose, they have studied firm-level behavior in an Italian furniture district and found that they play different role due to the complex nature of knowledge. Gatekeepers are extensively involved in codification or translation activities that aim at expressing knowledge that comes from another region into meaningful messages for smaller local firms. They also find that gatekeepers are rather large players enjoying innovation leader positions in their network. They are highly committed to the knowledge flow process as shown by their important investment in knowledge transfer activities. In this regard, formal and structured communications seem to dominate the landscape.

Felin and Hesterly (2007) study the effect of individual contributions to innovation and argue that heterogeneity is at the center of learning and knowledge creation. Here, heterogeneity in individual knowledge is the answer to the lock-in situation that can be the result of too much cognitive proximity. A large firm can be seen as the locus of innovation by harboring a collection of micro-level interactions of heterogeneous individuals.

Breschi and Catalini (2010)'s study of scientists-inventors shows that a small number of individuals enjoy a knowledge-bridging role between the scientific and the technological communities. These individuals tend to have superior publication as well as patenting performance than other researchers or inventors. From a network point of view, they also enjoy a more central position which places them at the heart of the regional and technological development.

CHAPTER 2

RESEARCH APPROACH AND MAJOR HYPOTHESIS

2.1 Research Objectives

As we have seen in the Chapter 1, the literature does not give a clear answer regarding the benefits of local versus distant search: one school of thought believes that geographical, social and technological proximity lead to better innovative capabilities, while the other states that exploration and brokerage lead to the creation of breakthroughs. This ambiguity makes it hard to draw policies that foster the creation of a particular type of innovation. This holds for basic innovations which are particularly important from an economic growth perspective. A first research objective of this thesis is to identify the factors that lead to the creation of basic innovations.

Also, while innovative capabilities are usually associated with competitive advantage in a knowledge economy, it is not obvious whether returns to all forms of innovations can be effectively appropriated by innovators. If markets do not offer incentives to create innovations that have broader impact, then it is incumbent upon public institutions to fill the gap. However, if one takes into account the role of complementary assets in the successful appropriation of returns from R&D, public institutions, compared to firms in the private sector, are not expected to be better able in leading their inventions to commercial success, even in favorable market conditions. Thus, the second research objective of this thesis is to identify the factors that lead to the successful appropriation of returns from basic innovations.

2.2 Data Description

Patents have been extensively used to measure innovative activity (Pavitt, 1985; Narin, 1994; Narin and Hamilton, 1996). Because they must be novel, non-obvious and useful, patents are indicators of technological progress and change (Basberg, 1987; Acs and Audretsch, 1989; Griliches, 1990; Archibugi and Pianta, 1996). This thesis thus falls within the class of such quantitative studies by employing a sample of Canadian nanotechnology patents registered at the USPTO will be examined. These patents where obtained by performing a lexical extraction on patents containing nanotechnology related keywords. The keywords originate from a set of bibliographic studies (Alencar et al., 2007; Fitzgibbons and McNiven, 2006; Noyons et al., 2003; Mogoutov and Kahane, 2007; Porter et al., 2008; Zitt and Bassecoulard, 2006). These studies, altogether, use more than 596 distinct keywords in their definition of nanotechnology with only 40 keywords being used in more than one study. As these figures show, experts do not agree on a unified lexical query delineating nanotechnology discipline (Hullmann and Meyer, 2003; Takeda et al., 2009; Maghrebi et al., 2011). However, keywords that are used in more than one study can be viewed as common agreement on what constitutes core nanotechnology keywords. In fact, Huang et al. (2011) show that the use of these common keywords leads to lexical queries that result in similar bibliographical extractions. For data extraction purposes, we choose this set of keywords to form a lexical query that is run on the USPTO database. The selection of the USPTO is motivated by the close commercial partnership between the US and Canada. The US economy is by far the largest marketplace for high technology. It thus attracts the highest level of competition and is therefore a clear indication of technological capabilities for those who are able to innovate in it. Li et al. (2007c) also show that Canadian assignees prefer filing patents in the US rather than the EPO. All granted patents that contain one of these keywords in all their fields and that have been granted to Canadian firms or for which one of the inventors resides in Canada are retrieved from the database. The sample is also expanded by patents classified under USPTO class 977 which has been reserved for nanotechnology. It should be noted that the USPTO currently assigns 156 Canadian patents to class 977, 12 of which are missed by the lexical query. We thus believe that our sample is a good representation of Canadian nanotechnology patents.

Table 4.1 shows the core keywords for which at least one Canadian patent was extracted from the USPTO database. For each patent, data about the title, abstract, grant date, number of claims, references, renewals, backward and forward citations, as well as the name, city and country of inventors and firms are extracted. After cleaning for duplicates and missing data, our sample contains 6,288 unique Canadian nanotechnology patents obtained from 1990 to 2009 at the USPTO.

2.3 Hypotheses

The first set of hypotheses will meet our first research objective which is concerned with the conditions that lead to the creation of basic innovations. The literature appears to associate technological exploitation to incremental innovations and exploration to radical innovations (Fleming, 2001; Kim et al., 2012). Thus, it can be supposed:

H1.1. Basic innovations will more likely result from the recombination of distant technologies.

While technological prowess is important, complementary skills in marketing are also important for technology diffision to occur (Slater and Narver, 1995). In this regard, a major difference between public and private institutions exists. The latter are market-driven and cannot be exclusively confined to a role of knowledge creators. They must therefore be market oriented if they want to survive. This know-how will allow them to be closer to markets, which will lead to a stronger diffusion of their inventions (Sainio et al., 2012). The following hypothesis can thus be stated:

H1.2. Distant recombination by the private sector produces a higher rate of basic innovations.

Inventions that are close to basic sciences are more complex and thus more difficult to absorb (Cohen and Levinthal, 1990; Nooteboom et al., 2007). This means that innovations that have strong links with basic science will diffuse more difficultly within markets. A third hypothesis is:

H1.3. Distant recombination is negatively moderated by linkage to basic science.

An industry's stage of its life cycle will impact its capacity to successfully perform distant recombination. Indeed, basic innovations are associated to competitive industries (Klepper, 1997; Malerba and Orsenigo, 1997). When an industry is dominated by a few players, most of the innovations that are adopted are cumulative in nature, which means that they consist mostly in incremental innovations. Thus, the following hypothesis is stated:

H1.4. Distant recombination is positively linked to basic innovations in competitive environments.

These hypotheses will be test in Chapter 5 (Barirani et al., 2012b). The second set of hypotheses will meet our second research objective which is concerned with the appropriation of returns from basic innovation. Innovators have incentives to perform research when appropriability regimes are strong (Arrow, 1962; Levin et al., 1987). When this condition is met, the incentive to perform a particular type of research (exploitation or exploration) depends on the industry's structure. As stipulated above, basic innovations are associated with dynamic industries. Thus, it can be supposed that in environments marked by strong appropriability regimes and industry dynamism, :

H2.1. Basic innovations are associated with a larger perceived private value.

However, external conditions do not guarantee appropriation of returns on innovations. Innovators must possess complementary assets to do so (Teece, 1986). Once again, firms are better equipped since their daily activities consist in developing resources required to capture benefits from knowledge that it has acquired. Thus, even under condition of industry dynamism and strong appropriability regimes, it can be hypothesized that:

H2.2. Private institutions are better able to appropriate returns from innovations that have proven to have application in various technological disciplines.

Routines within firms is concentrated on the development of specific markets with which the firm is familiar (Levinthal and March, 1993; Ahuja and Lampert, 2001). On the contrary, routines within public institutions are developed around the generation of knowledge that has broader impact on society. Therefore, compared to the private sector, public institutions will have a different perspective on innovations that will have diversified impact in the future. It can thus be supposed that:

H2.3. Public institutions commit more resources to innovations that will spread over various technological disciplines in the future.

These hypotheses will be tested in Chapter 6 (Barirani et al., 2012c).

2.4 Methodology

Patents have been extensively used to measure innovative activity (Pavitt, 1985; Narin, 1994; Narin and Hamilton, 1996). Because patents must be novel, non-obvious and useful, they are indicators of technological progress and change (Acs and Audretsch, 1989; Archibugi and Pianta, 1996). Although the use of patenting activity is attractive for emerging industries in which commercial data is not yet easily available, their use for evaluating innovative activity is not straightforward because patents are not all valuable as only a small percentage succeed in generating income (Allison et al., 2004; Moore, 2005). It should also be noted that patents are not always filed with the intention of building new products. For instance, firms can license patents for defensive or plain trolling purposes (Hall and Ziedonis, 2001; Gallini, 2002; Moore, 2005; Reitzig et al., 2007). Such activities are, however, less widespread in discrete technologies such as chemicals, pharmaceuticals and biotechnology (Cohen et al., 2000; Hall and Ziedonis, 2001). In these industries, patents constitute strong regimes for appropriating returns from R&D, and are thus better indicators of innovative activity (Levin et al., 1987; Merges and Nelson, 1990).

This need for distinguishing patents from different technological classes raises a methodological challenge. By definition, emergent disciplines are continuously growing and are redefined through what the communities of practice believe are promising applications or technological paths. This makes it difficult for observers such as those within the USPTO in setting up standard classification of patents in nanotechnology. Of course, the USPTO has reserved class 977 to nanotechnology patents, but this class only contains a small proportion of nanotechnology patents. The lexical query of Porter et al. (2008) returns nearly 50,000 patents between 1990 and 2005, while the USPTO currently (as of June 2012) classifies only 4,193 patents in class 977 for the same period. This first methodological challenge will be met by performing cluster analysis to group technologically similar patents together.

2.4.1 Patent clustering

Because patents must contain references to all relevant prior art, patent citations can, theoretically, be used to build a network in which co-citation communities represent major fields of technological development. Finding such communities can come down to finding areas of high inter-citation between patents. Among unsupervised learning methods, cluster analysis can be performed on network data in order to identify these areas, in which case it can be viewed as a way to achieve community detection in graphs (Girvan and Newman, 2002). Such a method would rely on the principle that co-citations can be viewed as a measure of similarity between documents (Small, 1973). Studies have extended this principle to patent citations in order to group technologically similar patents together (Breitzman and Mogee, 2002; Breitzman, 2005; Li et al., 2007b). Thus, these studies have extended the principle used for papers to patents. It is worthwhile to mention that this assumption cannot be readily made without considering the difference between patent and paper citations. In fact, co-citation classification of scientific articles finds justification in the fact that citations in scientific publications can be easily associated with knowledge flows (Meyer, 2000a; Leydesdorff, 2008). However, the interpretation of patent citations must be put in context due to the fact that 1) a large proportion are added by examiners, and 2) that applicants can add them for strategic reasons (Sampat, 2010). Meyer (2000a) also points out that time constraints can also lead to examiners adding citations than are only remotely linked to the filed patent.

Therefore, patent citations do not automatically indicate knowledge flows from cited to citing patent and thus the argument used for scientific publications cannot be automatically used for patents. However, one can interpret citations as indicators of technological relatedness due to the fact that they result from and are strongly related to USPTO's patent classification process (Lerner, 1994). It is therefore possible to interpret patent citations as a measure of how close two inventions are from a technological point of view rather than as a measure of knowledge flows from one patent applicant to another. Besides the hypotheses reported above, another contribution of this thesis is to validate whether citations can be used to measure technological relatedness between patents. Numerous indicators can be used to test the above hypothesis. The more citations are away from being the result of a controlled process and the more they result in arbitrary assignments (due to lack of time from examiners for instance), the more patent citation networks will resemble random graphs. On the other hand, if citation assignment process is relatively well defined, our network should exhibit small-world and scale-free characteristics common to real-world networks.

Furthermore, once community detection algorithm is applied to the patent citation network, assignee information can also contribute in testing our hypothesis. Since organizations are more likely to specialize in one or a few technological fields, their patents should not be uniformly distributed within partitions. Rather, partitions should be dominated by a few firms. It should also be noted that the domination of all partitions by one single organization could also mean that the partitioning procedure was not effective in grouping similar technologies developed by different organizations. This could mean that modularity optimization of patent citation network does nothing more than grouping together patents from the same organizations. We thus expect partitions to be represented by more than one assignee. Of course, it is possible that one or a few partitions be dominated by one firm, as monopolies do exist in various industries. This aspect of the methodology is implemented in Chapter 3 (Barirani et al., 2011), which uses agglomerative hierarchical clustering to group similar patents together and Chapter 4 (Barirani et al., 2012a) which uses the community detection method by Clauset et al. (2004) for the same purpose.

2.4.2 Econometric analysis

In attempting to link distant recombination with innovation basicness, our econometric approach mainly consists in analyzing the statistical relationship between the spread of a patent's backward-citations with the spread of its forward-citations. We therefore associate distant recombination with the use of inventions from a multitude of disciplines and its basicness with its use by subsequent inventions in a multitude of disciplines. These models will allow use to verify H1.1. Because we also try to measure the impact of the sector of activity (H1.2), science linkage (H1.3) and industry dynamism (H1.4), we perform a hierarchical analysis that will measure the moderating effect of these factors over distant recombination.

To answer the second set of hypotheses, we will use econometric models that are based on patent renewal. USPTO policies dictate that patent owners must pay maintenance fees at the 4^{th}, 8^{th} and 12^{th} year of a patent's legal life. Failing to pay these fees leads to the loss of the exclusivity conferred by the patent, in which case the owner cannot prevent others from using the invention. Patent renewal can be related to the firm's expectation of future private returns associated with withholding the patent and the obsolescence of the disclosed invention (Pakes and Schankerman, 1984). Indeed, if new competing inventions are introduced and that they displace a patent, its owner will no longer have any advantage in keeping the patent unless revenue streams are still expected from ancillary products.

It should also be noted that assignees, in an *ex post* valuation of their patent, go through a learning period where they try to get market feedback about possible commercialization of the technology. Until this process is complete, firms might renew a patent even if no income is forecast. Various studies claim that this period could take between 5 to 7 years (Lanjouw et al., 1998; Bessen, 2008). Renewal decisions in the earlier period (4^{th} year) can therefore be associated with the patent holder's *a priori* about an invention, and does not indicate that private gains are expected. Furthermore, expecting revenue streams implies that patent holders attempt, *ex post* of their initial decision to conduct R&D and file a patent, to predict future applications that the invention will have on ancillary products. Given that R&D as well as filing costs are much higher than the renewal fees, not renewing a patent can be viewed as a clear signal that withholding the patent does not confer any form of advantage to its owner (Thomas, 1999).

Our method consists in performing hierarchical probit and logit regressions with different renewal periods (4^{th}, 8^{th} and 12^{th} year) as dependent variables and patent basicness on periods prior, current and subsequent to the renewal year as the main dependent variables. It should be noted that at every renewal year, only those patents that have been renewed so far are considered in our models. Controlling for patent basicness in past, current and future periods allows us to observe whether basic innovations are generally associated with higher perceived private value, which will contribute to validating H2.1. By interacting basicness at different periods with the sector of activity of an assignee, we can observe whether there is a difference between how the private and public sectors perceive the value of present and possible future spread of an invention, which will then contribute to validating H2.2 and H2.3.

2.4.3 Contributions

The results of the research conducted for this thesis have been discussed in the following original contributions:

- Barirani, A., Agard, B., and Beaudry, B. (2011). Competence maps using agglomerative hierarchical clustering. *Journal of Intelligent Manufacturing*. Available from: `http://dx.doi.org/10.1007/s10845-011-0600-y`.
- Barirani, A., Agard, B., and Beaudry, C. (2012a). Discovering and assessing fields of expertise in nanomedicine: a patent co-citation network perspective. *Scientometrics*. Available from: `http://dx.doi.org/10.1007/s11192-012-0891-6`.
- Barirani, A., Beaudry, C., and Agard, B. (2012b). Distant Recombination and the Creation of Basic Innovations. *under review at Technovation.*
- Barirani, A., Beaudry, C., and Agard, B. (2012c). What Happens to Basic Innovations? The Paradox of Technology Exit Under Conditions of Strong Appropriability Regimes and Industry Dynamism. *under review at Research Policy.*

CHAPTER 3

COMPETENCE MAPS USING AGGLOMERATIVE HIERARCHICAL CLUSTERING

Abstract[1]

Knowledge management from a strategic planning point of view often requires having an accurate understanding of a firm's or a nation's competences in a given technological discipline. Knowledge maps have been used for the purpose of discovering the location, ownership and value of intellectual assets. The purpose of this article is to develop a new method for assessing national and firm-level competences in a given technological discipline. To achieve this goal, we draw a competence map by applying agglomerative hierarchical clustering (AHC) on a sample of patents. Considering the top levels of the resulting dendrogram, each cluster represents one of the technological branches of nanotechnology and its children branches are those that are most technologically proximate. We also assign a label to each branch by extracting the most relevant words found in each of them. From the information about patents inventors' cities, we are able to identify where the largest invention communities are located. Finally, we use information regarding patent assignees and identify the most productive firms. We apply our method to the case of the emerging and multidisciplinary Canadian nanotechnology industry.

Keywords: knowledge mapping, innovation, citation networks analysis, data mining, agglomerative hierarchical clustering, vector space model, nanotechnology.

3.1 Introduction

Globalization is marked by a hyper-competitive economic landscape (Westphal et al., 2010). Advances in industrial engineering and logistics have given the possibility for advanced countries to offshore their manufacturing activities to developing countries that offer cheaper labor wages. After a long period of rationalization, the same advanced countries are now facing the situation where those once developing countries are catching-up the technological gap (Albayrak and Erensal, 2009). In fact, emerging countries are suddenly leaders in certain high technology fields.

[1]Barirani, A., Agard, B., and Beaudry, B. (2011). Competence maps using agglomerative hierarchical clustering. *Journal of Intelligent Manufacturing*. Available from: `http://dx.doi.org/10.1007/s10845-011-0600-y`.

This new reality has an important impact on the industrial organization of advanced countries that are now forced to be more innovative if they want to benefit from economic growth. It has become vital for advanced countries to put in place institutions and policies that foster the development of their high technology industries. Innovation can be boosted when there are interactions among different technological fields (TaşKin et al., 2004). Among multidisciplinary fields, one of the most promising high technology sectors is that of nanotechnology. Nanotechnology is often thought as a field that can have revolutionary applications in a wide range of industries. All advanced countries agree on the importance of this new field in the development of their economy. They have also put in place policies that would help develop their knowledge and competence levels in this promising area.

Innovative activities must however be performed in a context of resource scarcity. Even though advanced countries have greater access to resources compared to developing or emerging countries, it is impossible to explore and exploit all the technological paths that are available to them. Firms, organizations and countries must take their technological strengths and weaknesses into consideration when making strategic decisions about the directions they are willing to take. An important step in finding the strengths and weaknesses at national level consist in drawing a technological competence map of the country. In such contexts, the access and integration of information systems into the decision making process is crucial (Hsu et al., 1994).

In this article,we propose a new method of assessing technological competences. Our method consists in developing a competence map of the Canadian nanotechnology industry by applying agglomerative hierarchical cluster analysis on a sample of patents obtained between 2005 and 2008. Nanotechnology has been selected because it is a recent, relatively well defined, active and still moving domain.We will be able to show the main branches of Canadian competences in nanotechnology and identify the most active regions and firms for each of these branches. The remainder of the article is organized as follows: the next section will provide some theoretical framework regarding strategic aspects of knowledge management and knowledge mapping as well as some elements regarding different methods used for knowledge mapping. We present two methods for measuring similarity between documents: citation network analysis and text mining. Then we provide a description of cluster analysis as a way to ordinate documents and techniques available for assigning labels to the groups of documents. The article then presents our methodology for mapping Canadian competences in nanotechnology. Finally, we will analyze the results of our study and make parallels with strategic management theory described.

3.2 State of the art

3.2.1 Knowledge management

The strategic managers' tasks often consist of performing an assessment of the organization's resources and core competences and of defining a strategic plan that will reinforce those competences (Barney, 1991; Prahalad and Hamel, 1990; Amin and Cohendet, 2004). In today's knowledge economy, the organization's stock of knowledge or intellectual capital is viewed as a strategic resource that constitutes its most valuable asset (Nahapiet and Ghoshal, 1998). This is the knowledge- based view of the firm in which organizations succeed because they have knowledge that is valuable, rare and inimitable (Grant, 1996). Another phenomenon which organizations are facing in the knowledge economy is constant change in their environment. In this regard, organizations need to have dynamic capabilities to reinvent themselves in the face of rapidly changing environment (Teece et al., 1997). They need to put in place processes that enable them to change their routines, products and markets over time.

This is part of the evolutionary economic perspective which studies the impact of initial technological decision on future directions (Nelson and Winter, 1982). In this regard, knowledge creation and diffusion is a path dependent process (David, 1985). Technologies that are developed and adopted at a certain point in time will shape the technological choices that are made at a later time. In other words, what organizations learn is always bound to what they have learned in the past (Cohen and Levinthal, 1990). It also follows from this line of thought that organizations can be trapped in technological lockin when they are unable to change their routines because they have invested too heavily in one technological branch (Arthur, 1989). Changing their technological paths becomes too cumbersome as these organizations are plagued with inertia. Taking into perspective the importance of intellectual capital and the path dependent nature of knowledge, it becomes vital for organizations to be self-aware of their core competences and of the opportunities that they have to absorb complementary knowledge (Feldman, 1994). It should be noted that knowledge is information in a specific context. In other words, it is useful only in that specific context. A firm's routines and best practices can change when the context changes (Chryssolouris et al., 2008; Wijnhoven, 2008).

One way to measure intellectual capital is through the analysis of patenting activity (Basberg, 1987). Patent databases have been used to derive the state of development in specific technologies (Duflou and Verhaegen, 2011). Patents are indications of research and development efforts endeavored by its inventors and assignees. They can therefore be counted as technological competence owned by the organization. Because patents must be novel and specific, they are also indicators of technological change. Organizations that are able to patent at a higher rate than others therefore show a capacity to bring technological changes to their industry. Certain organizations perform better than otherswhen it comes to patenting. Larger firms that dispose of a greater quantity and diversity of resources are better equipped to patent than other. More important, they are able to patent in a much broader set of technological fields because their diverse knowledge-base allows them to innovate acrossmany areas (Cantner and Graf, 2006; Boschma and ter Wal, 2007; Morrison, 2008).

3.2.2 Knowledge mapping

Börner et al. (2003) provide a thorough literature review regarding knowledge mapping. Knowledge mapping consists in gathering, analyzing and synthesizing bibliographical data in order to discover the location, ownership and value of intellectual assets. Knowledge maps can be used for the identification of scientific and technological know-how at firm, university or national level. Knowledge maps can be used for indicating current technological trends and can be helpful in forecasting future technological developments. Finally, knowledge maps can be used to find new opportunities to explore in emerging technological disciplines.

The first step in knowledge mapping usually consists in extracting a set of documents (articles or patents) from a bibliographical database (such as ISI-Thomson, Scopus or USPTO). Most studies use a Boolean keyword-based document retrieval method, i.e. documents that contain specific keywords are retrieved from the database for analysis. The process then consists in selecting similarity attributes for the documents. The two most popular attributes are citations and words, i.e. documents are similar if they cite the same sources or if they use the same words in their description. Based on the similarity attributes, documents are then grouped together, usually through cluster analysis or dimension reduction. Each of the resulting groups represents a knowledge branch to which a label is assigned by analyzing the content of the documents it contains. By analyzing other information associated with the documents, such as the authors, address or affiliations, it is possible to see who owns the intellectual capital and where the inventor communities reside. Interdependence between branches can be found by aggregating the citations made by the documents contained in each branch. For example, if many articles from branch A cite articles from branch B, then it can be said that branch A is technologically dependent upon branch B.

3.2.3 Measuring similarity through citation network analysis

In order to consider citation network analysis for similarity computing purposes, we will introduce some key concepts related to network theory. A network is defined by a pair of sets $G = \{P, E\}$ where P is a set of N nodes $P_1, P_2, \cdots, P_n$ and E is a set of m edges that connect two nodes in P (Wasserman and Faust, 1994). Each node has a *degree distribution* defined by the number of edges it shares with other nodes in the network. The number of edges that separate two nodes is called the *geodesic distance*. The shortest path is the smallest geodesic distance between two nodes. *Betweenness centrality*, for a node i , is therefore defined by

$$C_B(i) = \sum_{j \neq k \neq i} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \tag{3.1}$$

where σ_{jk} is the shortest path between nodes j and k, and $\sigma_{jk}(i)$ is the number of shortest paths between nodes j and k that pass through node i. Betweenness centrality is often an indication that a node is connecting two groups of nodes that would otherwise be disconnected (Granovetter, 1973; Burt, 1992). These central nodes therefore are agents that imply a certain similarity between the groups of nodes that they help to move closer. For any given node i, the *clustering coefficient* C_i is defined by

$$C_i = \frac{2E_i}{K_i(K_i - 1)} \tag{3.2}$$

Figure 3.1 Network with 7 nodes and 8 edges where E_i represents the number of edges between K_i nodes that are linked to node i. This metric shows the degree with which nodes connected to i are also connected to each other. A *clique* is a group of nodes that are all interconnected. A *community* is a network subgroup of nodes that are densely connected (Newman and Girvan, 2004). In both cliques and communities, average clustering coefficients are high since nodes tend to be interconnected. The presence of a clique or a community is therefore an indication of affinity and similarity between the nodes.

A network *component* is a subnetwork where at least one path exists between all nodes of the subnetwork. Disconnected components usually indicate that there is little similarity between nodes in each component.

Figure 3.1 is an example of a small network. Nodes 1, 2 and 3 are part of a clique and we can say that there are two communities in the network: one composed of nodes 1, 2 and 3 and the other composed of nodes 4, 5, 6 and 7. The network in Figure 3.1 is composed of only one component since all nodes can be reached from any other node in the network. If

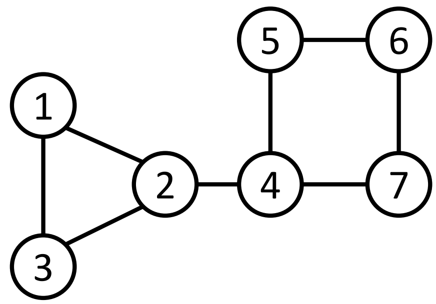

Figure 3.1 Network with 7 nodes and 8 edges

node 2 and 4 were not connected, then the network would have contained two components: one composed of nodes 1, 2 and 3 and another composed of nodes 4, 5, 6 and 7. Nodes 1 and 3 have a clustering coefficient of 1.0 while node 2 has a clustering coefficient of 1/3. Betweenness centrality for nodes 2 and 4 are equal to 8 and 9, since nodes 1 and 3 must go through them to connect to nodes 5, 6 or 7. In this example, we can say that nodes 1, 2 and 3 are very similar. Also, node 4, 5, 6 and 7 are also similar to each other but at a lower degree.

Many kinds of networks have been observed in nature. Biological, social, electrical and hypertext networks are among some of the examples (Albert and Barabási, 2002). Citation networks are networks where nodes are defined by documents and where edges are defined by the citations that connect the documents together. Citation networks are often categorized under directed networks, meaning that the relationship between the two nodes is unidirectional. In this regard, citation networks express interdependence and knowledge flows between documents (Small, 1999).

(Small, 1999) uses citation networks as a way to measure similarity in bibliographical data. Areas of high intercitation density then become indications of scientific activity around a certain subject. Bassecoulard et al. (2007) measure similarity and interdependence between nanoscience branches by using citation flows. From a seed of articles obtained by Boolean keyword-based retrieval, they build a larger sample by retrieving articles that often cite and get cited by the seed.

3.2.4 Cluster analysis

Cluster analysis is a data mining technique that consists in grouping a set of observations in a way such that similar elements are placed in the same group, called cluster (Berry and Linoff, 2004). These techniques are classified under unsupervised learning techniques. There are different types of clustering methods. All of the methods based on similarity require a measure of distance between two elements. The *Euclidean distance* between two documents q and p is a very popular metric that is computed by the following equation:

$$d_{q,p} = \sqrt{\sum_i (q_i - p_i)^2} \tag{3.3}$$

where q_i and p_i are the attribute i's values for documents p and q respectively. Other metrics such as the cosine or dice similarity can be used for the same purpose. The goal of a clustering algorithm is to maximize intercluster distance while minimizing intracluster distance (Manning et al., 2008).

Clustering can be used to solve a variety of problems (Malakooti and Raman, 2000). Cluster analysis can be used in the customer support and relationship management industry (Berry and Linoff, 2004). Chen et al. (2007) use cluster analysis to perform customer segmentation aimed at improving customer retention in the telecommunication industry. Choudhary et al. (2009) provide a thorough review of clustering techniques used to solvemanufacturing problems such as defect analysis, system rule generation, yield improvement and process optimization. Given the general purpose of unsupervised learning methods, cluster analysis has also been used for generating knowledge maps based on bibliographical data. The following two sub-sections provide a literature review of some of the most common techniques used in this area.

3.2.4.1 Partitional clustering

Partitional clustering techniques, such as k-means, group elements into a fixed (k) number of segments. The user can predefine or, after a few trials, deduct this number. The partitioning process starts by assigning one element to each cluster. This element will become the cluster's core. Remaining elements are then assigned to a cluster according to their distance with its core. At the next iteration, a new core is selected for each cluster from the elements that are assigned to it. Remaining elements are again assigned to the cluster having the less distant core (Berry and Linoff, 2004). The process stops after a maximum number of iterations or when a local optimum is found. Bassecoulard et al. (2007) use a variation of

k-means clustering on citation networks to group articles into 7 broad scientific branches. By using affiliation data regarding articles, the authors were able to identify specialization levels of major countries in each branch of nanoscience. In addition, the authors show the interdependence between branches by analyzing citation flows at the cluster level. (Kim et al., 2008) apply k-means clustering on a keyword vector space obtained from a sample of patents. Each formed cluster represents a technological branch. Branches are then linked together based on the co-occurrence of keywords in the clusters. By finding the patents that were filed earliest in each cluster and by linking clusters through citation analysis, the authors build a timeline showing when technological branches where introduced and to what technological branches they have led to.

3.2.4.2 Hierarchical clustering

Hierarchical clustering classifies observations under a tree structure after a number of iterations (Berry and Linoff, 2004). Clustering can be done by agglomeration (bottom-up: HAC, CURE) or by division (top-down: DIANE, BIRCH). Agglomerative methods initially assign each element to a segment. In a set of iterations, clusters that are similar are merged to form a larger cluster. The process stops when there is only one cluster left. Divisive methods in contrast start with one cluster that contains all the elements. In each iteration, clusters are split in a way that maximizes the distance between elements of one cluster and the other. The process stops when all segments constitute of only one element.

Newman and Girvan (2004) use hierarchical clustering for community detection in networks. They use network betweenness centrality as an indication of community boundaries. They place the most central nodes at the top of the dendrogram and the less central nodes at the bottom. Combined with citation networks analysis, hierarchical clustering also has the advantage of showing the relationship between scientific branches (Wallace et al., 2009). Documents that cite sources common to lower-level clusters that do not cite common sources will more likely be positioned on higher levels of the dendrogram. They therefore connect those clusters and represent a broader branch. Tseng et al. (2007) have developed a hierarchical topic map by performing a multi-stage clustering method. They first cluster a large set of patents into small clusters based on their vector space similarity. At the next stage, these small clusters are then regrouped together based again on their vector space similarity.

3.2.4.3 Cluster labeling

Weiss et al. (2004) list different methods for labeling clusters. Feature selection techniques are often applied in order to select a relevant set of words from a larger list. A simple approach in labeling clusters is to select the most frequent words in each cluster. Term ranking methods such as the tfidf metric can also be used for the purpose of feature selection. The following procedure is usually applied in order to compute the tf-idf for terms appearing in a set of documents (Manning et al., 2008).

1. **Tokenising:** for every document in the sample, sentences are broken into single words. This leads to a vector of words representing each document.

2. **Stopwords removing:** commonwords (such as the, and, or, etc.) are removed for each vector representing a document.

3. **Weighting terms:** here the relative frequencies with which stemmed words appear in a single document with respect to the whole sample are computed. The *tf-idf* rank is the most common method used for this purpose. To compute the *tf-idf* rank of a term i in a document j, we first need to compute the *term's frequency* in the following way:

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \tag{3.4}$$

where n_i, j is the number of occurrence of the term in document d_j and the denominator is the sum of the occurrences of all terms in document d_j. Then, we need to compute the *inverse document frequency* by using the following equation:

$$idf_i = \log \frac{|D|}{|j : t_i \in d_j|} \tag{3.5}$$

where $|D|$ is the total number of documents in the sample and $|j : t_i \in d_j|$, called *document frequency*, is the number of documents in which the term appears. The *tf-idf* is then computed as follow:

$$tfidf_{i,j} = tf_{i,j} \times idf_i \tag{3.6}$$

Resulting from this definition, the *tf-idf* will be (a) highest for terms occurring many times within a small number of documents, (b) lower for terms occurring fewer times in a document or occurs in many documents, and (c) lowest for terms appearing in virtually all documents (Manning et al., 2008). Therefore, terms that have higher *tf-idf* scores can be selected as labels representing each document. This method can be extended to clusters where terms are taken from the documents that are assigned to each cluster Weiss et al. (2004).

Tseng et al. (2007) perform cluster labeling in the following manner. First, they find the most frequent words used by patents in each cluster from which they remove words that also frequently appear in other clusters. They then use an automatic Wordnet-lookup algorithm to classify those words into broad technological fields such as material, chemistry and biomedicine. Sometimes, labeling is performed manually. For example, if the most frequent word in a cluster is biology, then the user can assign that topic to the cluster.

3.3 Methodology

The method proposed in this article is based on five steps (Figure 3.2). In order to simplify the reader's comprehension each step will be explained throw an example in building a map of Canadian competences in nanotechnology based on patent citation networks.

Step 1: Keyword selection

We first need a set of nanotechnology related keywords. These keywords are obtained from bibliographic studies on nanotechnologies (Alencar et al., 2007; Fitzgibbons and McNiven, 2006; Mogoutov and Kahane, 2007; Porter et al., 2008; Noyons et al., 2003; Zitt and Bassecoulard, 2006). These studies, altogether, use more than 596 distinct keywords in their definition of nanotechnology. Yet, only 21 of them appear in more than one study. Therefore, we can see that there is great disparity in what these authors define as being nanotechnology-related keywords. In order to select significant keywords that represent the core of nanotechnology patents, we will select keywords that are used in more than one of the studies to form a query that is run on the United States Patent and Trademark Office database (USPTO, 2009). This method can be seen as an approximation to *tf-idf* weighting of keyword significance. Other weighting and indexing methods will be considered in future works.

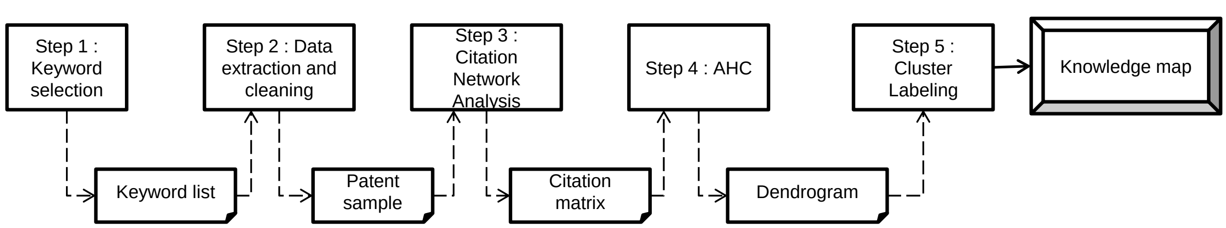

Figure 3.2 Methodology steps

Step 2: Data extraction and cleaning

All patents that contain one of the keywords and that have been granted to Canadian firms or for which one of the inventors resides in Canada are retrieved from the USPTO database. For the reminder of the article, these will be referred to as Canadian patents. For each patent, data about the title, abstract, application and granted date, number of claims, references, citations, as well as the name, city and country of inventors and firms are extracted. We will refer to the patents that are cited by our Canadian patents by cited patents. The resulting sample is then cleaned of incomplete entries and different representation of the same assignee names (ex: *Nortel* and *Nortel Networks* are the same assignee). Finally, suburban areas are associated to their metropolitan areas (for instance, Laval is associated to Montreal's metropolitan area).

Step 3: Citation network analysis

The third stage of our study consists in building the citation network from our sample of Canadian nanotechnology patents. In our citation network, the nodes are the Canadian patents in our sample and the patents that are cited by them, and the edges are defined by the citation relationship between Canadian patents and those that they cite. We use the open source software application NodeXL (CodePlex, 2011) for this step of our study. From the resulting network, we select the largest component for the next step in our analysis. This is a necessary measure given the fact that we use agglomerative hierarchical clustering (AHC). Since we use the co-citation as a way to measure similarity, it is unavoidable that AHC groups two disconnected network components at a certain point in the process. In such cases, the AHC will perform an arbitrary merger of the two components, which will lead to incorrect representations of technological fields' hierarchies. By selecting the largest network component, we are certain that cluster mergers always involve a certain level of similarity in patent co-citations. Another advantage of working with the largest citation network component resides in that it acts as a natural cleaning process on the patents obtained by Boolean keyword-based retrieval. In fact, this retrieval method is bound to precision and recall issues, i.e. that the retrieval process will always miss some of the relevant documents and will add some undesirable documents to the retrieved sample. Removing patents that are not part of the largest citation network will rid us of some irrelevant patents that figure in our sample. However, this method has the disadvantage of discarding, from the competence map, relevant nanotechnology patents that are not connected to the main network component. This is a limitation imposed by the choice of AHC as a method for competence mapping.

Step 4: Hierarchical clustering

In the fourth step of our method, we first build the citation matrix used for cluster analysis. This matrix will have rows representing Canadian patents from the largest component and column representing all the cited patents. In order to reduce the size of the attribute set (i.e. cited patents), we will only consider patents that have been cited by at least two Canadian patents. This is natural since patents that have been cited by only one patent do not contribute to the similarity of that patent with other patents. The citation matrix will be filled with "1"s when a Canadian patent in the rows cites one of the cited patents in the columns and with "0"s otherwise. We then perform the actual AHC on the citation matrix. We will use the open source software application RapidMiner (Rapid-I, 2011) for this purpose.We will use cosine similarity as a way to measure patent similarity and the average linkage method of merging clusters together. Cosine similarity between Canadian patents A and B represents whether patent A and B cite the same patents. Average linkage means that clusters are merged together based on the average similarity of the patents they contain. Proceeding in this way has the advantage of merging clusters based on their overall citation patterns and will be helpful in measuring interrelatedness between different branches of the Canadian nanotechnology competences. From the dendrogram resulting from the AHC process, we select the clusters at the top levels to build our competence map.

Step 5: Cluster labeling

Our final step consists in finding labels for the clusters that are at the lower level of the competence map. By merging patent titles for each cluster, we build a vector space representing the *tf-idf* rank of the words appearing in each cluster. We then sort the words based on their *tf-idf* rank and select the top five words as labels for each cluster. As a result, clusters are represented by the words that they most frequently contain relative to other clusters.

3.4 Results and analysis

This section will show detailed results of the methodology and final analysis of the knowledge map.

Step 1: Keyword selection

The first column in Table 3.1 shows the keywords selected for our study and the number of patents our extraction process has provided in December 2009. As described in Section "Methodology", these keywords have been used at least twice in a collection of bibliographic studies regarding nanotechnologies.

Step 2: Data extraction and cleaning

Data extraction was performed using PatentBot, a software application developed internally by our team. The second column in Table 3.1 shows the number of patents our extraction process has provided in December 2009. From these 8,076 patents, 5,811 have been selected after cleaning was performed on incomplete patent documents. From these patents, we have selected those that were obtained during the years 2005–2008. This gives us a more accurate map of current Canadian competences in nanotechnology. Our sample contains 1,697 Canadian nanotechnology patents granted between 2005 and 2008.

Step 3: citation network analysis

By analyzing the sample of patents obtained in the previous step, we find that the 1,697 Canadian patents obtained between 2005 and 2008 cite 22,017 distinct patents and the citation network is composed of a total of 36,961 citations. From the 22,017 distinct patents, only 6,712 ($\sim$30%) are cited more than once by the Canadian patents. The citation network has (1,697 Canadian patents + 22,017 cited patents =) 23,714 nodes and 36,961 edges, implying that it is expected to be relatively fragmented. In fact, when building the citation network (Figure 3.3) with the help of NodeXL, we observe that the main network component is formed by 10,853 out of 23,714 nodes ($\sim$46%). Furthermore, only 691 ($\sim$41%) patents from our initial list of 1,697 Canadian patents are part of the main network component. The network is composed of 622 disconnected components, 484 of which contain only one Canadian patent. These are patents that (a) are not cited by any of the Canadian patents and (b) do not cite any of the other patents that have been cited by the Canadian patents. Although we cannot conclude that these 484 patents are false positives (that they have been extracted because containing ambiguous nanotechnology keywords), we cannot use them for the purpose of knowledge mapping with regards to our methodology. In fact, not having any citation in common with other Canadian patents, they will be at infinite distance of other patents or clusters. This will wrongfully place them at the top of the dendrogram which will result in a loss of precision in our technological hierarchy. The 3 largest components after themain component contain respectively 38, 26 and 22 Canadian patents. While these components are large enough to be treated as clusters, they suffer from the same issue than

Table 3.1 Nanotechnology keywords

	Number of patents extracted
nano*	4,568
atom* force microscop*	88
biosensor	231
mesoporous material*	31
molecular beam pitaxy	95
molecular switch	25
nems	9
polymer composite*	379
polymer dna	10
polymer rna	3
quantum	1,287
scanning probe microscop*	16
self assem*	219
supramolecular chemistry	18
tunnel* microscop*	2
photonic*	969
scanning prob*	41
single electron*	85

those 484 patents. Although we could apply AHC on each of those components, we cannot situate them with regards to the clusters found for the main component because no similarity in terms of co-citations exists between them. Figure 3.3 shows the Canadian nanotechnology network's main component. Big-colored nodes represent Canadian patents and small-black nodes represent patents cited by the Canadian patents. Each color represents one of the clusters found during our AHC (4^{th}) step. As we can see, the clustering process regroups patents that are situated in the same region in the network graph.

Step 4: Hierarchical clustering

From the citation network of the main component, we build a citation matrix of size 691 by 3,765 (this is the number of patents that are cited more than once by the 691 Canadian patents). By running an AHC on this matrix, we obtain the dendrogram shown on the right side of Figure 3.3. As expected, the average linkage method offers a better hierarchical representation of the technological branches than the single linkage method (left side of Figure 3.4) which has a stairway-like shape. This is due to the fact that single linkage, by merging clusters based on the most similar elements, will delay the merger of outsider patents to later steps in the linkage process. The competence map resulting from the selection of

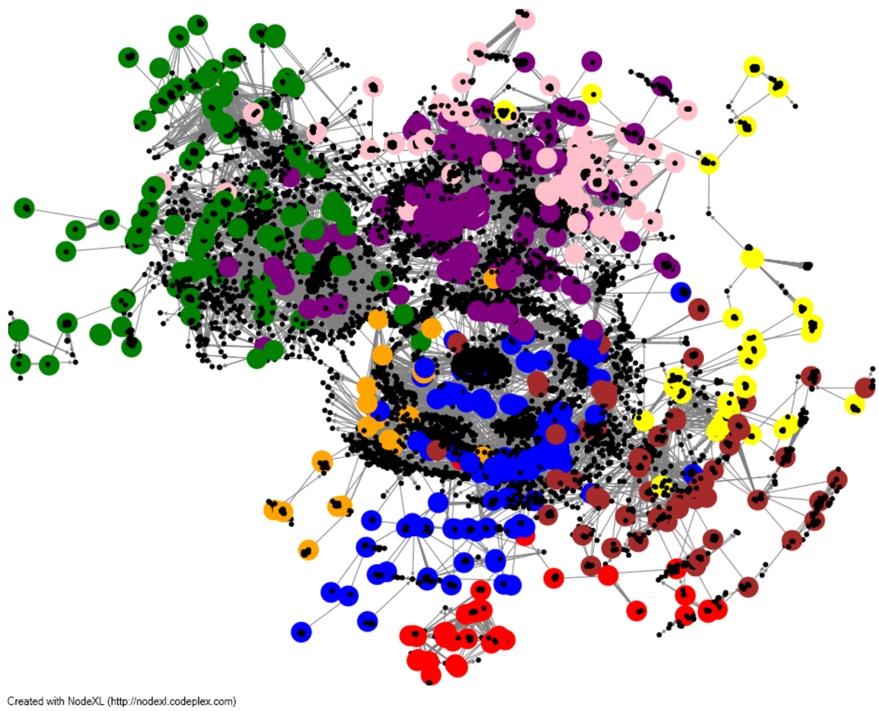

Figure 3.3 Canadian nanotechnology patents citation network's main component between years 2005 to 2008. Big-colored nodes represent Canadian patents. Small-black nodes represent patents cited by Canadian patents. Each color represents one cluster found by our AHC method. Since the two-dimensional representation of the network will place nodes that cite the same sources in the same region, nodes from the same cluster are also located in the same regions.

top-level clusters will show distinct technological branches separately but will embed them one into another instead of having a balanced tree of branches.

At the highest level of the dendrogram resulting from the average linkage method, the two top level clusters are at a distance of 1.57078. We then select all clusters that have a distance above 1.57 for our competence map, which gives us around 20 clusters, with the smallest clusters having more than 20 patents. This seems reasonable, given the fact that we need to have clusters large enough to be able to have meaningful labels for each of them. As shown in Figure 3.5, each cluster is represented by a circle that is sized according to the number of patents it contains. Child clusters are drawn inside the parent cluster to represent the hierarchical dimension of clusters. Each cluster is also identified by the cluster ID provided by RapidMiner. This ID represents the iteration number in which the cluster was created. As we can see in Figure 3.5, higher-level clusters have higher IDs because they are formed later in the clustering process.

Step 5: Cluster labeling

To label clusters, we merge the titles for the 8 clusters that are at the lowest levels of our competence map (clusters 1349, 1362, 1363, 1365, 1368, 1369, 1370 and 1375) and select the highest tf-idf ranked terms appearing in the merged titles of each cluster. We also search for the top three patent holders and active cities in each cluster. The results are shown in Table 3.2. As we can see, Xerox Corporation, Nortel Networks and D-Wave are globally the most active firms. Xerox is particularly dominant in electrophoretic technologies for printer toner solutions (cluster 1375) and polithiophenes technologies (cluster 1368). Nortel Networks, as expected, is very active in optical solutions for networking and communications (clusters 1349 and 1365). D-Wave is the leading firm in quantum computing technology (cluster 1362). On the other hand, some branches, such as nanomedecine (cluster 1370), are not dominated by one big player. For instance, the biopharmaceutical company Geron Corporation is the number one patent holder in nanomedecine but owns less than 8% of all patents in this branch of nanotechnology. The same observation applies to LED and lighting technologies (cluster 1363) where the main player (Brasscorp Ltd.) holds less than 15% of all patents.

3.5 Analysis

If we examine Canadian cities and the number of inventors residing there, we obtain the graph shown in Figure 3.6 As we can see, the Ottawa metropolitan area, dubbed the Silicon

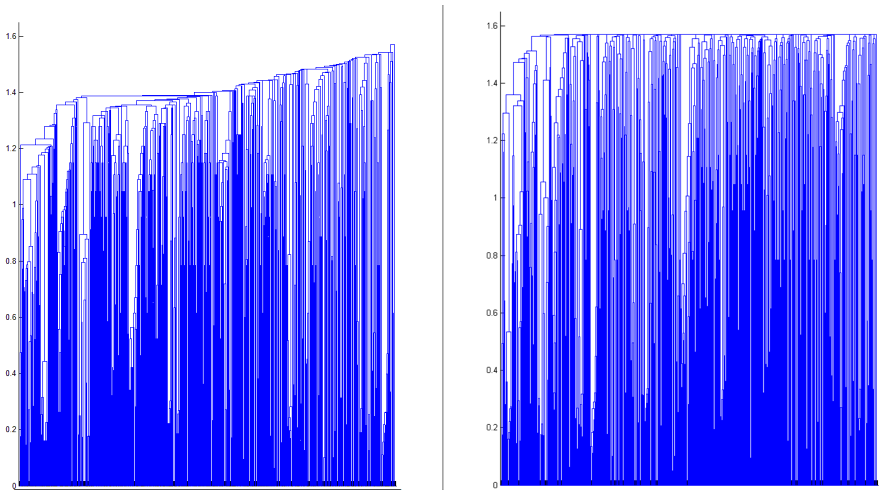

Figure 3.4 Dendrogram resulting from AHC using single linkage (left) and average linkage (right). (Plot using Matlab (2009))

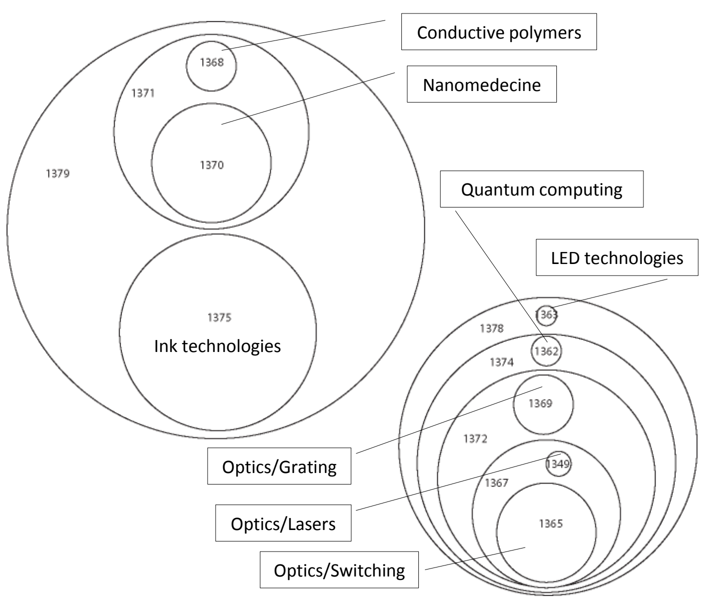

Figure 3.5 Competence map based on the main components of Canadian nanotechnology citation network

Valley North, hosts the largest community of nanotechnology inventors. Toronto, Vancouver and Montreal follow with the second, third and fourth positions with somehow smaller communities given their population size compared to Ottawa. Table 3.2 shows the concentration of nanotechnology inventors in top Canadian cities. As we can see, Ottawa has an incredibly higher ratio of nanotechnology inventors by population. Quebec City has the second largest ratio of inventors per thousand inhabitants. Yet, Ottawa's ratio is 2.7 times larger than Quebec City's. Other cities have ratios of the same magnitude although small differences exist between cities. Toronto, Montreal and Vancouver, the three largest Canadian metropolitan areas, have relatively the same ratio of inventors by population.

Although Figure 3.6 indicates the domination of the technological scene by two cities (Toronto and Ottawa), the last column in Table 3.3 shows that Montreal and Vancouver are not in such bad positions. For instance, Vancouver is the national leader in two technological areas (quantum computing and LED technologies) and has second position in nanomedecine. The latter technological branch is led by Montreal. Interestingly, these technological areas are either smaller (quantum computing and LED) or not dominated by one firm (LED and nanomedicine). Given the importance of nanomedicine and the fact that it is not dominated by a big player, Montreal and Vancouver must take proper measures to strengthen their competitive position in this area. A complementary strategy for these cities can be to develop competences in neighboring branches. For instance, nanomedicine (cluster 1370) is very close to conductive polymers technologies (cluster 1368) as our knowledge map shows that they rely on the same technological base. Incidentally, Vancouver and Montreal (the leaders in nanomedicine) have the second and third most important communities in conductive polymers technologies even if they are far behind Toronto.

Table 3.2 Ratio of nanotechnology inventors by metro area population

City	Population	Number of inventors	Ratio (per thousand inhabitants)
Ottawa	1,130,761	182	0.16
Toronto	5,113,149	165	0.03
Vancouver	2,116,581	95	0.04
Montreal	3,635,571	94	0.03
Quebec	715,515	42	0.06
Edmonton	1,034,945	22	0.02
Hamilton	692,911	16	0.02

Table 3.3 Ratio of nanotechnology inventors by metro area population

Cluster	Top Words	Top Firms (# of patents obtained)	Top Cities (# of inventors)
1349	optical	Nortel Networks (16)	Ottawa (42)
	ray	Applied Micro Circuits	Montreal (5)
	x	Corporation (3)	Toronto (3)
	communications	FSONA Communications Corporation (2)	Quebec (3)
	compensation		
1362	qubit	D-Wave (25)	Vancouver (12)
	Quantum	University of Toronto (3)	Toronto (7)
	Resonant	Luxtera, Inc. (2)	Montreal (6)
	Superconducting	MagiQ Technologies, Inc (2)	
	fiber		
1363	LED	Brasscorp Ltd. (4)	Vancouver (12)
	lamp	EXFO Photonics (3)	Toronto (11)
	Light	UView Ultraviolet Systems, Inc. (2)	
	inspection	Mattson Technology Canada, Inc. (2)	
	systems		
1365	switch	Nortel Networks (56)	Ottawa (87)
	network	PTS Corporation (5)	Vancouver (8)
	switching	Enablence Inc. (4)	Edmonton (4)
	optical	JDS Uniphase Corporation (4)	
	wavelength	Raytheon Company (4)	
1368	Polythiophenes	Xerox Corporation (36)	Toronto (18)
	Organic	LG Display Co., Ltd. (6)	Vancouver (18)
	film	Chemokine Therapeutics Corp. (3)	Montreal (11)
	devices		
	gelable		
1369	optical	Lxsix Photonics (7)	Ottawa (36)
	grating	Teraxion Inc. (6)	Quebec (29)
	chromatic	Photintech Inc. (5)	Montreal (10)
	wave		
	wavelength		
1370	expression	Geron Corporation (10)	Montreal (52)
	protein	Arius Research Inc. (6)	Vancouver (34)
	cells	QLT Inc. (6)	Toronto (16)
	compositions		Quebec (15)
	acid		Edmonton (11)
1375	members	Xerox Corporation (136)	Toronto (103)
	Toner	iFire Technology, Inc. (13)	Montreal (11)
	processes	Nucryst Pharmaceuticals (12)	Hamilton (7)
	display		Vancouver (7)
	Electrophoretic		Ottawa (5)

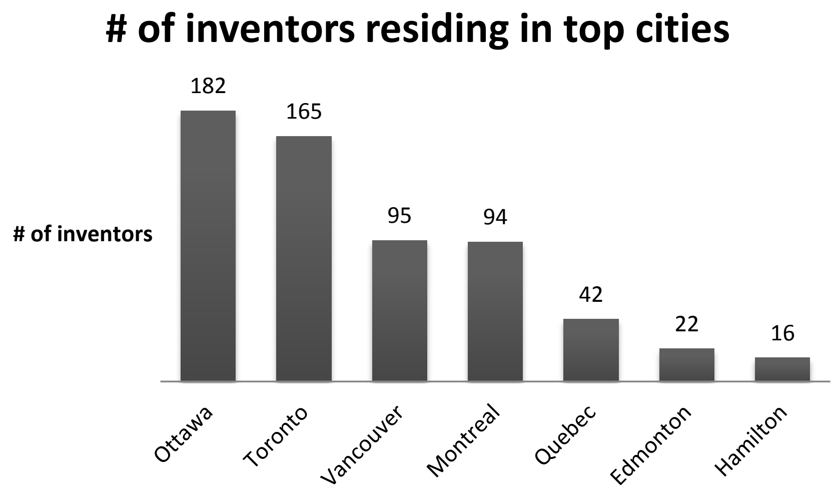

Figure 3.6 Top cities per number of inventors living in metropolitan area

3.6 Conclusion

This paper proposes a method to build a citation network from a sample of patents. It explains how to select the main network component and to build a citation matrix that is used to perform an AHC. With the hierarchical structure of the dendrogram generated by the AHC, we are able to deduce the technological relationship that exists between the clusters. Furthermore, an analysis of the patent titles for each cluster shows the most relevant words in each cluster. We use these words as labels describing the different branches of competences. By examining major patent holders in each branch we are able to identify the most active firms and institutions in each branch. Furthermore, by aggregating data about inventor cities, we are able to see where the largest community of practitioners resides.

We validated the method with the analysis of Canadian nanotechnology patents. From this application, many conclusions could be observed with a large practical impact for politics, deciders and researchers. The results show that Toronto and Ottawa are the most important Canadian centers for nanotechnology development with Nortel Networks and D-Wave being the most important Canadian firms holding patents in the USPTO. This shows that Canadian firms are in a stronger position in optical networking and communication solutions (with Nortel Networks) as well as in quantum computing (D-Wave). Since patenting is an indication of past investment in research and development, these firms have proven that they own a greater proportion of the stock of knowledge than any other Canadian firm when it comes to nanotechnology. The vast amount of knowledge these firms hold should give them the power to act as central players in the development of Canadian competences in nanotechnology. It is regrettable for Canada that Nortel has filed for bankruptcy and that Google has bid for its patent portfolio (Google, 2011). If Nortel's bankruptcy leads to the dismantling of activities that were previously performed its nanotechnology R&D units, then a national-level intervention thatwould keep these activities running at more or less the same pace than before is highly recommended. In fact, high technology inventors have the privilege to be mobile, which could lead to their relocation to nanotechnology poles outside the country if local firms do not fill the void left by Nortel. Given the size of Nortel's nanotechnology patent portfolio compared to other Canadian firms, it wouldn't be sound to expect that all of its R&D activities can be taken over by one or even a group of local firms.

Finally, our study shows that our competence maps can be used as a decision tool when it comes to questions regarding the exploitation of a technological position or the exploration of new technological areas. We have seen that cities with limited overall capabilities can concentrate in developing one or a few areas of expertise and then expand their competences to other areas that rely on the same technological know-how. This is especially important in the case of cities like Montreal and Vancouver that are two main Canadian cities that are shadowed by a smaller but more technologically savvy city that is Ottawa. The former can take advantage of their leading position in the area of nanomedecine and expand their sphere of influence to conductive polymers technologies.

Next studies in this area may consider improving the visualization approach of the results.Also an interactive approach that will precise a step by step analysis, adding keywords search facilities at any time, will help decision makers for a more accurate competence map. One of the limitations of our methodology consists in the discarding of secondary network components from the competence map. As discussed in the article, this is a limitation due to the choice of AHC technique for organizing technological branches hierarchically. In future work, we hope to tackle this limitation by developing methods for the interaction of technological branches from disconnected network components.

3.7 Acknowledgements

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CHAPTER 4

DISCOVERING AND ASSESSING FIELDS OF EXPERTISE IN NANOMEDICINE: A PATENT CO-CITATION NETWORK PERSPECTIVE

Abstract[1]

Discovering and assessing fields of expertise in emerging technologies from patent data is not straightforward. First, patent classification in an emerging technology being far from complete, the definitions of the various applications of its inventions are embedded within communities of practice. Because patents must contain full record of prior art, co-citation networks can, in theory, be used to identify and delineate the inventive effort of these communities of practice. However, the use of patent citations for the purpose of measuring technological relatedness is not obvious because they can be added by examiners. Second, the assessment of the development stage of emerging industries has been mostly done through simple patent counts. Because patents are not all valuable, a better way of evaluating an industry's stage of development would be to use multiple patent quality metrics as well as economic activity agglomeration indicators. The purpose of this article is to validate the use of 1) patent citations as indicators of technological relatedness, and 2) multiple indicators for assessing an industry's development stage. Greedy modularity optimization of the 'Canadian-made' nanotechnology patent co-citation network shows that patent citations can effectively be used as indicators of technological relatedness. Furthermore, the use of multiple patent quality and economic agglomeration indicators offers better assessment and forecasting potential than simple patent counts.

Keywords: Knowledge discovery, nanomedicine, self-organization, trend analysis, citation network analysis, S-curve.

4.1 Introduction

Bibliometric data can be used to assess and forecast technological progress (Martin, 1995; Watts and Porter, 1997; Daim et al., 2006). Among the many purposes it serves, bibliometric data can be used for trend analysis. Such analysis can show how a given field has evolved

[1]Barirani, A., Agard, B., and Beaudry, C. (2012a). Discovering and assessing fields of expertise in nanomedicine: a patent co-citation network perspective. *Scientometrics*. Available from: `http://dx.doi.org/10.1007/s11192-012-0891-6`.

over time, help to forecast future technological directions, identify promising research areas and support new product development decisions. Trend analysis often consists in fitting the progress and growth of bibliometric data with technology diffusion models. In this regard, cumulative technology development is generally recognized to follow an S-shaped curve over time (Andersen, 1999; Daim et al., 2006). In this model, development in a discipline grows exponentially until an inherent upper limit is reached. At this point, growth slows down and eventually saturates. These two phases of growth and saturation are representative of technological opportunities in a given disciplines (Andersen, 1999). An emerging discipline initially offers great opportunities and thus exhibits exponential growth in terms of bibliometric indicators. As novelties accumulate and occupy the technological landscape, smaller areas of opportunities are left available which leads into a slowing down of bibliometric indicators. This process is self-propagated and results from the collective effort of opportunity seeking innovators.

Within the available bibliometric data sources, patents have been extensively used to measure innovative activity (Pavitt, 1985; Narin, 1994; Narin and Hamilton, 1996). Because patents must be novel, non-obvious and useful, they are indicators of technological progress and change (Acs and Audretsch, 1989; Archibugi and Pianta, 1996). Moreover, the accumulation of patent stocks in a discipline takes place because of interactions between scientists, inventors and entrepreneurs. Changes in patenting activity can therefore be used to assess the development stage of various technological sectors (Andersen, 1999). Naturally, the analysis of trends and patterns of patenting activity in emerging industries is a popular subject of research. Among these, nanotechnology has been experiencing rapid development which leaves traces through growth in research grants, the publication of academic papers and the granting of patents (Hullmann, 2006; Kostoff et al., 2007; Alencar et al., 2007; Takeda et al., 2009; Porter et al., 2008; Dang et al., 2010; Grieneisen, 2010). Numerous countries have put in place initiatives to foster their scientific and technological capabilities in this field (Alencar et al., 2007; Li et al., 2009). Nanotechnology results from the combination and integration of scientific and technological concepts from different fields such as physics, chemistry, biology, material sciences, mechanics and electronics. In this regard, it can also be viewed as a multidisciplinary field (Meyer and Persson, 1998). This intrinsic nature of nanotechnology makes its definition, the identification of its field as well as the delineation of its boundaries difficult to achieve.

Within all applications of nanotechnology, nanomedicine is of particular interest, because it may partly be the result of nanotechnology and biotechnology convergence. Freitas Jr. (2005)

for instance defines the concept as the medical application of nanotechnology. According to the European Science Foundation, this field aims at "ensuring the comprehensive monitoring, control, construction, repair, defense and improvement of all human biological systems, working from the molecular level using engineered devices and nanostructures, ultimately to achieve medical benefit" (ESF, 2005). It has various application fields in drug delivery, cancer treatment, surgery and medical imaging to name a few. Given the importance of these various applications to human healthcare, nanomedicine is one of the most promising fields of nanotechnology.

So far, the bibliometric literature has been mainly concerned with the study of trends in nanotechnology as a whole. Although a few studies have concentrated on sub-disciplines within nanotechnology, nanomedicine has not yet been tackled in a great deal of details. Two quantitative studies can be associated with nanobiosciences. The first is by Pei and Porter (2011) who use the relevant WOS subject categories to extract nanobioscience articles from a nano-dataset. In a similar fashion, Li et al. (2007a) identify patent classes that can be potentially associated with nanomedicine, but these classes are not reserved for nanomedicine and could also contain patents for the nanobiotechnology sector. Furthermore, patent classes do not reveal much detail about the nature of applications that are developed in an emerging field. By definition, emergent disciplines are continuously growing and are redefined through what the communities of practice (Wenger, 1999) believe are promising applications or technological paths. This makes it difficult for observers such as those within the USPTO in setting up standard classification of patents in nanotechnology. Of course, the USPTO has reserved class 977 to nanotechnology patents, but this class only contains a small proportion of nanotechnology patents. The lexical query of Porter et al. (2008) returns nearly 50,000 patents between 1990 and 2005, while the USPTO currently (as of June 2012) classifies only 4,193 patents in class 977 for the same period.

The second quantitative study is by Takeda et al. (2009) which focused on nanobioscience articles as the unit of analysis and uses a very general lexical query ('bio*' and 'nano*'). The authors use greedy modularity optimization to discover major fields of scientific research in nanobiosciences from scientific paper citation networks. They find that the discipline is divided into four fields: nanostructures, drug delivery, bio-imaging and biosensors. For the period 1990 to 2005, theses field all show exponential growth indicating that nanobiosciences have not yet reached the inflection point associated with the abovementioned S-shaped growth curve. While the adoption of such unsupervised learning techniques to the case of patents seems attractive, certain theoretical issues need first to be raised. Indeed, if one can easily conclude that paper citations can indicate knowledge flows, it is not so obvious in the case of patents, mainly due to the existence of examiner citations. As a result, the study of the commercial applications of nanomedicine are mostly qualitative in nature. In a study of the most promising application fields for nanomedicine (therapeutics, drug delivery, tissue reconstruction and imaging and diagnosis), Perkel (2004) states that nanomedicine development is still in its infancy as it will be decades before dominant firms that are equivalents to the "IBMs, Intels, or Microsofts of the world" emerge in this new sector.

Another issue related to the use of patent data as progress indicators is in the sole reliance upon patenting activity trends for the assessment of emerging industries. Porter et al. (2008) show that nanotechnology patent production experienced three major leaps for the years 1998, 2001-2002 and 2005 at the international level. Dang et al. (2010) find similar results when looking at international patent applications. Fitting these trends against logistic curves could indicate that nanotechnology has yet to reach its inflection point where growth starts slowing down. However, this is not always true about nanotechnology sub-fields. In a study of nanotube field emission display patents between the years 1994 to 2007, Chang et al. (2010) show that the number of patent applications has slowed down after 2004. Meyer (1994) introduces the concept of bi-logistic growth. This model describes a system that contains two S-shaped curves: a first period of stagnation can be followed by new period of growth and stagnation manifested through two serial logistic curves. This second growth leap is due to environmental changes that lead to a new carrying capacity of the technology. From this perspective, curve fitting of simple patent counts against a logistic curve might miss the complex relationship that technological development has with other economic phenomena that could predict changes in the carrying capacity.

Furthermore, although the use of patenting activity is attractive for industries in which commercial data is not yet easily available, their use for evaluating proximity to commercialization is not straightforward because patents are not all valuable as only a small percentage succeed in generating income (Allison et al., 2004; Moore, 2005). It should also be noted that patents are not always filed with the intention of building new products. For instance, firms can license patents for defensive or plain trolling purposes (Hall and Ziedonis, 2001; Gallini, 2002; Moore, 2005; Reitzig et al., 2007). Even though strategic patenting is less often employed for discrete products such as chemicals, pharmaceuticals and biotechnology applications (Cohen et al., 2000; Hall and Ziedonis, 2001), it is customary enough to justify for the analysis of trends in cumulative patent stocks in tandem with other metrics to control for the variance in patent quality (Lanjouw and Schankerman, 2004a) and have a better understanding of the technological landscape.

This article fulfills the need to answer the two above-mentioned issues. Our first objective is to verify whether patent citations be used as a measure of technological relatedness. Our second objective is to verify if multiple patent metrics and economic indicators can offer better insight about the stage of development of an emerging industry. Our methodology consists in partitioning projected patent co-citation networks of the Canadian nanomedicine industry and to verify partition quality in order to validate the use of patent citations as indicators of technological relatedness. We then perform trends analysis on the top partitions, which represent leading Canadian fields of expertise in nanomedicine. The use of multiple indicators will validate that they can contain useful information not conferred by simple patent counts.

The remainder of the article goes as follows: Section 2 presents some of the implementation issues regarding patent citation networks partitioning and our approach to test their validity ; Section 3 presents the conceptual framework used for assessing emerging fields of expertise; Section 4 describes the data used; Section 5 explains the methodology used; Section 6 presents the results of our analysis; and finally Section 7 concludes.

4.2 Discovering Know-How: Implementation Issues

Given the difficulties of identifying the nature of technological development – and thus national competences – in an emerging discipline, the first objective of this article is to provide a method for characterizing the self-organized nature of technological development in the Canadian nanomedicine community of practice. Inventive activity can be viewed as a complex dynamic system involving the collective effort of autonomous opportunity seeking agents (Fleming and Sorenson, 2001). Another aspect of knowledge creation is that it is a path dependent process, where new knowledge is built on top of old knowledge (Rosenberg, 1994). Thus, inventors evolve in a community which is constantly combining existing knowledge to create new ones. This search-and-combine effort results in a complex system where pieces of old knowledge and new knowledge are interlinked. This linkage does not follow a random pattern as ideas that solve common problems are linked to at a higher rate (Fleming, 2001). This self-organized behavior leads to the formation of small-world and scale-free networks (Watts and Strogatz, 1998; Barabási and Albert, 1999). In such settings, communities which exhibit dense inter-linkage of ideas emerge. Finding these communities can thus indicate the kind of knowledge that practicians in a technological discipline are producing. Since our intention is not to study the progress of disciplines that fall within predefined classes, unsupervised learning methods for knowledge discovery seem to be a natural choice for this purpose.

Because patents must contain references to all relevant prior art, patent citations can, theoretically, be used to build a network in which communities represent major fields of technological development. Finding such communities can come down to finding areas of high inter-citation between patents. Among unsupervised learning methods, cluster analysis can be performed on network data in order to identify areas, in which case it can be viewed as a way to achieve community detection in graphs (Girvan and Newman, 2002). Cluster quality functions – such as the network modularity – can be used to detect an optimal number of communities (Newman and Girvan, 2004). Modularity computes the degree to which vertices inside a community are interconnected compared to the probability of them being interconnected in a random graph of similar density.

Community detection algorithms have been used by scientometricians to map scientific papers and identify scientific disciplines (Wallace et al., 2009; Takeda et al., 2009). These studies rely on the principle that co-citations can be viewed as a measure of similarity between documents (Small, 1973). Other studies have extended this principle to patent citations in order to group technologically similar patents together (Breitzman and Mogee, 2002; Breitzman, 2005; Li et al., 2007b; Barirani et al., 2011). Thus, these studies have extended the principle used for papers to patents. It is worthwhile to mention that this assumption cannot be readily made without considering the difference between patent and paper citations. In fact, co-citation classification of scientific articles finds justification in the fact that citations in scientific publications can be easily associated with knowledge flows (Meyer, 2000a; Leydesdorff, 2008). However, the interpretation of patent citations must be put in context due to the fact that 1) a large proportion are added by examiners, and 2) that applicants can add them for strategic reasons (Sampat, 2005). Meyer (2000a) also points out that time constraints can also lead to examiners adding citation than are only remotely linked to the filed patent.

Therefore, patent citations do not automatically indicate knowledge flows from cited to citing patent and thus the argument used for scientific publications cannot be automatically used for patents. However, one can interpret citations as indicators of technological relatedness due to the fact that they result from and are strongly related to USPTO's patent classification process (Lerner, 1994). It is therefore possible to interpret patent citations as a measure of how close two inventions are from a technological point of view rather than as a measure of knowledge flows from one patent applicant to another. The second research question covered in the present study concerns the validity of this hypothesis. Indeed, even if our conception of technological relatedness is not in any way synonymous to that of knowledge flow, it is worthwhile to verify whether examiner citations can become obstacles to the soundness of citation-based community detection techniques. In other words, we are interested in verifying the degree with which co-citations result from a controlled process that can indicate technological relatedness between patents.

Numerous indicators can be used to test the above hypothesis. The more citations are away from being the result of a controlled process and the more they result in arbitrary assignments (due to lack of time from examiners for instance), the more patent citation networks will resemble random graphs. On the other hand, if citation assignment process is relatively well defined, our network should exhibit small-world and scale-free characteristics common to real-world networks.

Furthermore, once community detection algorithm is applied to the patent citation network, assignee information can also contribute in testing our hypothesis. Since organizations are more likely to specialize in one or a few technological fields, their patents should not be uniformly distributed within partitions. Rather, partitions should be dominated by a few firms. It should also be noted that the domination of all partitions by one single organization could also mean that the partitioning procedure was not effective in grouping similar technologies developed by different organizations. This could mean that modularity optimization of patent citation network does nothing more than grouping together patents from the same organizations. We thus expect partitions to be represented by more than one assignee. Of course, it is possible that one or a few partitions be dominated by one firm, as monopolies do exist in various industries.

4.3 Assessing National Capabilities: Conceptual Framework

As we have observed earlier, patents are not always accurate in indicating progress from a commercial point of view. Other patent quality indicators can be used in tandem with patent counts in order to assess the progress of an industry. Among these metrics, patent claims are generally recognized as indicators of patent value since they define the patent's scope (Merges and Nelson, 1990). Indeed, the broader a patent's scope, the larger the number of competing patent that infringe upon it. As a result, patent applicants are willing to have as many claims as possible, while examiners must make sure than all claims are justified and that the patent's scope is correctly defined (Meyer, 2000a). It should however be noted that more claims do not automatically translate into legal protection for patent holders. Indeed, the USPTO and courts often have contradictory views about the interpretation of patent claims (Merges and Nelson, 1990). The USPTO follows the doctrine of disclosure, meaning that the applicant is granted a patent if it provides adequate disclosure of the invention. Courts, however, follow the enablement principle in which infringement occurs when an equivalent use of claims is made by a competing product. Nevertheless, studies find statistically significant relationship between the number of claims and patent value (Tong and Frame, 1994; Allison et al., 2004).

Patent citations are also signals for patent quality. With regards to the examiner citation issue, it should however be noted that they are not strictly synonymous with noise. For instance, Alcácer and Gittelman (2006) find that examiners add a larger proportion of self-citations than the inventors themselves. Hegde and Sampat (2009) find that examiner citations are more significantly associated with patent value. Without being an indication for knowledge flow, examiners' involvement in the prior art citation process can also be viewed as a smoothing process that insures a thorough citation of prior art. This is generally more recognized for the USPTO patenting system (Meyer, 2000a). Other studies find that a number of characteristics such as firm size and the industrial sector have an impact on the proportion of examiner citations (Alcácer and Gittelman, 2006; Alcácer et al., 2009; Azagra-Caro et al., 2011). In the case of discrete technologies, a larger proportion of citations originate from applicants (Alcácer et al., 2009). Sampat (2005) also points out that examiner-added citations represent a smaller proportion of citations in new fields where the majority of prior art resides outside the USPTO patents. Thus, following aggregate citation trends within a discipline that is homogenous in terms of firm size, technology type (discrete vs. complex) and industry characteristics allows to control for variations in the examiner/applicant citations proportions and lead to robust conclusions about the progress of the said discipline.

It is also worthwhile to distinguish between different interpretations that can be made from forward and backward citations. Forward citations to a patent are generally recognized as indicators of the patent's economic value but also of its technological importance (Albert et al., 1991; Trajtenberg, 1990; Archibugi and Pianta, 1996; Hall et al., 2005; Abraham and Moitra, 2001). The number of backward citations is another indicator of patent quality. Allison et al. (2004) suggest that citing more prior art will lead to stronger patents in the face of litigation. The number of backward citations to patents can also be used to assess the novelty of a technology (Carpenter et al., 1981). New technologies are often sourced in science and have little links to existing patents. As solutions to technological problems are found, future inventions can rely on them, which lead to a rise in the number of backward citations to patents. Patents in emerging technologies are therefore expected to experience an increase in the number of backward citations to other patents as the sector matures.

Non-patent references (NPRs) have also been considered in the literature. These are references made to other prior art such as books, journal articles or standards. Callaert et al. (2006) find that most NPRs are references to scientific journals. Discrete technologies have a higher proportion of NPRs than complex technologies or processes. NPRs are also less likely to be added by examiners, which can be linked to a propensity by examiners to concentrate on citing USPTO patents (Sammarra and Biggiero, 2008). Thus, NPR trends within a technological field can indicate the progress of that discipline's need upon basic science. Meyer (2000b) also points out that science-technology linkage is not a linear process and that the presence of NPRs does not imply that cited literature was used during the invention process. Instead, science-technology linkage involves the circular interaction of technological exploitation and scientific exploration. The process of scientific exploration can be viewed as a way to reach new insights that can lead to new inventions which, in turn, can be further improved and optimized during the technological exploitation process. Allison et al. (2004) find that the number of NPRs is positively linked to litigation possibilities. Given the high legal expenses generated by litigation processes, NPRs can be linked to patent value.

Although patents are not all of equal value, patent protection increases the chance of an invention reaching the commercialization stage (Webster and Jensen, 2011). Furthermore, commercialization possibilities increase with patent strength (Dechenaux et al., 2008). It should be noted that technology commercialization is not limited to the production and distribution of new products. Technology transfer mechanisms such as patent licensing and buyouts are other channels for monetizing inventions. This principle holds for public institutions, for which licensing is a source of monetizing publicly funded research in North America. Even patent trolling can be viewed as a form of market intermediation and legitimate income seeking in the knowledge economy (McDonough III, 2006). Therefore, for a given technological sector, increases in metrics such as the patent count, forward citations, backward citations, NPRs and claims can be viewed as indicators of closeness to the commercialization stages (Breitzman and Mogee, 2002; Nerkar and Shane, 2007; Chang and Breitzman, 2009; Cheng et al., 2010). Furthermore, it would be interesting to study whether growth or slowdown in the overall number of patents granted is accompanied by similar growths or slowdowns in the number of backward citations and NPRs. This will allow for a better understanding of the intertwined science-technology link in nanomedicine (Meyer, 2000b).

The interpretation of trends in patent metrics must however be nuanced given the complex regulatory framework in which nanomedicine evolves. Indeed, the use of nanomedicine is still a socially controversial subject. Since technological progress is to a certain degree independent from social and legal concerns, growth in trends do not automatically indicate commercialization opportunities. Furthermore, the conclusions taken based on these metrics are not an absolute indication of closeness to income generation. Rather, they must be used to indicate how one discipline is positioned compared to another.

Compiling information about patent applicants such as inventors and assignees can provide information about dominant firms, technological proximity between firms (which can lead to partnerships as well as merger and acquisition possibilities) and the location of communities of practice (Breitzman and Mogee, 2002; Breitzman, 2005; Pei and Porter, 2011). Concerning the geographical dimension, inventive activity often clusters in a region because of supply-side and demand-side benefits associated with geographical proximity (Krugman, 1991; Porter et al., 2008). Among these benefits, the agglomeration of innovators in a region leads to knowledge spillovers (Jaffe et al., 1993; Audretsch and Feldman, 1996; Maskell and Malmberg, 1999). Patenting activity involves high levels of technological experimenting, part of which is tacit knowledge and thus reflects the localized learning that occurs in a region (Andersen, 1999). The clustering of inventive activity in a geographical region can therefore be a sign of increasing returns for that region but also of the formation of an industry (Zucker et al., 1998).

The centrality of the position that public institutions play within the knowledge network of an industry can also be used as an indication of the industry's stage of development. Owen-Smith and Powell (2004) show that universities played a central gatekeeping role in the early days of the biotechnology cluster in Boston. As the industry matures, large corporations become the central players in the network. Based on this parallel, we believe that public institutions, and especially universities, play a similar central role in the Canadian nanomedicine sector which is expected to be in its early days. It could also be interesting to put our findings in perspective with studies concerned with nanotechnology as a whole. In this regard, literature points to mixed results. For instance, in results by (Alencar et al., 2007, table 2), only 2 public institutions appear in the top 5 assignee list. Li et al. (2007c, table 6) show that public institutions represent 1 out of 5 top patent assignees in the USPTO.

4.4 Data

To fulfill our research objectives we analyze a sample of Canadian nanotechnology patents that are registered at the USPTO. These patents where obtained by performing a lexical extraction on patents containing nanotechnology related keywords. These keywords were obtained from a set of bibliographic studies (Alencar et al., 2007; Fitzgibbons and McNiven, 2006; Noyons et al., 2003; Mogoutov and Kahane, 2007; Porter et al., 2008; Zitt and Bassecoulard, 2006). These studies, altogether, use more than 596 distinct keywords in their definition of nanotechnology with only 40 keywords being used in more than one study. As these figures show, experts do not agree on a unified lexical query delineating nanotechnology discipline (Hullmann and Meyer, 2003; Takeda et al., 2009; Maghrebi et al., 2011). However, keywords that are used in more than one study can be viewed as common agreement on what constitutes core nanotechnology keywords. In fact, Huang et al. (2011) show that the use of these common keywords leads to lexical queries that result in similar bibliographical extractions. For data extraction purposes, we choose this set of keywords to form a lexical query that is run on the USPTO database. The selection of the USPTO is motivated by the close commercial partnership between the US and Canada. The US economy is by far the largest marketplace for high technology. It thus attracts the highest level of competition and is therefore a clear indication of technological capabilities for those who are able to innovate in it. Li et al. (2007c) also show that Canadian assignees prefer filing patents in the US rather than the EPO. All granted patents that contain one of these keywords in all their fields and that have been granted to Canadian firms or for which one of the inventors resides in Canada are retrieved from the database. The sample is also expanded by patents classified under USPTO class 977 which has been reserved for nanotechnology. It should be noted that the USPTO currently assigns 156 Canadian patents to class 977, 12 of which are missed by the lexical query. We thus believe that our sample is a good representation of Canadian nanotechnology patents.

Table 4.1 shows the core keywords for which at least one Canadian patent was extracted from the USPTO database. For each patent, data about the title, abstract, grant date, number of claims, references, backward and forward citations, as well as the name, city and country of inventors and firms are extracted. After cleaning for duplicates and missing data, our sample contains 6,288 unique Canadian nanotechnology patents obtained from 1990 to 2009.

Table 4.1 Keywords used in lexical patent extraction.

Term	Patents	Term	Patents	Term	Patents
atom* force microscop*	88	molecular beam epitaxy	77	polymer protein	38
biosensor	231	molecular engineering	44	polymer rna	3
drug carrier	182	molecular motor	5	polymer virus	2
drug delivery	972	molecular switch	22	quantum	1,077
gene delivery	239	molecular template	3	scanning prob*	30
gene therapy	906	nano* (excluding nano2, nano3, nano4, nano5, nano*aryote*, nanoalga*, nanobacteri*, nanofauna*, nanoflagel*, nanoheterotroph*, nanoliter*, nanomeli*, nanophtalm*, nanophyto*, nanoprotist*, nanosecond*, plankton*)	3,188	scanning probe microscop*	16
immobilized dna	22	nems	5	self assem*	219
immobilized polynucleotide	1	photonic*	868	single electron*	75
immobilized primer	1	polymer composite*	261	supramolecular chemistry	12
immobilized template	2	polymer dna	9	transmission electron microscopy	198
mesoporous material*	20	polymer enzyme	15	tunnel* microscop*	2
molecular beacon	13	polymer polynucleotide	3		

4.5 Methodology

We build the backward citation network obtained from the extracted Canadian nanotechnology patent data. Backward citations have the advantage of being fixed over time as opposed to forward citations. Therefore, using both backward and forward citations to cluster patents will create a bias towards clustering older patents together. Our technology network is a bipartite graph, i.e. a graph in which vertices are divided in two classes p and q where edges only connect vertices of class p to vertices of class q. In our case, p is the set of Canadian nanotechnology patents and q is the set of patents that are cited by them. From this bipartite graph, we build its weighted projected graph which is a network where nodes are Canadian patents and where edges' weights represent the number of patents that Canadian patents have in common. The projected Canadian nanotechnology backward citation network is then partitioned by using the greedy modularity optimization algorithm by Clauset et al. (2004). Subsequently, we summarize relevant information regarding the partitions found in the previous step by adopting the method proposed by Barirani et al. (2011). For each partition, we merge the titles and abstracts of the patents that are assigned to them. Each partition therefore represents a document for which 3-grams will be built after removing common stopwords. Then, tf-idf term weighting will be computed for each document, each of the 3-grams being treated as a term. We will then select the top 10 3-grams for each partition. Summarization will also be complemented by information regarding patent assignees. Once 3-grams and top assignees are identified for each partition, we perform an expert search in order to identify partitions that are related to nanomedicine. Here, we use our initial definition of nanomedicine, i.e. the application of nanotechnology for medical purposes. Assignee information will help experts in correctly identifying partitions that contain nanomedicine patents as it could be confusing to rely solely on 3-grams for the distinction of nanomedicine partitions in the case of nano-devices or nano-molecules. Partitions for which top keywords and assignees can be associated with health sciences will be selected as nanomedicine partitions. Nanobiotechnology applications (such as plants, hybrid seeds, water treatment applications, etc.) are thus not retained as nanomedicine patents. This step is finalized by performing a second modularity optimization partitioning of the 'nanomedicine-only' projected network. This step is motivated by the resolution limitation associated with modularity optimization (Fortunato, 2010). Indeed, modularity will give partitions that are sized similar to the network's scale. Since the initial partitioning is performed on a larger graph representing nanotechnology as a whole, a second partitioning of the smaller nanomedicine network will result in a resolution obtained at a smaller scale.

A few words must be said with regarding expert search. First, this procedure is only practical when dealing with datasets representing a narrow technological field and where a relatively small number of clusters must be identified. Patent titles and abstracts are indeed very technical in nature and difficult to understand for those who are outside the field of expertise. Applying this method to patents coming from a broad set of fields is not effective as it becomes difficult for experts to discriminate between clusters that use similar terms but applied in different technological sectors. Nevertheless, expert searches are common in the scientometrics literature and can constitute a reliable method in our case due to the fact that we deal with a small number of patents that will be assigned to a relatively small number of clusters. Second, one can raise the question as to why expert search is not introduced earlier in the process so that non-nanomedicine patents are removed earlier from the initial sample. The main justification for using our method is that manual classification of patents is a costly process that is not free of error. On the other hand, the task of distinguishing between different domains of application is already performed once by USPTO examiners and this effort leaves traces in the form of patent classification and citations. Our method takes advantage of this available information for grouping technologically similar patents and minimizing subjective intervention to a smaller number of items that are clusters. Of course, citation-based clustering is not a perfect science and it can lead to the arbitrary assignment of patents that are in between two disciplines. However, given the expected scale-free and small-world characteristics of citation networks, these central patents will constitute a small proportion of patents and thus have negligible impact on the aggregate results.

The next steps will consist in assessing the nanomedicine industry by analyzing patent metric trends at different levels. The analysis is performed at field of expertise, city and organization levels. Visualization of technological and organizational maps is also performed following Harel and Koren (2002)'s force directed placement technique. At the field of expertise level, we consider patent counts as well as the average number of claims and citations. Based on trends in these metrics, we will identify fields that are closer to maturity and commercialization compared to the others. A technological map will indicate the level of technological relatedness between fields and the degree of interdisciplinarity of the nanomedicine industry. At city level, we identify Canadian metropolitan areas in which the largest communities of nanomedicine inventors reside. We then compare the ratios of nanomedicine inventors to the number of inhabitants and identify areas that have a larger proportion of their population working in the nanomedicine industry. These ratios will be used as indicators of the clustering of innovative activities in a geographical region. For each city, we compute the degree of specialization in the fields of expertise. This allows us to compare cities that are specialized in a few fields versus those that are diversified in many of them. At the organizational level, we will compute top assignees in our Canadian nanomedicine patent sample. This will indicate the degree of competitiveness and the role played by public institution in total patent production. The organizational map will also show the network position filled by public institutions. Again, mapping is performed through co-citation analysis, based on our assumption that citations are an indication of technological relatedness.

4.6 Results

4.6.1 Discovering expertise

Our initial sample of 6,288 Canadian nanotechnology patents cite 50,504 distinct patents which lead to a citation network composed of 56,454 vertices and 100,467 edges. The main connected component contains 3,876 Canadian patents, 33,674 distinct cited patents and a network containing 78,234 edges. The main component is therefore more than half the size of the initial set of Canadian patents. Furthermore, it contains more than 75% of the edges in the initial network. Taking into account that the initial network contains 1,522 disconnected components, which are mostly singletons (see Table 4.2), we select the main component as a representation of the core Canadian nanotechnology landscape. It should also be noted that the selection of the largest connected component is imposed by our choice of backward citations as measures of technological similarity as well as modularity optimization for graph partitioning. Since modularity optimization consists in minimizing inter-partition links, a modularity optimization algorithm fed with a disconnected graph will find that the graph's connected components represent the best modularity, which is equivalent to finding the number of disconnected components. Furthermore, force directed layout requires edges between vertices in order to position vertices on a two-dimensional map. The absence of edges between disconnected components means that they cannot be positioned one relative to another.

Figure 4.1 shows the graph obtained by projecting the main connected component. As we can see, this is a complex network with many areas of dense inter-citation. The maximum and average geodesic distances in the connected component are equal to 24 and 5.96 respectively. This network can therefore be classified as a small-world. The network also exhibits scale-free characteristics with skewed distribution of centrality among patents (see Figure 4.2). So far, these characteristics seem to indicate that the use of co-citations for measuring technological similarity between patents is sound. Furthermore, these characteristics make our citation network a good candidate for modularity-based graph partitioning techniques.

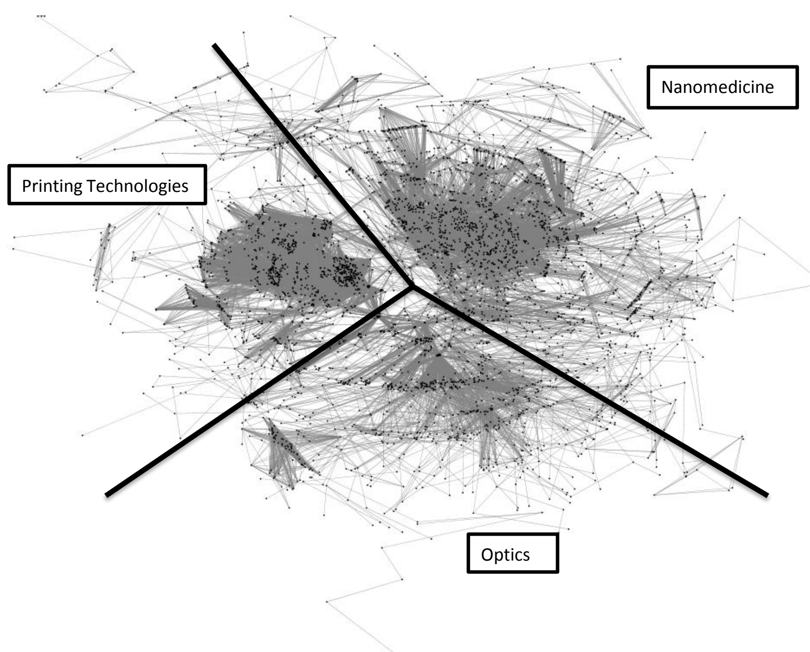

Figure 4.1 Projected graph of the Canadian nanotechnology patent citation network. Separation lines represent manual (somehow arbitrary) partitioning of the graph.

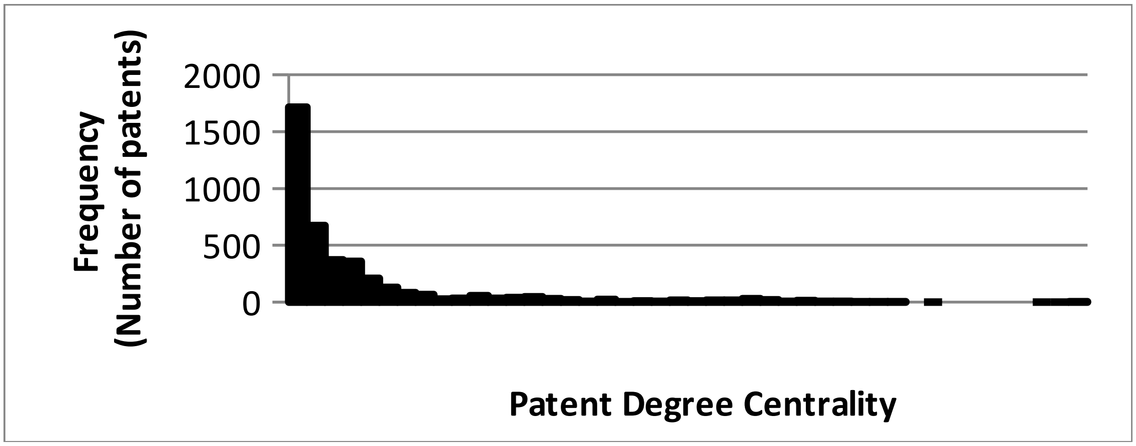

Figure 4.2 Network's degree distribution follows a power law: very few patents have many connections with other patents with most patents having few connections with other patents. The graph shows that the network exhibits scale-free characteristics.

The execution of greedy modularity optimization leads to the discovery of 62 fields of expertise for the Canadian nanotechnology sector. The best modularity found by the algorithm is 0.8997. Given the theoretical maximum modularity value of 1, partitioning found by the Clauset et al. (2004) algorithm is excellent given the nature of nanotechnology industry. Because of multidisciplinarity, different fields within nanotechnology might be commonly linked through basic technologies. Also, such fields will have a higher proportion of in-between patents, which will increase inter-partition linkage. In such cases, good partitioning of the network will still lead to relatively low modularity. The emerging nature of nanotechnology also contributes to increasing the number of common sources between different fields of expertise. This is due to the fact that a new technological sector must initially source itself in a few basic technologies that contribute to the propinquity of seemingly distant fields.

We further evaluate the partitioning of the greedy algorithm by analyzing the top keywords and assignees for the 4 largest fields of expertise in nanotechnology. The results are shown in Table 4.3. We can see that each partition has specific top terms and top assignees. Furthermore, there is a link between the top terms and the top assignees. For instance, partition N1 contains keywords that are related to optics applied to networking while the top assignees are firms that networking solutions companies. Top terms in Partition N3 are related to nanomedicine and the main assignees are pharmaceuticals or universities. From this perspective, modularity optimization partitioning of patent citation networks seems to be an effective way of delineating technological fields of expertise. Another aspect for evaluating the partitioning is the distribution of patents for assignees within partitions. Regarding

Table 4.2 Number of components of the same size. There is one large component with 3,876 Canadian patents, while 1,219 components are singleton Canadian patents.

Component size (number of Canadian patents)	Number of components
3876	1
13	1
10	3
9	1
8	2
7	3
6	12
5	11
4	22
3	57
2	190
1	1219

this issue, we further analyze partitions N2 and N4. These partitions are all dominated by one company: Xerox Corporation. Examining these partitions one at a time might be an indication that the partitioning is only grouping patents from the same company. However, a closer look at the top keywords for each one indicates that these are three different types of technologies related to printing solutions: N2 and N4 contain applications for laser and inkjet printers respectively. Therefore, the modularity-based partitioning of patent citation networks seems also effective in delineating different fields of expertise possessed by a very large company such as Xerox Corporation. It should be noted that the domination of printing technologies clusters by Xerox is natural given the fact that our sample contains Canadian-made patents only. Therefore, other large producers of printing technologies which are not present in Canada are not represented here.

By examining partition N2, we find that the last three assignees aren't printing technology companies. This is due to the fact that these patents are linked to similar technologies than printing patents and that their assignment to partition N2 gives result to better network modularity. Such cases represent a small proportion of patents and will not have significant impact on the aggregate results. Indeed, the top 4 disciplines in Table 4.3 contain more than 958 patents, with only 3 of them that are falsely assigned.

Table 4.3 Top 10 terms and top 5 assignees for the 5 largest partitions in the Canadian nanotechnology network.

Partition ID	Top 10 Terms	Top 5 Assignees (% of patents in partition)
N1	optical	Nortel Networks (28.3)
	grating	JDS Uniphase Corporation (4.6)
	waveguide	Teraxion Inc. (4.2)
	fiber	Institut National d'Optique (3.3)
	signal	Her Majesty the Queen in Right of Canada (2.9)
	compensation	
	dispersion	
	bragg	
	polarization	
	wavelength	
N2	toner	Xerox Corporation (97.5)
	latex	Palo Alto Research Center, Inc. (0.7)
	resin	Angiotech Pharmaceuticals (0.4)
	particles	Ballard Power Systems Inc. (0.4)
	surfactant	Ocean Nutrition Canada Limited (0.4)
	pigment	
	emulsion	
	toner particles	
	colorant	
	ionic surfactant	
N3	lipid	Inex Pharmaceuticals Corp. (11.2)
	liposomes	The Liposome Company, Inc. (9.8)
	liposome	University of British Columbia (8.8)
	liposomal	RTP Pharma Inc. (2.9)
	drug	McGill University (2.4)
	lipids	
	vesicles	
	nucleic	
	therapeutic	
	lipid-nucleic	
N4	phthalocyanine	Xerox Corporation (98.2)
	photoconductive	Fuji Xerox Co., Ltd. (1.2)
	charge transport	Group IV Semiconductor Inc. (0.6)
	photoconductive imaging	University of Rochester (0.6)
	photogenerating	
	charge transport layer	
	photogenerating layer	
	transport layer	
	charge	
	titanyl	

It is also worthwhile noticing that top terms extracted from the titles and abstracts of patents in the 4 largest nanotechnology partitions are different from those that were initially chosen for patent extraction from the USPTO database (see Table 4.1). This finding seems to indicate that the world of technology is developing its own technical corpus to describe the inventions that it is developing. Of course, the fact that these documents were extracted with the use of keywords originating from the world of science is an indication that there is knowledge flows from the world of science to the world of technology. However, once basic concepts are transferred to the world of technology, they are transformed into applications which are described with brand new expressions. This finding can point in favor of citation-based query expansion methods (Zitt and Bassecoulard, 2006) to complement lexical document extractions. Indeed, patents that don't link to terms from the scientific literature will be missed if the extraction process is limited to lexical extractions. This is even more important for mature fields that are relying increasingly on technology and decreasingly on science.

By examining the top keywords and assignees for the 103 nanotechnology partitions, we have identified 46 partitions related to nanomedicine. Altogether, these partitions cover 1,479 patents which represent an average annual production of nearly 80 patents for the period 1990 to 2009. The second partitioning of this smaller network finds 38 distinct fields of expertise. Table 4.4 shows the six largest nanomedicine domains identified from the sample of nanomedicine patents. These partitions group patents that have applications mainly in Liposomal formulations, cancer treatment and regenerative medicine. Our results coincide with the nanomedicine report by the ESF (2005, p. 43) where liposomal formulations (Doxil®/Caelyx® and Ambisome®) are said to have reached the market stage and generated considerable sales ($300M and $100M respectively for the two drugs) in 2004. Given the very competitive nature of the pharmaceutical industry, the profits associated with gaining market share and the fact that patents in this industry are usually of better value, we can conclude that the domain of liposomal formulation offers the best opportunities in terms of commercial potential. The other major disciplines are also of comparable size relative to the latter discipline, which could mean that they also have commercial potential. Trends analysis for other patent quality metrics will add to this perspective.

4.6.2 Industry assessment

Figure 4.3 shows the cumulative number of patents produced in nanomedicine by Canadian inventors from 1990 to 2009. As we can see, patent production is on the rise. It is however difficult to tell in which stage of the S-shaped growth the field is from this graph. Figure 4.3

Table 4.4 Six largest fields of expertise in nanomedicine.

Technological field	Size
Liposomal Formulation	187
Therapeutics (Alzheimer)	138
Tumor Suppression (Reovirus)	118
Tissue Engineering	112
Therapeutics (Stem Cells)	110
Cancer Treatment (Telomerase)	104

also shows the evolution of patent metrics over the years. As we can see, there was a slowdown in terms of patent production between years 1999 to 2005 with a second wave of rise between 2005 and 2007. Furthermore, trends in the average number of NPRs seem to indicate two cycles that are aligned with patenting rises and slowdowns.

The first slowdown period (1999 to 2005) is also marked by a slowdown in the number of NPRs. Again, the 2005-2007 rises in patenting are also accompanied with a rise in the average number of NPRs. This is a very interesting finding regarding the science-technology relationship in nanomedicine. During slowdowns, new patents seem to involve incremental technological improvements. Once technological opportunities are exhausted, communities of practice tend to source their knowledge from basic science which leads to another growth cycle in patenting. The number of backward citations is clearly improving over the years, but also follows a trend that is relatively parallel to that of granted patents. Here, the average number of backward citations seems to depend upon the available technologies. As patent production rises, the technological base on which new patents rely also seems to rise. Concerning the 2008-2009 slowdowns in the number of granted patents, we observe that it is accompanied by rises in both NPRs and backward citations. This could indicate that a third wave of development attracting greater resources is on its way, but that the field is increasingly linked to the technology world even if it still relies on basic science. The evolution of the number of claims is stable over time. Considering the number of forward citations after 7 years of a patent's grant date, we do not notice any clear rise. This seems to indicate that nanomedicine is still linked to other technological fields. Indeed, if nanomedicine patents where increasingly relying on nanomedicine patents, we would see a rise in forward citation similar to that of backward citations. These figures seem to indicate that, although getting closer to commercialization, the Canadian nanomedicine industry is still far from reaching its maturity.

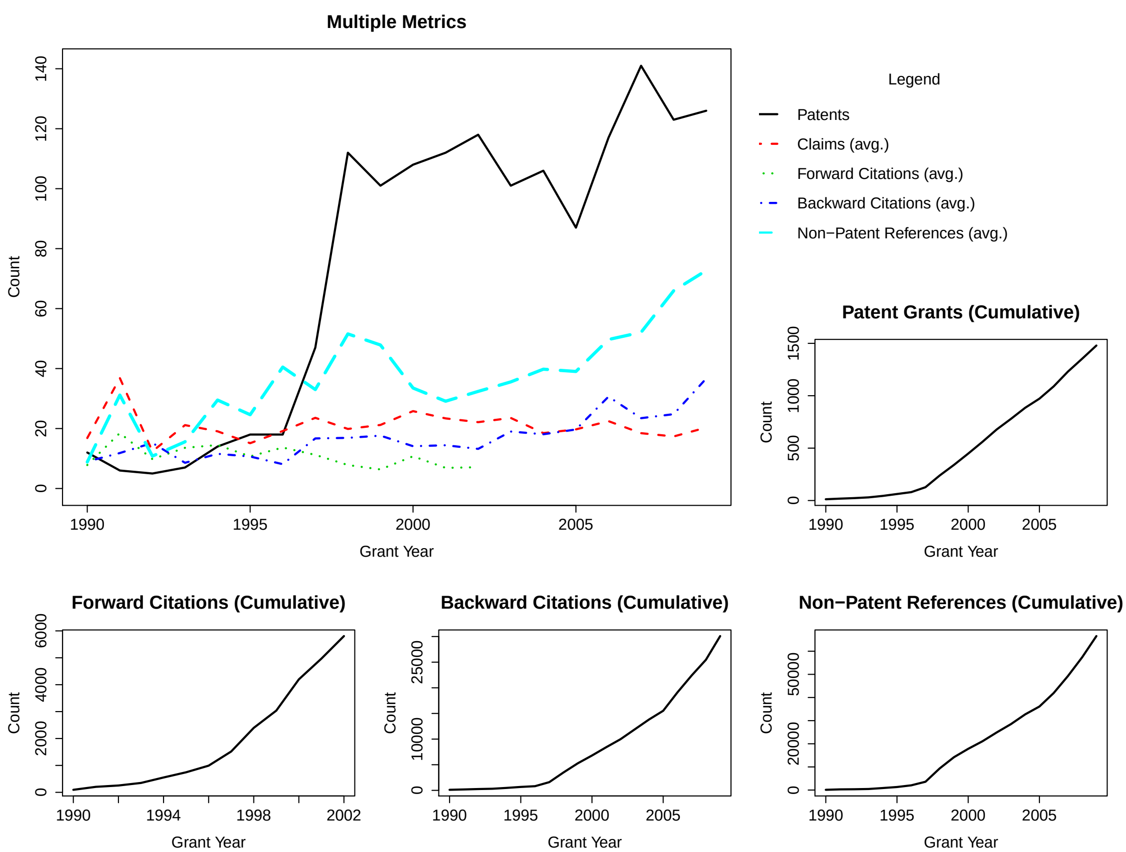

Figure 4.3 Nanomedicine patent metrics trends (all sub-disciplines included)

Figure 4.4 shows patent metrics for the largest nanomedicine subfields. Patent production is on the upside for most of the fields of expertise except for liposomal formulation and tumor suppression which seems to have slowed down. For liposomal formulation, there is a trending rise in NPRs and backward citations. This could indicate that the field might be going through an exploitative cycle where reliance upon technology is growing. The same observations can be made for tumor suppression applications. Since the number of backward citations and NPRs are stable, and that first patents have appeared in 1995, this field seems to be relatively young. The initial rapid growth of the field is thus an indication of higher perceived technological opportunities, with a period of knowledge resourcing that could be ahead. None of the other top fields however shows any sign in reaching its S-shaped growth inflection point.

The average number of backward citations and NPRs are also generally on the rise. This is an indication that major fields of expertise are increasingly linking with both the technology and science world. This is especially true for Telomerase applications which are increasingly linked to technology and science bases. We therefore expect to witness future cycles of growth in this field. Concerning the number of claims, figures show stability over the years. Finally, forward citations trends seem mostly on the downfall. This could be an indication that Canadian patents in nanomedicine are generally failing to lead to subsequent developments from within the industry. These trends seem to point out that Canadian nanomedicine patents have quite some development ahead before commercialization. Although patent quality is improving within the sector, it still links heavily with technologies from other disciplines. Even if we observe rises in forward citations in certain areas, they are temporary as dominant designs do not seem to emerge from within the industry.

Figure 4.5 shows the map of Canadian fields of expertise in nanomedicine. Force-directed placement assigns coordinates to patents that cite the same sources in the same region of the graph. Vertex size represents the number of patents produced in that field of expertise and edge size represents the number of citations that the two fields have in common. As the graph shows, nanomedicine fields of expertise are highly interrelated. Indeed, our map of major nanomedicine fields of expertise is closer a complete graph rather than a small-world. This seems to indicate that these fields are related to a common set of technologies.

As we can see in Table 4.5, Vancouver, Toronto and Montreal are the main centers for nanomedicine technology development. However, for a country that covers a very large geographical area, it is worthwhile observing that the majority of Canadian nanomedicine

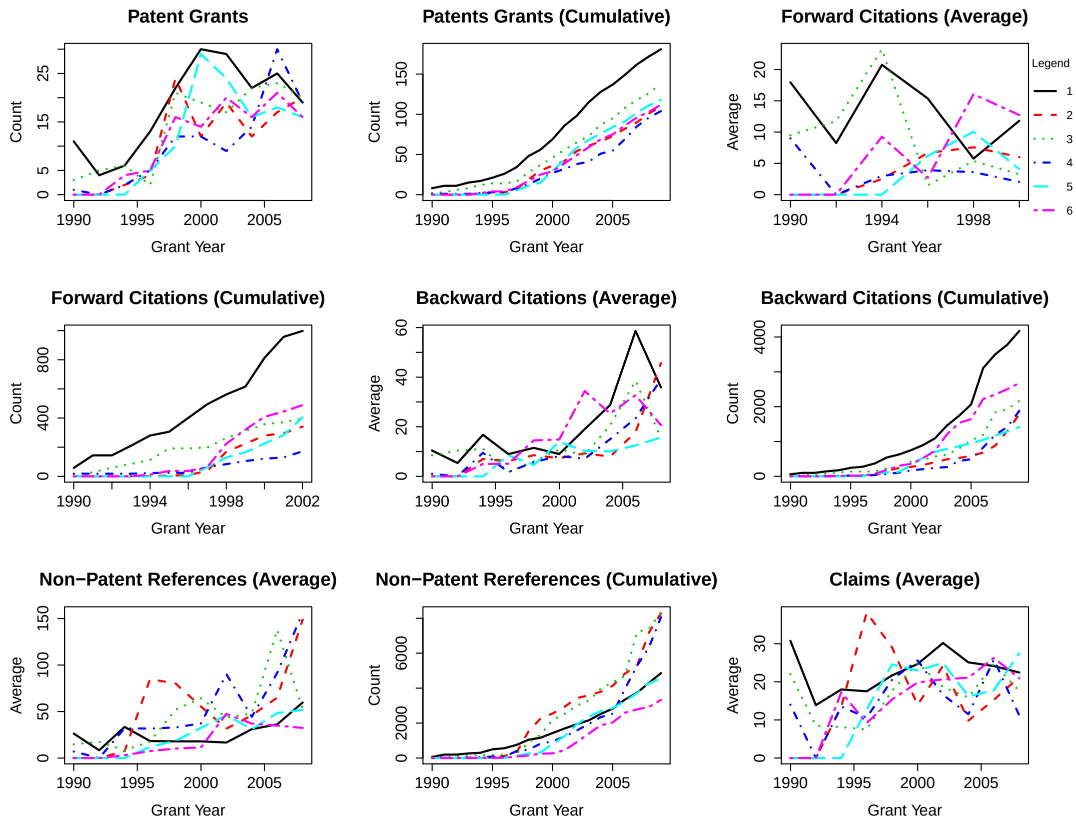

Figure 4.4 Trend analysis for top nanomedicine sub-disciplines. Definition of disciplines for legend: (1) Liposomal Formulation, (2) Stem Cells, (3) Alzheimer, (4) Telomerase, (5) Tumor suppression and (6) Tissue engineering

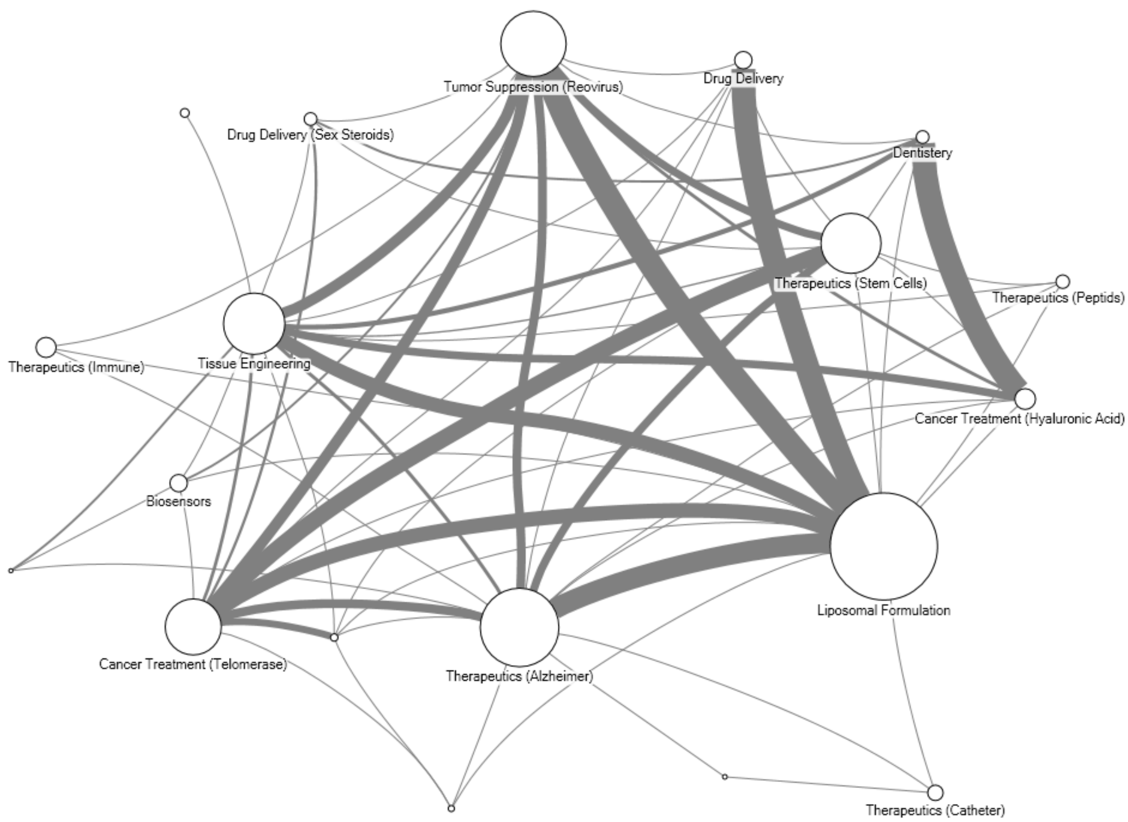

Figure 4.5 Knowledge map of Canadian nanomedicine fields of expertise

inventors reside on the south-eastern region of the country. This is somehow representative of the distribution of the general population in the Country. It should also be observed that some cities have a higher concentration of nanomedicine inventors. In this regard, Vancouver and Quebec City are the leading regions in terms of the clustering of nanomedicine communities of practice.

The Herfindahl index in Table 4.5 shows to what degree innovative activity is diversified within cities. This measures how uniformly patents produced by inventors residing in the city are distributed among the disciplines. Since our analysis covers 38 fields of expertise, a perfectly diversified city (one that produces the same number of patents in each of the 38 disciplines) will have a Herfindahl index of 0.026. As we can see from the results, cities are more or less diversified at the same level. Diversification is generally associated with city and community of practice size as we can see for Montreal and Toronto. Vancouver seems to be an outlier however as it has both the largest community and the highest level of technological concentration.

Table 4.6 shows how expertise in the largest nanomedicine fields is distributed within Canadian cities. Here, the Herfindahl index indicates the level with which patent production in a field of expertise is distributed among Canadian cities. Given the fact that we study 6 cities, a field of expertise for which an equal number of patents are produced in each city will have and index of one sixth. As we can see, the development of application related to stem-cell-based therapeutics is more equitably spread within major Canadian cities. However, the major field of expertise (Liposomal formulation) is mostly concentrated in Vancouver. Given the size of the discipline and the fact that it is the most market-ready solution in nanomedicine, the above results mark the importance of Vancouver as a center for nanomedicine development. The emergence of Vancouver as a pole for innovative activity in nanomedicine is a sign that the industry is gaining traction. However, activities have not clustered in Vancouver to a degree where it shadows other leading cities.

From the 38 fields of expertise discovered, we can identify 586 distinct organizations. The Herfindahl index taking the share of patents that each firm owns is equal to 0.01, indicating that the industry is very competitive in the sense that there isn't one single firm that produces most of the innovations. Table 4.7 shows the top 20 organizations in terms of patent production. Endorecherche, Inc. (Quebec City) is the largest private patent holder headquartered in Canada with only 2.16% of the patents in the sector. Other top organizations share a very small fraction of patents in the industry. This very competitive nature of nanomedicine also

Table 4.5 Nanomedicine inventors as a percentage of total population in the largest nanomedicine metropolitan areas.

	Edmonton	Montreal	Ottawa	Quebec	Toronto	Vancouver
Population	1,159,869	3,824,221	1,236,324	765,706	5,583,064	2,313,328
Number of nanomedicine inventors	82	255	74	77	276	289
Proportion (per thousand inhabitants)	0.071	0.067	0.061	0.097	0.049	0.125
Herfinahl Index	0.1071	0.0764	0.134	0.164	0.080	0.1492

seems to point at the distance that it has to commercialization.

As we can further see in Table 4.7, public institutions play an important role in the production of patents. Indeed, four out of the top five patent holders in nanomedicine are public institutions. This can once again be explained by the fact that nanotechnology is an emerging multidisciplinary field where science linkage is a dominant pattern in inventions. Being the generators of basic knowledge, public institutions are closer to science and have access to broad set of expertise. As the nanotechnology sector matures, we can expect larger private firms, similar to Nortel and Xerox in their respective sectors, to have a more dominant role in patent production as inventions will rely less on basic science and as private firms will have access to more resources.

Figure 4.6 shows technological proximity between inventing organizations. Again, the size of the vertex is an indication of the number of nanomedicine patents produced by the organization and the size of edge represents the number of common citation that patents from two organizations have in common. We can notice the central role of the University of British Colombia (UBC) as well as other universities and public institutions. As it is characteristic of the early stages of an industry, universities play a gatekeeping role that binds private firms together (Owen-Smith and Powell, 2004). Indeed, geographical and technological proximity to the UBC seems to coincide with the dominant position that Inex Pharmaceuticals plays in the liposomal formulation industry.

Table 4.6 Concentration of production for major nanomedicine fields of expertise.

	Liposomal Formulation	Therapeutics (Alzheimer)	Tumor Suppression (Reovirus)	Tissue Engineering	Therapeutics (Stem Cells)	Cancer Treatment (Telomerase)
Edmonton	0.0803	0.0147	0.1028	0.0795	0.0568	0.0105
Montreal	0.1387	0.2941	0.1495	0.1364	0.3864	0.1789
Ottawa	0.0146	0.0294	0.0187	0.0341	0.1136	0.0632
Quebec	0.0657	0.0000	0.0467	0.1250	0.0795	0.1263
Toronto	0.1168	0.4118	0.2897	0.5227	0.1818	0.3684
Vancouver	0.5839	0.2500	0.3925	0.1023	0.1818	0.2526
Herfindahl index	0.3848	0.3196	0.2735	0.3254	0.2379	0.2516

Table 4.7 Top 20 organizations in terms of the number of patents produced.

Organization	Number of patents	Share of patents produced (%)
University of British Columbia	58	3.92
National Research Council of Canada	39	2.64
Queen's University	39	2.64
Hyal Pharmaceutical***	38	2.57
McGill University	36	2.43
Endorecherche* (Quebec City)	32	2.16
Inex Pharmaceuticals* (Vancouver)	24	1.62
Adherex Technologies	22	1.49
Geron Corporation	22	1.49
Generex Pharmaceuticals* (Toronto)	20	1.35
The Liposome Company	20	1.35
Arius Research***	17	1.15
Nucryst Pharmaceuticals** (Toronto)	16	1.08
NeuroSpheres Holdings* (Calgary)	15	1.01
Aegera Therapeutics* (Montreal)	14	0.95
LAM Pharmaceuticals* (Toronto)	14	0.95
Oncolytics Biotech*	14	0.95
Supratek Pharma* (Montreal)	14	0.95
QLT	13	0.88
University of Alberta	12	0.81
All Others	948	67.71

* firms headquartered in Canada; ** firms acquired by Canadian firm; *** firms acquired by non-Canadian firm

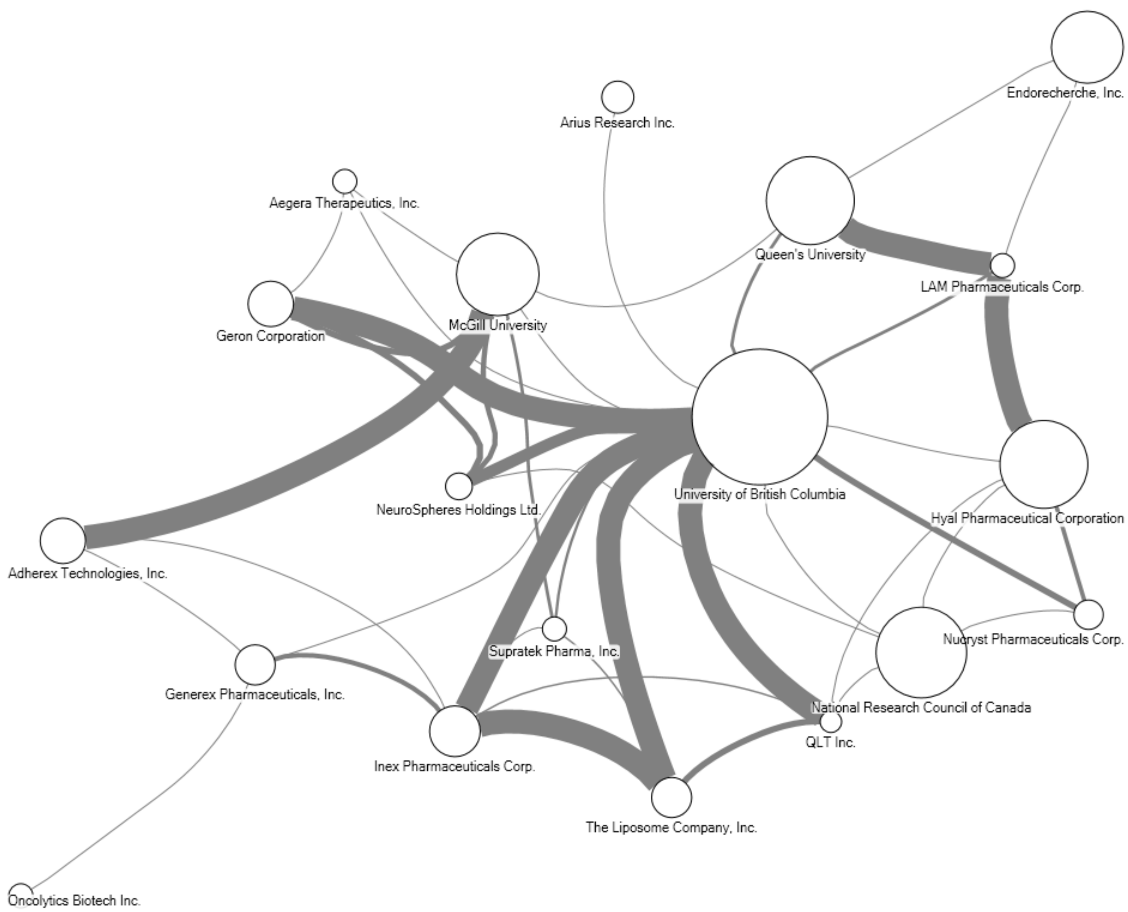

Figure 4.6 Map of the most innovative nanomedicine organizations

4.7 Conclusion

In this article, our main objective was to develop a method to discover and map fields of expertise in an emerging industry. Our method was based on the greedy modularity optimization of patent backward citation networks. As a case study, we have selected Canada's nanomedicine industry. With regards to the self-organizing nature of technological development by communities of practice, our method promises clear advantages over US-class-based patent mapping techniques. First, US class 977 is currently assigned to only 156 Canadian patents granted between years 1990 to 2005. This represents a mere 2% of the 6,288 identified by our extraction method. Second, since class assignment and citations are somehow related, our method does not give results that are contradictory to class-based patent mapping methods. Instead, it takes into account the complexity of technological interrelatedness between patents. It thus is a more refined representation of intellectual organization.

From a methodological point of view, our results support the relevance of patent citations as a way to measure technological proximity between inventions. First, graphs resulting from co-citations exhibit small-world and scale free characteristics common to many real-world networks. Second, we observe that modularity optimization of patent citation networks allows for discerning the subtle differences between fields of expertise in a multidisciplinary industry. Third, patent citations are also detailed enough to distinguish between different fields of expertise for very large organizations such as Xerox Corporation. Fourth, the major field of expertise identified by partitioning the Canadian nanomedicine co-citation network is liposomal formulation, a field that has shown market readiness in other countries. Whether added by examiners or applicants, patent citations do not appear to be the result of an arbitrary and noise-adding process. Citation-based unsupervised learning techniques allows us to obtain refined knowledge about the application domains within an emerging industry in which continuous development are ultimately defined by the collective effort of the communities of practice and for which standard classification is yet incomplete.

We have identified 6 major fields of expertise in nanomedicine. The central theme of innovative development appears to be around drug delivery applied to cancer treatment. To the 6 major fields of expertise, we have applied a multi-metric approach for assessing their development stages. Generally speaking we cannot conclude that Canadian nanomedicine fields of expertise are ready for commercialization purposes. By performing multi-metric trends analysis, we observe that not all fields are at the same stage of development. Comparisons between trends in NPRs forward and backward citations show that nanomedicine still sources itself in basic science as well as other technological sectors and disciplines. Also, the progress of these metrics does not seem to follow a pattern that could clearly indicate the leap of one discipline from other disciplines. Rather, each discipline is making progress of different nature, without one making progress in all metrics.

We have also identified leading Canadian organizations developing technologies applied to nanomedicine. Our results show that this sector is very competitive and that landscape is still many years away from the emergence of dominant private firms. The absence of dominant players further hints at the embryonic stage of this field. Whether large nanomedicine corporations will emerge, or whether smaller ones will be merged to large pharmaceutical companies who will become main producers seems to be still many years away. We have also observed that public institutions play an important role in patent production as well as bridging different technological fields together. Canadian public institutions, and especially universities, represent 4 out of the top 5 producers of intellectual property in nanomedicine. This is much higher than what is reported by studies about nanotechnology as a whole, where one or two out of top 5 leading organizations where public institutions. Among them, the UBC plays the most central role within the nanomedicine industry. This finding is aligned with those concerning the birth of the biotechnology industry in Boston (Owen-Smith and Powell, 2004). Canadian universities are both large as well as central players on the nanomedicine front line. They also play an important role as sources of knowledge when technological opportunities stagnate. Furthermore, although our city-level analysis seems to point to the dominance of Vancouver as an attractive location for further expansions of innovative capabilities in nanomedicine, the geographic agglomaration of inventive activities is not strictly limited to this metropolitan area. Other cities such as Toronto and Montreal are leaders in tissue engineering and stem cells technology respectively. In this regard, the presence of McGill University as both a top patent holder and a central player in the assignee network seems to indicate agglomeration trends in Montreal. Such conclusions about the stage of development of an emerging industry cannot be made by relying solely on patent counts. These observations thus show that following trends in multiple indicators offers new insights for forecasting future development in an industry.

A first limitation of our research lies in the difficulty of assigning central patents to a community. The adoption of overlapping community detection or multiresolution modularity optimization techniques can help overcome this issue. Another limitation in our method resides in the classification of clusters based on expert search. Although cluster labels are obtained based on the relevance of keywords from patent titles and abstracts, they are subjectively contextualized by the expert. Depending on the knowledge background of the expert, different classifications can be given to the same cluster. Ontology libraries can help overcome this limitation and constitute the second potential improvement to our method. However, this is a challenging task given the fast evolving nature of technical terms in highly innovative sectors. Finally, the regulatory aspect of nanomedicine commercialization means that there is a lag between when technological developments flourish and when they can reach acceptance for market deployment. Using bibliometric data that solely reflects technological development cannot be used as an absolute metric for market readiness.

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CHAPTER 5

DISTANT RECOMBINATION AND THE CREATION OF BASIC INNOVATIONS

Abstract[1]

Basic innovations have implications across industries and serve as the basis for future incremental innovations. Despite their great importance from an economic perspective, little is agreed about the conditions that lead to the creation of such novelties. In this article, we explore the impact of distant knowledge recombination as well as other indicators on the type of innovations produced. Our analysis of a sample of Canadian nanotechnology patents shows that basic innovations are more likely to result from R&D efforts involving the combination of distant technologies. We also find that although private organizations are less likely to produce basic innovations, their effort in combining distant technologies is more successful than that of public institutions. Furthermore, increasing reliance upon basic science moderates the effect of distant recombination.

Keywords: Distant Search, Exploration, Industry Life Cycle, Science-Technology Linkage, Market Orientation

5.1 Introduction

Basic inventions serve as technological basis for a broad set of industries: they have implications across disciplines and serve as the necessary basis for subsequent incremental inventions (Mensch, 1979; Mokyr, 1990; Rosenberg, 1994; Mowery and Rosenberg, 1999; Arthur, 2007). Although very important from an economic point of view, little is known about the conditions that lead to the creation of basic innovation. While literature generaly recognized the importance of distant search and basic science as sources for the creation of innovations that have broad impact, the sources of failure are not well understood (Fleming, 2001; Kim et al., 2012; Nemet and Johnson, 2012).

In this article, we try to shed light on the factors that lead to the creation of basic innovation by analyzing a sample of Canadian nanotechnology patents registered in the US.

[1]Barirani, A., Beaudry, C., and Agard, B. (2012b). Distant Recombination and the Creation of Basic Innovations. *under review at Technovation.*

Nanotechnology is an emerging and multidisciplinary discipline, hence a great locus for novel creations and breakthrough inventions. We first investigate the impact of search strategies moderated by other factors on the creation of inventions that spread across technological boundaries. Our results show that inventions that result from the combination of distance technologies are more likely to lead to basic innovations. Also, private institutions will less likely produce basic innovations, but their explorative search efforts are more successful than public institutions.

5.2 Literature Review and hypotheses

5.2.1 A taxonomy of innovation

From the perspective of evolutionary economics, innovation consists in combining resources and components in new ways (Schumpeter, 1939; Nelson and Winter, 1982; Kogut and Zander, 1992). New combinations are not always done in the same manner and do not always have the same impact. Following a Schumpeterian view with regards to the importance of entrepreneurs (Schumpeter, 1934) versus large firms (Schumpeter, 1942) in introducing novelties that lead to long-term economic growth, innovation patterns can be classified as Mark I and Mark II types (Malerba and Orsenigo, 1995). The Mark I pattern is associated with the concept of creative destruction, where radical innovations introduced by new entrants displace those possessed by incumbent firms. Innovations resulting from such conditions lead to the widening of technological paths and to the disruption of rents associated with established innovations. The Mark II pattern is associated with the concept of creative accumulation, where an industry is dominated by large firms and the presence of barriers to entry for new entrants. Innovations introduced in such conditions mostly contribute to deepening technological paths and strengthening the competitive advantage of established innovations.

Mark I innovations have been articulated through different terminology by management authors. Christensen (1997) has introduced the concept of disruptive technologies to characterize inventions that create a new market and who disturb existing markets. Christensen and Rosenbloom (1995) define radical innovations as those that launch new technological trajectories. Henderson and Clark (1990) call radical inventions that involve the replacement of core concepts along with peripheral technologies. Others use the intensity with which subsequent inventions are built on top of an initial invention to measure its radicalness or to identify whether they are breakthroughs (Ahuja and Lampert, 2001; Dahlin and Behrens, 2005; Schoenmakers and Duysters, 2010). Trajtenberg et al. (1997) introduce the notion of basic inventions which are inventions that serve as basis of subsequent inventions in different industries. Although some conceptual differences exist among these definitions, they all emphasize on the broad impact that such technological novelties have from an economic point of view.

At the other end of the spectrum are Mark II innovations that are generally referred to as incremental innovations. According to Christensen (1997), incremental innovations are novelties that sustain an industry's productivity and improve an incumbent's position. Christensen and Rosenbloom (1995) define incremental innovations as making progress within dominant technological paths. Henderson and Clark (1990) define these as inventions where core concepts and peripherals are improved without being changed or overturned. One can be inspired by the concept of basic inventions and call focused inventions those that are only used in a narrow number of industries. Again, these definitions have in common the limited impact that a single invention has from an economic point of view.

Mark I and Mark II innovations can also be interpreted from the industry life cycle perspective (Schumpeter, 1939; Abernathy and Utterback, 1978; Klepper, 1997; Malerba and Orsenigo, 1997). Here, industries go through cycles of radical change introduction followed by periods of incremental improvements which eventually lead to stagnation and recession. This perspective also implies that each technology has inherent limits in terms of the productivity gains that it can allow for. Once these limits are reached, radical changes introduced by entrepreneurs represent new opportunities that shift productivity rates. Once dominant designs are adopted, another cycle of incremental change leads to the accumulation of technological skills by dominant firms.

Given the generally skewed distribution of performance between innovations, only a few can be accounted as breakthroughs that have very broad impact (Harhoff et al., 1999; Fleming, 2007). While it is conceivable that the aggregate productivity gains generated by the vast quantity of incremental innovations represents the largest part of economic growth, it is undeniable that they are all directly or indirectly based on innovations of more basic nature (Mokyr, 1990; Rosenberg, 1994; Mowery and Rosenberg, 1999; Arthur, 1989). Thus, the study of factors that lead to their creation are of primordial importance from the perspective of economic growth.

5.2.2 Innovation, learning and search strategies

Prior to combining existing knowledge in novel ways, firms must *search* (March and Simon, 1958). This selection process is not *blind*, if one takes the biological analogy (Nelson and

Winter, 1982), but depends on the firm's *absorptive capacity* (Cohen and Levinthal, 1990). Because a great variety of solutions available to solve problems reside outside its boundaries, a firm's learning and innovative capabilities are associated with its ability to assimilate external information (Cohen and Levinthal, 1989). This perspective essentially views innovating and learning as two faces of the same coin.

When searching for existing knowledge, firms can either *exploit* known technological paths or *explore* new ones (March, 1991). Knowledge exploitation involves *local search*, i.e. searching for solutions in the immediate periphery of dominant routines. It involves the improvement of current procedures and an ever increasing specialization in a few fields of expertise. Technological exploration in contrast involves searching or experimenting in ways that break away from dominant routines. It requires learning radically different ways to solve encountered problems. This can be referred to as *distant search*. Although one can intuitively imagine that either strategy leads to different outcomes, various findings seem to indicate that technological exploitation is more often favored by firms that have short-term visions and need to cash on the dominant path they have learned so far (Fang et al., 2010).

5.2.2.1 Exploitation and local recombination

Arguments in favor of technological exploitation generally apply to success stories in collaborative settings. This line of thought stipulates that technological proximity, coherence and relatedness are the essential ingredients that allow for learning to occur (Breschi et al., 2003; Nesta and Saviotti, 2005; Tanriverdi and Venkatraman, 2005). Without propinquity between knowledge that is possessed and one that is searched, learning cannot occur. Empirical studies show that similarities in partnering firms' knowledge bases have a positive impact on inter-organizational collaboration (Powell et al., 1996; Stuart, 1998; Owen-Smith and Powell, 2004; Penner-Hahn and Shaver, 2005). Learning is also more likely to occur from within an industry as knowledge flows more easily when there is technological overlap between firms (Fung and Chow, 2002). Empirical evidence from Cantner and Graf (2006) is in support of this claim as firms prefer alliances with firms with whom they have technological overlap rather than with firms with whom they have worked in the past. Their study shows that central and permanent members in a network of innovators tend, over time, to increase the technological overlap with each other. They mainly engage in technologies that are similar to those that they have accumulated so far. Technological proximity between firms also increases success rate for mergers and acquisitions which can be viewed as a way to absorb external knowledge (Ahuja and Katila, 2001).

5.2.2.2 Exploration and distant recombination

Although local search seems to be a natural strategy for economic agents faced with complexity, firms that over-exploit existing routines can be stuck in a competency trap and eventually exhaust all the possibilities for new combinations (Levitt and March, 1988; Levinthal and March, 1993). Ahuja and Lampert (2001) identify three pathologies with which the majority of incumbent firms are afflicted: they tend to prefer search for solutions with which they are familiar rather than unfamiliar (familiarity trap), they prefer solutions that are mature rather than nascent (maturity trap) and they prefer to search for solutions that are close to existing know-how rather than search for completely new solutions (propinquity trap). They argue that firms must invest in explorative search in order to avoid these traps.

Distant search also implies the combination of old with new technologies. While older technologies can be associated with obsolescence, they can also exhibit reliability and quality as they go through the scrutiny of communities of practice (Katila and Ahuja, 2002). Katila and Ahuja (2002) further compares the use of older knowledge in intra-industry and extra-industry settings. Their study shows that using older knowledge from other industries increases the capacity to introduce new products in the robotics industry. This further support the claim that explorative search can be positively linked to innovation capabilities in knowledge intensive industries.

Exploration is also close to the concepts of *weak ties* and knowledge *brokerage* (Granovetter, 1973; Burt, 1992). This perspective states that redundant network links do not contribute to being exposed to novel ideas. Here, being able to build ties with distant communities allows for the creation of better ideas (Burt, 2004). Large firms who have ties with different industries can combine distant knowledge and introduce breakthrough inventions Hargadon and Sutton (1997). Boschma and ter Wal (2007) also come to similar conclusions in their study of the Italian footwear district where large firms with both central network positions and non-local connections were much more innovative than other firms that played a more peripheral role and were mostly connected to local players. Brokers play roles similar to *gatekeepers* that integrate knowledge that is developed in different regions and industries (Wink, 2008). Disposing of large stocks of knowledge, these firms have the ability to go beyond local search. In fact, their knowledge base spans across many technological fields which precisely allows them to recombine distant knowledge. Exploration and brokerage are not solely a matter for technical knowledge recombination. Collaboration with diverse set of suppliers, clients and partners also yields positive impacts on innovation output (Nieto and Santamaría, 2007; Hernández-Espallardo et al., 2011).

5.2.3 Search strategies and innovation type

Given the conceptual differences between radical and incremental innovations, some researchers have concentrated their research effort on the impact of either search strategy on the type of innovations produced. In this regard, many studies have associated exploitation with innovation impact and radicalness. Fleming (2001) argues that local search represents lower levels of risk, thus contributing to the creation of incremental innovations but that the recombination of distant knowledge is more likely to lead to radical innovations. Similarly, Kim et al. (2012) find that exploitative search is associated with innovation rates but negatively associated with impact, while exploratory search shows the opposite relationship.

However, the association of explorative activity with radical innovations is not unanimously admitted. Nemet and Johnson (2012) show that important inventions more often result from the combination of components in proximate technological domains rather than distant ones. They argue that the incorporation of external knowledge is difficult and risky, and that inventions resulting from such combinations are difficult to incorporate in subsequent inventions. As a result, exploitative search offers the best guarantee with regard to the diffusion and thus the impact of innovations. This study, however, does not take into account the various disciplines in which an invention is subsequently used.

Most of the above studies however have focused on the intensity of future use of inventions to measure their importance. Only a few have considered the impact of either search strategy on the diffusion pattern of an invention. The study of organizational and technological exploration in the optical disk industry by Rosenkopf and Nerkar (2001) is the closest article concerned by this question. Here, the authors show that searching beyond the technological boundaries of the optical disk industry leads to the production of inventions that have greater overall technological impact, i.e. they would subsequently be used in industries other than the optical disc industry. However, it is not straightforward to associate overall impact with innovation basicness. Indeed, an invention can be used in many industries, but that the bulk of this use is generally concentrated in one industry. Such inventions can hardly be considered basic innovations. Furthermore, industry characteristics such as emergence and reliance on basic science can have an impact on both search strategies and outcomes associated with them. The framework by Rosenkopf and Nerkar (2001) seems to indicate that local technology recombination is more likely going to lead to focused inventions, whereas technological exploration enlarges the domains of application of an innovation. The above evidence raises the hypothesis that:

H1. Basic innovations will more likely result from the recombination of distant technologies.

5.2.4 Complementary assets and the sector of activity

Basic science is socially desirable because it generate knowledge spillovers (Griliches, 1958; Bernstein and Nadiri, 1989; Jaffe et al., 1993; Audretsch and Feldman, 1996). However, private firms have incentives to perform R&D only when expected private returns are strong enough to justify taking part in the risky business of novel solutions finding. For projects where private returns are low but where social returns are high, public investments must be made in order to fill the void left by the private sector.

Viewed as providers and repositories for public knowledge, universities take part in R&D activities that have broad scientific and technological implications and that have tremendous knowledge spillovers (Jaffe, 1989; Adams, 1990; Dasgupta and David, 1994; Stephan, 1996; Zucker and Darby, 1996; Cohen et al., 2002; Nelson, 2004; Furman and MacGarvie, 2007). The recognition of the impact that public institutions have on economic growth has led to the suggestion of policies that encourage university-industry collaboration. This rapprochement with the private sector goes progressively further as universities are expected to increase their involvement in industrial and entrepreneurial activities (Etzkowitz et al., 2000,?).

According to Trajtenberg et al. (1997), the fact that universities have a strong background in basic research and science, gives them direct access to knowledge that offers better opportunities to produce innovations that have a broad impact. Although policies can influence the nature of research within universities, innovations produced by these institutions are still more basic than those produceed in the private sector (Henderson et al., 1998; Mowery and Ziedonis, 2002; Sampat et al., 2003). A question that hasn't been studied however, and that could shed light on the question is how the private sector performs when it engages in distant recombination.

Innovation diffusion is among the main issues related to the adoption and, ultimately, the success of innovations. According to Nooteboom et al. (2007), too much cognitive distance between knowledge owned and searched is detrimental to its transfer because it is more difficult to absorb. If one is willing to assume that basic innovations result from the combination of distant technologies, then one must also assume that they are more difficult to absorb. Nemet and Johnson (2012) find that the difficulty encountered by firms to absorb external knowledge can explain why many inventions resulting from distant search end-up being failures. Borrowing from the epidemic model of knowledge diffusion (Geroski, 2000), one would conclude that the basic innovator needs to supply markets with sufficient information in order to facilitate technology adoption.

From a marketing perspective, this could mean pushing technology towards the market. In such cases, disposing of complementary skills such as production, management and marketing know-how improves the probability for complex knowledge to be diffused across industries because such skills allow for solutions that are market-ready (Sainio et al., 2012). In this matter, private firms have an advantage over public institutions due to the fact that their operations routinely incorporate activities from these complementary areas. Due to their daily routines which turn around the creation of basic knowledge, public institutions are less market oriented (Slater and Narver, 1995). This fundamental difference between private and public sectors gives a distinctive advantage to firms from their superior capabilities in combining distant technological components into a successful product from a technology transfer point of view. We thus state our second hypothesis:

H2. Distant recombination by the private sector produces a higher rate of basic innovations.

5.2.5 Science linkage and industry characteristics

Proximity to basic science leads to the creation of innovations that have broad applications. However, beside the risk associated to the many failures that it can cause (Kim et al., 2012), knowledge that is close to basic research is more difficult to absorb outside the academic environment, that is a locus where access to basic science is the strongest (Cohen and Levinthal, 1990; Nooteboom et al., 2007). This observation hints at the direction that inventions that have strong linkage with basic science will not always succeed in finding adoption. Being strongly linked to basic science can thus be an inhibitor when it comes to innovation diffusion. Incidentally, if an invention that is close to basic science results from distant recombination, it could be that it has too much cognitive distance from what can be promptly absorbed in the industry. Given that firms operate under conditions of time constraint in which they tend to prefer short-term solutions to current problems, such for of radical innovations can be overlooked and at the end appear useless. In other words, such inventions could in theory have a very broad impact, but they could also be *too innovative* to satisfy current customer needs (McGrath, 2001; Lo et al., 2012). We thus hypothesize that:

H3. Distant recombination is negatively moderated by linkage to basic science.

Technological exploration does not always lead to the same outcomes depending on industry life cycle. Malerba and Orsenigo (1996) show that Mark I innovations are more likely to thrive in an environment marked by high levels of competitiveness. Mark II innovations on the other hand thrive in conditions of increasing cumulativeness. These two technological regimes are very similar to the industry life-cycle (Klepper, 1997; Malerba and Orsenigo, 1997). Industries are thus initially evolving in technological regimes with characteristics similar to the Mark I pattern and, as they later mature, switch into the Mark II pattern. Basic innovations thus thrive in industries where technological regimes could be characterized as Mark I. As a result, when an industry is competitive, the relevance of performing distant recombination should be higher as the probabilities that players in the industry find use of such new technologies should be higher. We thus expect distant search to be positively moderated by industry dynamism and propose our last hypothesis:

H4. Distant recombination is positively linked to basic innovations in competitive environments.

5.3 Methodology

5.3.1 Data

From a legal point of view, patents confer monopolistic power with regards to the use, production and commercialization of an invention in exchange of its disclosure. Since patents are granted to inventions that are novel, non-obvious and useful, they can generally be viewed as indicators of technological change and innovative activity (Basberg, 1987; Acs and Audretsch, 1989; Griliches, 1990; Archibugi and Pianta, 1996). However, various studies point out that the majority of patents have little economic value (Allison et al., 2004; Moore, 2005). Patenting can sometimes be compared to gambling where firms bet on slots (Lemley and Shapiro, 2005). Penin (2005) also points out that patents can be used as strategic devices and consequently that they cannot be used in a straightforward manner to measure innovation. Since the term innovation usually refers to the successful commercialization of an invention, the analysis of factors impacting patent counts cannot be transposed to draw conclusions about innovation. However, some patent quality indicators are known to be associated with commercial success: patent citations are associated with firm value (Trajtenberg, 1990; Hall et al., 2005) and patents deposed in the US by foreigners are known to be highly valuable (Bessen, 2008).

With these concerns in mind, we analyze a sample of patents from the Canadian nanotechnology industry registered in the US. Nanotechnology is an emerging and multidisciplinary field, which makes a great locus for novel creations. The US represent the largest global markets and is the most important economic partner for Canada. Li et al. (2007c) show that Canadian firms prefer filing patents in the US over Europe. Barirani et al. (2012a) offer a lexical query for the extraction and clustering of technologically similar 'Canadian-made' nanotechnology patents. The study identifies three broad fields of expertise for Canada: nanobiotechnology, display technologies and optics. Because the method employed by Barirani et al. (2012a) only takes into account patents connected to the main network component, the whole set of patents that are extracted from the lexical query are not classified. We thus use the title and abstracts from these classified patents for training a K-NN model that would subsequently classify the non-connected patents into the three fields of expertise identified. We then select patents that were obtained from 1990 to 1997 for which we have extracted information regarding their grant date, inventors, number of claims, forward citations and renewal decisions until 2009. The sample contains 1,031 patents.

5.3.2 Models

In attempting to link distant recombination with innovation basicness, our methodology mainly consists in analyzing the statistical relationship between the spread of a patent's backward-citations with the spread of its forward-citations. We therefore associate distant recombination with the use of inventions from a multitude of disciplines and its basicness with its use by subsequent inventions in a multitude of disciplines. These models will allow use to verify H1. Because we also try to measure the impact of the sector of activity (H2), science linkage (H3) and industry dynamism (H4), we perform a hierarchical analysis that will measure the moderating effect of these factors over distant recombination.

Before we proceed to the analysis, a few precisions are in order regarding patent citations. First, applicants have the obligation to cite all related sources of knowledge, but they are not legally obliged to perform prior art search. In fact, it is incumbent upon USPTO examiners to make sure that all appropriate sources are cited. Because patents constitute a legal documents, they go through a thorough search process in which examiners attempt to add all citations that are relevant to a patent. This process is essential in order to preserve the legal validity of a patent's scope: because a patent's scope is defined by the novel features of an invention, proper reference to prior art should be made in order to correctly define the technological boundaries legally protected by the patent.

Based on these premises, Jaffe et al. (1993) argue that patent citations represent knowledge spillovers generated by patents. This view has been, to a certain degree, brought into question for two reasons. On the one hand, because citations restrict the patent's scope, applicants often choose not to perform prior art search, and when they do, they can cite other patents strategically (Sampat, 2010). On the other hand, variations among patent examiners have been found meaning that some patents could contain citations that are more accurate than others (Cockburn et al., 2002; Alcácer and Gittelman, 2006). Also, time constraints can lead examiners to add citations that are only remotely linked to the applied patent in order to make sure that nothing has been missed (Meyer, 2000b). There are reasons, nevertheless, to believe that patent citations contain relevant information that can have analytical value.

Studies argue that applicants have more incentives to search for prior art for discrete technologies such as pharmaceuticals or chemicals while the opposite hold for complex technologies such as electronics or telecommunication (Lemley and Shapiro, 2005; Sampat, 2005; Alcácer et al., 2009). Hegde and Sampat (2009) further show that examiner added citations are better predictors of patent renewal than applicant added citations. In addition, examiner citations are more likely to be added when there is technological and geographical distance between citing and cited patent (Criscuolo and Verspagen, 2008). It is also worthwhile to note that examiners add a larger share of self-citations than the inventors themselves (Sampat, 2005; Alcácer et al., 2009). Based on these considerations, the patent examination process can also be viewed as a smoothing process that can sometimes close citation gaps between related inventions. USPTO citations are indeed generally viewed as thorough in terms of containing links to relevant prior art (Meyer, 2000b; Von Wartburg et al., 2005).

Examiner citations can also be interpreted from a social learning perspective (Amin and Cohendet, 2004). Although the validity of using patent citations to measure knowledge flows can be brought into question, it is undeniable that applicants must, to a certain degree, be aware of contemporary technological developments before engaging in R&D activities. Since learning can be viewed as a social process and that technological development is path dependent (Rosenberg, 1994), it is difficult to imagine that in knowledge intensive industries, inventors can be totally unaware of current technological challenges and potential solutions, and yet be successful in introducing novelties. Being part of the social process of learning, inventor who search for novel solutions must somehow be embedded within its community of practice. Furthermore, the tacit dimension of knowledge spillovers implies that they do not always leave traces in the form of citations and do not necessarily require formal transfer of knowledge (Krugman, 1991). Since this embedding is likely to encompass even inventors who are employed by competitors, an applicant's failure to cite a relevant prior art does not necessarily rule out tacit knowledge about related technologies.

5.3.3 Dependent variable

Many studies have associated forward citations with technological impact and patent value (Trajtenberg, 1990; Deng et al., 1999; Harhoff et al., 1999; Hall et al., 2005). To measure the level of a patent's basicness, we propose to observe the spread of the patent's forward citations across technological classes. As such, this conception of basicness differs from classical definitions of radical inventions that are solely based on the number of forward citations (Ahuja and Lampert, 2001; Dahlin and Behrens, 2005; Schoenmakers and Duysters, 2010). Our definitions has the advantage of allowing a distinction between successful inventions that are used in a multitude of industries and those that are used within a few industries.

Given a patent with n forward citations falling into m 3-digit classes, Trajtenberg et al. (1997) measure the degree with which future use of a patent spans technological classes with the following equation:

$$BASICNESS = 1 - \sum_{i=1}^{m} \left(\frac{CLASS_i}{n} \right)^2 \tag{5.1}$$

Where $CLASS_i$ is the number of the patent's forward citations that fall within class i. As this value gets closer to zero, future inventions are focused in a narrow set of technological areas, and a value close to one indicates a more basic invention which is used in numerous technological areas. In our models, we use forward citations for a 12-year period after the grant year to measure a patent's basicness. This is justified by the fact that radical innovations enjoy a rather slower adoption rate due to their inherent complexity (Schoenmakers and Duysters, 2010). Furthermore, patents that receive citations for a longer period are more likely to be important patents since high rates of technological obsolescence in emerging industries means that lower quality patents could stop receiving citations earlier in their lifetime.

Because this variable is continuous, our main statistical method will use ordinary least squares (OLS). Also, because many patents will fall within the definition of focused innovations and will have a value of zero, we use the left censored Tobit regression to test the robustness of our model.

5.3.4 Independent variables

The number of backward citations can be used as an indication of the intensity with which an invention is linked with existing technologies (Carpenter et al., 1981; Jaffe et al., 1993; Schoenmakers and Duysters, 2010). In a similar way as patent forward citation classes can be used to measure invention basicness, the diversification of backward citation classes can be used to measure the degree with which inventors have endeavored explorative search (Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002; Yoshikane et al., 2012). Given a patent with p backward citations falling into q 3-digit classes, the degree with which a patent combines technologies from distant classes can be computed with the following equation:

$$DISTANT = 1 - \sum_{i=1}^{q} \left(\frac{CLASS_i}{p} \right)^2 \tag{5.2}$$

Prior studies indicate that within the three major areas of expertise, nanobiotechnology is an emerging industry with high level of dynamism (Barirani et al., 2012a). The other disciplines where dominated by a smaller number of players and thus exhibit maturity although, given their activities in the nanotechnology industry, these industries are obviously very knowledge intensive. Nanobiotechnology patents (encompassing pharmaceuticals and biotechnology applications). To distinguish between dynamic and mature industries, we will add the *NANOBIO* dummy variable using the patent classification described earlier.

We account for the type of activity (private or public) using information on patent assignees. Patents are classified based on whether they are owned by corporations or public institutions. Patents are classified based on whether they are owned by corporations or public institutions, the latter including universities. We employ the dummy variable PRIVATE to identify private corporations.

We use the number of non-patent references (*NPRS*) as a proxy for the strength of the linkage between a patent and basic science. Callaert et al. (2006) find that most NPRs are references to scientific journals and the effect is stronger for knowledge intensive industries. Given the emerging nature of the nanotechnology industry, we thus believe that it is reasonable to use the number of non-patent references to measure proximity to basic science.

5.3.5 Control and dummy variables

The variable *DISTANT* is dependent upon the number of backward citations that a patent contains. In other words, the higher is the number of backward citations, the higher is the probability that all of them are not assigned to one class. Mowery and Ziedonis (2002) propose a normalized version of the equation to control for this. However, this method will put a patent that has a few equally spread backward citation at par with a patent that has many that are not equally spread as well. To account for this, we therefore propose to control the degree of distant recombination by the patent' total number of backward-citations (*NBACKCIT*). Similarity, variable *BASICNESS* depends on the number of forward citations.

We thus add control variable *NFORWCIT* to our model which is a measure of the number of forward citations for a 12-year period after the patent's grant year.

The scope of a patent's claims determines the monopoly power of the patent holder by defining the main novel features of the invention (Merges and Nelson, 1990). Inventors have an incentive to claim as much as possible while patent examiners must narrow down the scope of the patent before granting it (Lanjouw and Schankerman, 2004b). The number of claims can therefore be used as an indication of a patent's quality (Tong and Frame, 1994). Patents that claim more are thus more likely to restrict the scope of other patents which also translates into being cited by those patents. This in turn can have an impact on the diffusion pattern of a patent. We thus employ the variable *CLAIMS* which counts the number of claims a patent makes to control for the impact of this variable on basicness. Technology classes in which a patent falls can also be used to measure its scope (Lerner, 1994). We use variable the *SCOPE* to measure the number of distinct 3-digit US classes to which each patent is assigned.

Organizational experience in patenting can also have an impact on diffusion outcome. This is especially true for universities whose accumulated experience in patenting and technology transfer can have a positive impact on the adoption of their innovations on the marketplace (Thursby and Thursby, 2007). We control for experience in patenting by measuring the total number of nanotechnology patents that a patent holder obtains between the 1990-1997 period. We report this variable as *EXPERIENCE*.

Since many advantages can be associated with being part of a patent's inventing team, it is natural to assume that only those who bring distinctive skills on the table will have the power to earn a place among the list of inventors. For instance, if an invention results from the work of a team composed of one senior-level researcher or engineer and a few junior-level engineers who play a less critical role in the development of the invention, it is more likely that only the senior-level member ends as the sole inventor. On the other hand, if a complex invention requires the involvement of many senior-level researchers and scientists who each come with their own special skills, then chances are that they will have to come to an agreement to include all of them be in the list of inventors. Since it is not likely that one individual has enough expertise to cover a broad range of technologies, we are expecting to see that teams composed of a greater number of inventors should cover different technological areas. We thus control for team size through variable the *TEAMSIZE*, which measures the number of investors listed in a patent.

Time can have various effects on patent metrics. For instance, technological progress goes through different stages, which can be visible over time, and policies can have an impact on patenting activity. Numerous studies therefore use the patent's grant date to control for various factors that may affect dependent variables (Schoenmakers and Duysters, 2010; Nemet and Johnson, 2012). We use patent grant year to measure for this effect. This is represented by year dummy variables *Y1991* to *Y1997*.

5.4 Analysis and Results

In light of our variable selection, a few clarifications need to be brought with regard to the relevance of attempting to link *DISTANT* to *BASICNESS*. This note must be made in relationship with Meyer (2000a) who points out that although USPTO patent contain citations of most of the relevant prior art, they also contain some that are irrelevant. This finding raises a question about whether the apparent spread of an invention over technological classes is not in reality due to the addition of irrelevant prior art by patent examiners. Although this is possible, our measures for basicness and the degree of distant knowledge recombination will contribute to minimizing the impact of such irrelevant citations. In fact, unless irrelevant citations constitute the majority of most patents' backward citations, a patent that should have a basicness of zero (one) if the examination process was perfect would still be close to zero (one) in an imperfect examination process. Furthermore, a statistically significant relationship between *DISTANT* and *BASICNESS* is very likely to be conclusive as it would otherwise mean that the examination processes of both the focal patent and all subsequent forward citing patents introduce such a high rate of irrelevant citations that it leads to the coincidental illusion of statistical link. It should also be noted that such assumptions would contradict findings about the relative quality of USPTO patent citations (Meyer, 2000b; Von Wartburg et al., 2005).

Table 5.1 presents our OLS regressions results. Model 1 obviously shows that the link between the number of forward citations and patent basicness is significant. Surprisingly, *EXPERIENCE* has a strong significant negative impact on *BASICNESS*. We believe this is mostly due to the fact that many large private organizations (such as *Xerox* and *Nortel Networks*) which happen to be active patenters in mature industries (display technologies and optics) are mostly concerned with producing focused innovations. Interestingly, we find a positive relationship between *SCOPE* and *BASICNESS*. This is probably due to the fact that patents with broader scope happen to be subsequently used in a multitude of disciplines. All things being equal, the total number of backward citation has a positive impact on *BASICNESS*.

Model 2 takes into account the independent variable to our experiment. We find a negative significant relationship of the variable *PRIVATE*. This observation corroborates the findings that firms produce a smaller share of basic innovations. It should be noted that there is a negative but not significant (although close to the 0.1 level) relationship *NPRS* and *BASICNESS*. This appears to be an indication that proximity to basic science is detrimental to innovation diffusion. The model also shows a significant relationship between *BASICNESS* and *DISTANT*, but interestingly, the impact from the number of backward citations (*NBACKCIT*) on invention basicness is no longer significant when we control for distant recombination. It appears that, all things being equal, patents that result from the combination of technologies from different fields will turn out to be eventually used in a multitude of disciplines. These findings support hypothesis H1: basic innovation will more likely result from distant recombination.

Model 6 incorporates interaction effects with *DISTANT* (models 3 to 5 incorporate interaction variables one-by-one for robustness checking). As we can see, the interaction between *DISTANT* and *PRIVATE* results into a significant positive relationship with basicness. It would thus appear the private sector produces a higher rate of basic innovations when it endeavors distant recombination. However, given that *PRIVATE* has a negative relationship with *BASICNESS*, this implies that they do not often do so. Of course, this can be due to a bias in our sample with most private firms being active in mature industries where distant recombination and basic innovations do not constitute a competitive advantage. Nevertheless, it appears that access to complementary skills such as marketing and production has a positive effect on innovation spread. Indeed, if it wasn't because of this fundamental difference between the private and public sectors, we should not observe any significance in the outcome of distant recombination between the private and public sector. This finding supports the hypothesis that distant knowledge recombination endeavored by private organizations is more likely to find adoption and result in basic innovations (H2). Hence, disposing of complementary knowledge seems to have a positive moderating effect on distant search.

As expected, we observe a negative and significant relationship between *BASICNESS* and the interaction of *DISTANT* and *NPRS*. It thus appears that the combining distant technologies and depending heavily on basic science have a negative impact on the patent's diffusion over multiple disciplines. Again, this interaction effect does not mean that the resulting invention will be useless. However, what it implies is that such innovations do not succeed in reaching widespread adoption. This finding supports H3 in that the combination of distant technological recombination with strong linkage with basic science results less often in

Table 5.1 Results - OLS hierarchical regressions

	Models					
	(1)	(2)	(3)	(4)	(5)	(6)
NCITFORW	0.00272****	0.00266****	0.00266****	0.00269****	0.00264****	0.00265****
	(0.000371)	(0.000332)	(0.000332)	(0.000332)	(0.000324)	(0.000319)
NCITBACK	0.00288**	-0.0000604	-0.000168	0.000159	-0.000159	-0.0000889
	(0.00141)	(0.00149)	(0.00150)	(0.00153)	(0.00154)	(0.00161)
EXPERIENCE	-0.000146****	-0.000112****	-0.000109****	-0.000113****	-0.000115****	-0.000114****
	(0.0000247)	(0.0000323)	(0.0000323)	(0.0000323)	(0.0000334)	(0.0000333)
SCOPE	0.0422****	0.0274***	0.0270***	0.0270***	0.0284***	0.0284***
	(0.0112)	(0.00983)	(0.00976)	(0.00978)	(0.00949)	(0.00937)
CLAIMS	-0.0000507	0.000216	0.000243	0.000244	0.000194	0.000239
	(0.000609)	(0.000549)	(0.000551)	(0.000542)	(0.000539)	(0.000535)
TEAMSIZE	-0.00582	-0.00575	-0.00602	-0.00525	-0.00563	-0.00517
	(0.00449)	(0.00411)	(0.00407)	(0.00416)	(0.00410)	(0.00411)
YEARS	yes	yes	yes	yes	yes	yes
DISTANT		0.268****	0.181****	0.286****	0.243****	0.146**
		(0.0290)	(0.0500)	(0.0311)	(0.0357)	(0.0582)
NPRS		-0.000711	-0.000685	0.000169	-0.000723	0.000433
		(0.000443)	(0.000448)	(0.000616)	(0.000439)	(0.000619)
PRIVATE		-0.0796****	-0.117****	-0.0802****	-0.0793****	-0.121****
		(0.0233)	(0.0320)	(0.0233)	(0.0232)	(0.0321)
NANOBIO		-0.00178	-0.00114	-0.000965	-0.0247	-0.0448
		(0.0213)	(0.0214)	(0.0214)	(0.0348)	(0.0339)
DISTANT × *PRIVATE*			0.110**			0.121**
			(0.0547)			(0.0565)
DISTANT × *NPRS*				-0.00241*		-0.00312**
				(0.00123)		(0.00131)
DISTANT × *NANOBIO*					0.0612	0.119**
					(0.0595)	(0.0589)
Constant	0.285****	0.298****	0.329****	0.289****	0.308****	0.338****
	(0.0384)	(0.0388)	(0.0423)	(0.0384)	(0.0405)	(0.0441)
Obs.	1031	1031	1031	1031	1031	1031
F	17.17	32.54	29.97	31.80	31.06	28.96
R^2	0.144	0.216	0.218	0.217	0.217	0.222
Adjusted R^2	0.133	0.203	0.204	0.203	0.203	0.206
Log likelihood	-59.10	-13.81	-12.51	-12.76	-13.19	-9.812

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 5.2 Results - Tobit hierarchical regression

	Models					
	(1)	(2)	(3)	(4)	(5)	(6)
NCITFORW	0.00333****					
	(0.000469)	(0.000425)	(0.000426)	(0.000424)	(0.000416)	(0.000408)
NCITBACK	0.00305*	-0.000324	-0.000454	-0.0000313	-0.000460	-0.000333
	(0.00166)	(0.00176)	(0.00177)	(0.00182)	(0.00181)	(0.00191)
EXPERIENCE	-0.000172****	-0.000133****	-0.000129****	-0.000134****	-0.000137****	-0.000137****
	(0.0000278)	(0.0000356)	(0.0000357)	(0.0000354)	(0.0000366)	(0.0000365)
SCOPE	0.0474****	0.0302**	0.0297**	0.0298**	0.0317***	0.0317***
	(0.0133)	(0.0119)	(0.0118)	(0.0118)	(0.0114)	(0.0112)
CLAIMS	0.0000473	0.000341	0.000374	0.000382	0.000306	0.000367
	(0.000698)	(0.000628)	(0.000629)	(0.000619)	(0.000615)	(0.000608)
TEAMSIZE	-0.00646	-0.00631	-0.00662	-0.00559	-0.00613	-0.00536
	(0.00521)	(0.00473)	(0.00470)	(0.00478)	(0.00470)	(0.00471)
YEARS	yes	yes	yes	yes	yes	yes
DISTANT		0.305****	0.203****	0.329****	0.268****	0.153**
		(0.0358)	(0.0594)	(0.0382)	(0.0426)	(0.0688)
NPRS		-0.000631	-0.000598	0.000534	-0.000643	0.000948
		(0.000506)	(0.000510)	(0.000708)	(0.000499)	(0.000733)
PRIVATE		-0.0922****	-0.137****	-0.0931****	-0.0918****	-0.143****
		(0.0275)	(0.0401)	(0.0275)	(0.0274)	(0.0405)
NANOBIO		-0.00771	-0.00704	-0.00650	-0.0419	-0.0693
		(0.0255)	(0.0256)	(0.0256)	(0.0443)	(0.0432)
$DISTANT \times PRIVATE$			0.130**			0.146**
			(0.0658)			(0.0683)
$DISTANT \times NPRS$				-0.00323**		-0.00434***
				(0.00148)		(0.00159)
$DISTANT \times NANOBIO$					0.0899	0.168**
					(0.0742)	(0.0737)
Constant	0.222****	0.243****	0.279****	0.230****	0.256****	0.292****
	(0.0504)	(0.0490)	(0.0537)	(0.0486)	(0.0518)	(0.0567)
σ	0.308****	0.294****	0.294****	0.294****	0.294****	0.293****
	(0.0100)	(0.00992)	(0.00996)	(0.00993)	(0.00996)	(0.0100)
Obs.	1031	1031	1031	1031	1031	1031
F	15.78	30.12	28.28	29.51	28.82	27.51
Pseudo R^2	0.156	0.236	0.239	0.239	0.238	0.246
Log likelihood	-418.8	-379.2	-378.0	-377.9	-378.3	-374.4

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

inventions that spread across technological classes.

Finally, we find a positive and significant relationship between basicness and the interaction of *DISTANT* with *NANOBIO*. The main difference between nanobiotechnology and the other industries (optics and display technologies) is that it is emerging, whereas the others are merely using new technology in a mature industry. When mature industries face competence destroying change, they have the capacity to withstand newcomer's attacks through their dynamic capabilities and complementary assets (Tripsas, 1997). But when a new industry is being born, the technological landscape is not yet defined nor monopolized by anyone. The competitive nature of such an industry encourages and gives incentives to firms to perform distant search. Nanobiotechnology has such a feature. As a result, we observe that distant recombination leads to basic innovations in this industry. These findings support H4.

5.5 Conclusion

This article is an inquiry about the factors that lead to the creation of basic innovations. From an economic point of view, this appears to be a central question given the social impact that boundary spanning technologies have. The main contribution of this article resides in the association of distant recombination with innovation basicness, or its future spread overs disciplines. This finding has important ramifications, one being that autonomous opportunity seeking agents could, if their search effort is left to their own, be inefficient resource allocators with regards to basic innovations. Indeed, time pressure and short-term imperatives force actors in the private sector to cash in on whatever skills they have developed so far. As a result, they tend to look for solutions with which they are familiar. As our finding suggest, such behavior is detrimental to the creation of breakthroughs. This consideration thus seems to indicate that policies that encourage distant search could have an impact on the tendency for firms in the private sector to search beyond their cognitive boundaries. A difficulty in developing such policies is in finding the right amount of distant search required for a given industry stage. In other words, one cannot say whether markets are wrong in their allocation of resources between explorative and exploitative research. Further research regarding the cost and income associated with different levels of distant search could elucidate this question.

Another aspect of our study is concerned with the inherent relationship between innovation and technology diffusion. Indeed, an invention can be a technological success, i.e. have great potential for productivity growth, but be a commercial failure if it is not adopted in the marketplace. From this perspective, other factors can have a moderating effect on distant recombination. An interesting finding in our study is the striking ability of private institutions to translate distant recombination into basic innovations. Indeed, our results show that private firms have a tendency to produce focused innovation. Such types of innovations are not likely to contribute to drastic changes in industrial productivity. Private firms can produce innovations that have a broad technological impact under the condition that they engage in distant recombination. Such initiatives would somehow imply that private firms should decide changing the nature of their innovative effort, starting from their human resource policies that should focus in recruiting higher education graduates. However, expecting firms to endeavor such changes could be wishful thinking. If dynamic capabilities imply that firms are able to adjust their organizational routines to changing environment, then private firms should have made the changes long time ago. Thus, the re-adaptation of private institutions is more likely going to result from the implementation of policies that encourage long term and multidisciplinary research efforts.

Proximity to basic science is often believed to be a source of inspiration for breakthrough creation. However, if one takes the risks associated with the failure of potential adopters to absorb novelties that are too complex, then combining both strong science linkage with distant recombination can have a detrimental effect on diffusion. In these cases, a new technology that has great potential could have been developed, but could also fail to find subsequent users. This perspective could explain why basic science can be associated with many failures (Kim et al., 2012). In our view, market orientation should come into play in order to minimize the risks associated with the development of such inventions.

Finally, our results show that distant recombination does not equally produce basic innovations in all industries. In the nanobiotechnology industry, where competition is high, distant recombination yields a greater amount of basic innovations. This is, to a certain degree, due to fact that mature industries will concentrate on focused innovations. In such fields, where a few players are dominant, innovations are cumulative in nature. R&D effort will therefore be concentrated on incremental improvement of dominant designs. Introducing radically novel ways of doing things in such industries will not translate into proper level of adoption.

These findings have important ramification with regards to our understanding of technological breakthroughs. While basic innovations can be generally associated with distant recombination, moderating factors can come into play and diminish the diffusion rate of an innovation. These factors can explain why exploratory research often fails to produce breakthroughs: it is therefore not that distant recombination does not produce radically different products, it is simply that under certain conditions, it fails to eventually get acceptance in the marketplace. Our results can thus complement studies regarding the trade-off between knowledge exploitation and exploration, especially the many failures of distant recombinations (Fleming, 2001; Nemet and Johnson, 2012).

An inherent limit of our study is in the use of citation US classes to measure distant recombination (basicness). The problem arises from the fact that US classes are not defined hierarchically. All three-digit US classes are at the same level and one cannot readily find the technological relationship or proximity between classes. Thus, two patents can have the same level of distant recombination (basicness), but that in reality, one combines (is used) in technological classes that are much more distant than the other one. Building co-citation networks and measure distant recombination (basicness) through centrality metrics, such as the betweenness, can offer interesting methodological opportunities. However, many difficulties (such as autocorrelation or auto-regression) must first be addressed. Also, our study is limited to the case of the Canadian nanotechnology sector. Similar experiments with larger samples or other industries can be used to confirm the findings of this article.

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CHAPTER 6

WHAT HAPPENS TO BASIC INNOVATIONS? THE PARADOX OF TECHNOLOGY EXIT UNDER CONDITIONS OF STRONG APPROPRIABILITY REGIMES AND INDUSTRY DYNAMISM

Abstract[1]

Basic innovations have implications across technological boundaries and serve as the basis for future incremental innovations. Despite their great importance from an economic perspective, little is known about the private benefits that they engender. In this article, we attempt to shed light on this question. We employ a sample of Canadian nanobiotechnology patents for which we assess the impact of past, current and future spread over technological disciplines on renewal decisions. Our results show that basic innovations generally enjoy a longer legal life, and thus higher perceived private value. However, discrepancies are found depending on the patent holder's sector of activity. Public institutions renew patents that will spread over disciplines in the future, but they subsequently discard a greater percentage of them. These findings indicate that differences in institutional routines can have an impact on how resources are allocated for innovative activity. The evidence in this paper has important ramifications regarding the involvement of public institutions in commercial activities.

Keywords: Industry Life Cycle, National Innovation Systems, Technology Transfer, Complementary Assets, Organizational Routines.

6.1 Introduction

From a *business cycles* perspective, economic growth (stagnation) can be rooted in the production (lack) of basic innovations (Schumpeter, 1939; Mensch, 1979). While it is conceivable that the aggregate productivity gains generated by the vast quantity of incremental innovations represents the largest part of the economic activity in an industrialized country, it is undeniable that they all lie on top of basic innovations (Mokyr, 1990; Rosenberg, 1994; Mowery and Rosenberg, 1999; Arthur, 2007). Yet, as important as they appear from a social point of view, little can be said about the private benefits that basic innovations can

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generate. Economic literature indeed views knowledge spillovers and the appropriation of returns as opposing forces: basic knowledge has implications across various fields but cannot be made private, in which case innovators can capture little of the social benefits that they generate (Arrow, 1962). Therefore, the production of basic innovations must be bestowed to universities because these are institutions that are not exclusively motivated by profitability and that their organizational culture is geared towards the production of knowledge that has broad scope (Dasgupta and David, 1994).

A closer examination of the economic literature, however, support the idea that innovators can appropriate returns from basic innovations under conditions of strong appropriability regimes and industry dynamism (Malerba and Orsenigo, 1997). When these conditions are met, transaction cost theory stipulates that a profit maximizing agents should find incentives in allocating resources to basic innovations (Williamson and Masten, 1995). Evolutionary economics, however, claims that decisions regarding the allocation of resources is not always made in rational fashion, but results from an organization's *routines* (Nelson and Winter, 1982). Given that cultural and organizational differences exist between private and public institutions, could there be a difference between how these organizations allocate resources to basic innovations?

In this paper, we answer this question by analyzing a sample of Canadian nanobiotechnology patents registered in the US. Because inventions in this field can be categorized as discrete technologies, patents represent a strong appropriability regime and thus cover a large part of the innovative activities (Cohen et al., 2000). Nanobiotechnology is also an emerging and multidisciplinary technological discipline which is in its early days. This industry is thus very competitive, which makes it a great locus for novel and breakthrough creations as well as lower entry barriers for small players. Our method consists in analyzing the link between a patent's renewal decision with its spread over technological classes in periods past, current and after the renewal decision. Our results confirms that, under conditions of strong appropriability regimes and industry dynamism, the spreading of an innovation over technological classes is generally associated with a longer legal life and thus greater perceived private value. However, we also find that the public sector more often renews patents that will spread over various disciplines in the future, but that the private sector more often renews patents that have already spread over technological disciplines.

The remainder of the article proceeds as follows: Section 2 explains the theoretical framework and hypotheses underlying our study; Section 3 presents the data and methodology;

Section 4 discusses the results; and finally Section 5 concludes.

6.2 Theoretical framework and hypotheses

Traditionally, the role of researchers in public institutions was to provide basic knowledge to the scientific community, and whatever reward they received was linked to their reputation as scientists within the community (Dasgupta and David, 1994; Stephan, 1996). Such a reward system has the benefit of assuring allocation of resources for knowledge creation where the appropriation of returns is difficult (Arrow, 1962).

This social setting under which scientists operated has somewhat changed over the last decades. With the observation that basic research was linked to technological innovation and economic growth (Griliches, 1958; Jaffe, 1989; Adams, 1990; Zucker and Darby, 1996; Narin et al., 1997; Cohen et al., 2002; Furman and MacGarvie, 2007), an increasing integration of university-industry-government relations has been proposed (Lundvall, 1992; Etzkowitz and Leydesdorff, 2000). Today's universities, are no longer confined to the production of basic science, but are also meant to be entrepreneurial (Etzkowitz et al., 2000). In this context, universities act like firms in that they seek private returns from their innovations.

This shift in the role of universities towards commercial activity has led to a debate about the impact that it will have on the nature of research produced in these institutions (Henderson et al., 1998; Mowery et al., 2001; Owen-Smith and Powell, 2003; Thursby and Thursby, 2011; Czarnitzki et al., 2011). Trajtenberg et al. (1997) show that, compared to the private sector, universities produce a larger share of basic innovations because of their proximity with basic research. However, Henderson et al. (1998) find that innovations produced by universities showed a decrease in generality after the Bayh-Dole Act of 1980. Other studies, however, explain this decrease with the increase in patenting by universities that weren't initially active "patenters", and that haven't yet learned to patent effectively (Mowery and Ziedonis, 2002; Mowery et al., 2002).

Another source of controversy regarding the involvement of universities in commercial activities is about whether it can hinder innovation (Heller and Eisenberg, 1998; Gallini, 2002; Murray and Stern, 2007). On the one hand, the argument that R&D cannot be justified under conditions of weak appropriability regime are forceful (Arrow, 1962; Levin et al., 1987; Cohen et al., 2000). The presence of strong intellectual property protection mechanisms would encourage the private sector to use technologies developed through public research (Mazzoleni and Nelson, 1998). Jensen and Thursby (2001) also points out that further development of university technologies will not happen unless there are economic incentives for academic inventors to do so. On the other hand, increased patenting by public institutions can lead to the shrinking of the "scientific commons" (Jaffe, 2000; Nelson, 2004). Fabrizio (2007) indeed shows that university patenting is associated with a slowdown in the pace of knowledge exploitation, and that this effect is stronger in science-based industries.

These hot debates raise an interesting question: if one supposes, for a moment, that public research quality is not impacted by involvements in commercial activity, are public institutions able to appropriate returns from basic innovations under favorable market conditions? In other words, if the private and public sectors are both facing market conditions that favor commercial success for basic innovations, who will be more able to profit from them and who will be more prone to commercialize them? This question can be answered by measuring the moderating effect of the sector of activity on the renewal of innovations that have successfully spread over a variety of disciplines and those that will eventually spread in the future. The following subsections will present the theoretical framework that will be used to emit hypotheses for this experiment.

6.2.1 Basic innovations, appropriability regimes and market structure

It goes without saying that firms will create knowledge only under the condition that they can appropriate returns from this knowledge (Arrow, 1962; Levin et al., 1987). If appropriability regimes are weak, firms cannot justify investment in R&D activities. However, under conditions of strong appropriability regimes, innovators are able to appropriate a larger part of the social benefits that their inventions generates. If such conditions are met, firms should find incentives to invest in R&D, but the decision about its nature will also depend on industry structure.

Innovation patterns can be classified as Mark I or Mark II types (Schumpeter, 1934, 1942; Malerba and Orsenigo, 1995). The Mark I pattern is associated with the concept of *creative destruction*, where innovations introduced by new entrants displace those maintained by incumbent firms. Innovations resulting from such conditions lead to the *widening* of technological paths and to the disruption of rents related to established technologies. The Mark II pattern is associated with the concept of *creative accumulation*, where an industry is dominated by large firms and the presence of barriers to entry for new entrants. Innovations introduced in such conditions mostly contribute to *deepening* technological paths and strengthening the competitive advantage of established players.

A parallel can be made between Mark I and Mark II patterns of innovation and an industry's different stages of development (Abernathy and Utterback, 1978; Klepper, 1997; Malerba and Orsenigo, 1997). In the early days of an industry, uncertainty favors entry of new firms which will attempt to break away from existing routines in radical ways. As the industry matures, dominant solutions are adopted and continuously improved by increasingly larger firms. Industries are thus initially evolving in technological regimes with characteristics similar to the Mark I pattern and, as they later mature, switch into the Mark II pattern. Basic innovations thus thrive in industries where technological regimes could be characterized as Mark I. In other words, the more an industry is emerging and competitive, the higher should be the perceived private returns associated with basic innovations. We thus propose the following hypothesis:

H1. In environments marked by strong appropriability regimes and industry dynamism, basic innovations are associated with a larger perceived private value.

6.2.2 Complementary assets: a tool for capturing returns

While essential, external conditions are not sufficient to guarantee profitability. Teece (1986) indicates that *complementary assets* are required to capture returns from technological innovations. Firms who possess little production, marketing or legal protection capabilities will have to share parts of their profits with other players who do possess such capabilities. In this regard, differences could exist between the private and public sector. Universities willing to obtain commercial benefits from their inventions have two broad options: they must either license their technologies or launch spinoffs.

Although the first option implies stronger capabilities in intellectual property protection, it also means that inventions will not be developed into products by the public institutions. In such cases, an inherent limit will be put on the share of the profit that public institutions will capture. Furthermore, even if universities set up intellectual property protection offices and build ties with venture capitalists, the role of faculty is crucial (Thursby and Thursby, 2004; Thursby et al., 2009). However, daily faculty tasks are not geared towards building industry relationships as they mostly engage in projects that have appealing research streams (Dasgupta and David, 1994; Agrawal and Henderson, 2002). Because building industry ties is crucial for successful technology transfer (Cohen et al., 2001; Owen-Smith and Powell, 2003; Debackere and Veugelers, 2005; Thursby and Thursby, 2007), universities could be underprivileged with complementary assets due to the fact that the most important members do not engage in building these ties. This may help understand why much of university patents are never commercially exploited (Thursby and Kemp, 2002).

The spinoff option can also be viewed as an attempt to build complementary assets from scratch, which is an implicit recognition that they may not be present. Spinoff creation is plagued inherent difficulties associated with access to skilled managers and financing (Lockett et al., 2003; Wright et al., 2006). Hence, even if universities have the strategic intent to create spinoffs, it is often difficult to have access to the resources required to reach commercial success.

This is a contrast from the private sector for which building capabilities complementary to knowledge creation is essential for firm survival. Indeed, firms attempt to grow can be viewed as an ongoing process of resource building (Barney, 1991; Eisenhardt and Martin, 2000). Contrary to public institutions, firms cannot be content with creating knowledge for the common good: they must continuously build the resources necessary for their commercialization (Teece et al., 1997). We thus propose the following hypothesis:

H2. In environments marked by strong appropriability regimes and industry dynamism, private institutions are better able to appropriate returns from innovations that have proven to be have application in various technological disciplines.

6.2.3 Routines, vision and resource commitment

Besides engaging in the development of disruptive technologies, firms need to have market visioning as well as commit resources to the conquest of those markets (O'Connor and Veryzer, 2001). This often requires firms to identify, interpret and act upon early signals from their internal and external environments (Cockburn et al., 2000). These reactions, however, are not always made in rational fashion. Because organizations behave under the condition of *bounded rationality*, transaction costs theory is not always a satisfactory explanation about how decisions are made (March and Simon, 1958; Nelson and Winter, 1982). Faced with the complexity of the world, organizations do not make choices *per se*, but operate through a set of *routines*. From this perspective, it os possible that an organization's routines could partly determine its reactions in the face of certain signals from its surrounding. There are reasons to believe that cultural and organizational differences between the private and public sectors lead to different perceptions with regards to innovation type and private returns.

Public institutions, in their classical role, are not solely motivated by profits (Lundvall, 1992). Leading personnel within public institutions have been trained in academic settings and their skill sets are mostly forged around basic science. Although a shift in the culture of public institution can be observed with regards to an increase in the propensity for commercial activity, it is not obvious that public institutions will adopt routines that mimic those of the private sector given the fact that the bulk of the former's innovative activities turn around the production of basic knowledge (Argyres and Liebeskind, 1998; Agrawal and Henderson, 2002). In a sense, routines within public institutions are geared towards building solutions that have broader scope.

In the market-driven private sector, in contrast, there is a tendency to search for solutions that focus on current customers needs (Christensen, 1997). Driven by short-term profits, organizations prefer to exploit paths that have been successful so far (Levitt and March, 1988; Fang et al., 2010). In such a context, learning myopia is a natural pathology that plagues organizations (Levinthal and March, 1993; Ahuja and Lampert, 2001). As a result, firms in the private sector could have a tendency to prefer innovations that have been successful in reaching different markets, but fail to support those that will spread over different disciplines in the future because they tend to prefer those that have application in focused fields.

It is thus natural to think that public institutions would have an a priori for innovations that would have application across different fields since this is the kind of thinking that they are used to perform on a daily basis. In contrast, private institutions will select innovations that will promise to have application in a focused set of disciplines. Public institutions could thus be prone to select innovations that will subsequently spread over disciplines more effectively than private institutions. We thus propose our last hypothesis:

H3. In environments marked by strong appropribility regimes and industry dynamism, public institutions commit more resources to innovations that will spread over various technological disciplines in the future.

6.3 Methodology

6.3.1 Data

Patents give exclusive rights to an innovator for a limited time in exchange for the public disclosure of the invention. Patents are granted to inventions that are novel, non-obvious and useful, and therefore can be viewed as indicators of technological change and innovative activity (Basberg, 1987; Acs and Audretsch, 1989; Griliches, 1990; Archibugi, 1992). Patents however do not represent the whole range of inventions that are created as secrecy or lead time is often used as an alternative method for intellectual property protection (Levin et al., 1987). Also, various studies point out that the majority of patents have little economic value (Allison et al., 2004; Moore, 2005). Patenting can be seen as *lottery tickets* where patent holders can never be sure of the value of their patent (Lemley and Shapiro, 2005). Furthermore, patents are sometimes used as a strategic devices such as defensive purposes or *trolling* which implies that they will not always translate into new product development (Hall and Ziedonis, 2001; Gallini, 2002; Reitzig et al., 2007).

Appropriability from patents is not perfect in practice because it can be circumvented and litigation does not guarantee repair of rights (Levin et al., 1987). Under certain types of technologies, however, patents offer better protection. In the case of discrete technologies, such as pharmaceuticals, biotechnology and organic chemicals, patents are efficient for intellectual property protection and are less often used for strategic reasons (Levin et al., 1987; Merges and Nelson, 1990; Cohen et al., 2000; Hall and Ziedonis, 2001). In these industries, inventing around is very difficult because it is relatively easy to show that a competing product is infringing upon the patent's claims (Merges and Nelson, 1990). Appropriability regimes are thus strong in these industries.

With these observations in mind, we analyze a sample of Canadian nanobiotechnology patents granted by the USPTO. The US is Canada's major trade partner and the world's largest market, which means that it is a very competitive place for intellectual property protection. The use of the nanobiotechnology industry fulfills our research objective of studying private returns to basic innovations under conditions of industry dynamism. Indeed, nanobiotechnology is a sector in emergence since the 1990's and marked by a very dynamic market structure (Perkel, 2004; Barirani et al., 2012a). Because it can also be classified as a science-based industry, nanobiotechnology is an interesting testbed for comparing private-public institutions with regard to their capacity to capture value from basic innovations.

Our sample was obtained by performing a Boolean extraction on patents containing nanotechnology related keywords, clustering similar patent based on their co-citations and selecting clusters that contained nanobiotechnology patents (Barirani et al., 2012a). Because this method only takes the main network component into account, we use the resulting nanobiotechnology sample for training a K-NN classifier that would subsequently classify the nanobiotechnology patents that are not connected to the main network component. The classifier is trained using patent titles and abstracts. Our sample contains 393 Canadian nanobiotechnology patents obtained from 1990 to 1997 for which we have extracted information regarding their grant date, inventors, number of claims, forward citations and renewal decisions until 2009.

6.3.2 Models

USPTO policies dictate that patent owners must pay maintenance fees at the 4th, 8th and 12th year of a patent's legal life. Failing to pay these fees leads to the loss of the exclusivity conferred by the patent, in which case the owner cannot prevent others from using the invention. Patent renewal can be related to the firm's expectation of future private returns associated with withholding the patent and the obsolescence of the disclosed invention (Pakes and Schankerman, 1984). Indeed, if new competing inventions are introduced and that they displace a patent, its owner will no longer have any advantage in keeping the patent unless revenue streams are still expected from ancillary products.

It should also be noted that assignees, in an *ex post* valuation of their patent, go through a learning period where they try to get market feedback about possible commercialization of the technology. Until this process is complete, firms might renew a patent even if no income is forecast. Various studies claim that this period could take between 5 to 7 years (Lanjouw et al., 1998; Bessen, 2008). Renewal decisions in the earlier period (4th year) can therefore be associated with the patent holder's *a priori* about an invention, and does not indicate that private gains are expected. Furthermore, expecting revenue streams implies that patent holders attempt, *ex post* of their initial decision to conduct R&D and file a patent, to predict future applications that the invention will have on ancillary products. Given that R&D as well as filing costs are much higher than the renewal fees, not renewing a patent can be viewed as a clear signal that withholding the patent does not confer any form of advantage to its owner (Thomas, 1999).

Three dummy variables are used as the outcomes in our models: *RENEW4*, *RENEW8* and *RENEW12* indicate whether the focal patent is renewed in year 4, 8 and 12 of a patent' life respectively. Our method consists in performing hierarchical probit and logit regressions with different renewal periods (4th, 8th and 12th year) as dependent variables and patent basicness on periods prior, current and subsequent to the renewal year as the main dependent variables. It should be noted that at every renewal year, only those patents that have been renewed so far are considered in our models. Controlling for patent basicness in past, current and future periods allows us to observe whether basic innovations are generally associated with higher perceived private value, which will contribute to validating H1. By interacting basicness at different periods with the sector of activity of an assignee, we can observe whether there is a difference between how the private and public sectors perceive the value of present and possible future spread of an invention, which will then contribute to validating H2 and H3.

6.3.3 Explanatory variables

Applicants have the obligation to cite all related sources of knowledge, but they are not legally obliged to perform prior art search. In essence, it is incumbent upon USPTO examiners to make sure that all relevant sources are properly cited (Meyer, 2000a). Because of the thorough process of examination with which citations are added to a patent, Jaffe et al. (1993) argue that they represent knowledge spillovers generated by patents. Forward citations have also been linked to a patent's social value and are thus an indication of its technological impact (Trajtenberg, 1990). This view has somehow been nuanced given the fact that applicants can cite other patents strategically and that examiners can add citations that are not always relevant to the invention (Meyer, 2000a; Cockburn et al., 2002).

However, other studies have observed that examiner citations represent the largest percentage of self-citations (Alcácer and Gittelman, 2006; Alcácer et al., 2009). Examiner citations are also more likely to be added when there is technological and geographical distance between the citing and cited patents (Criscuolo and Verspagen, 2008). Hegde and Sampat (2009), show that examiner citations are better predictors of patent renewal than applicant citations. They argue that since applicants try to avoid building inventions on top of compromising patents, examiners cite prior art that restrict the patent's scope. From these perspectives, examiner citations can also be viewed as a smoothing process that ensures that most of the relevant prior art is cited (Meyer, 2000a; Von Wartburg et al., 2005).

From an economic perspective, Hall et al. (2005) link forward citations to market value. If markets can be viewed as a place where prices are allocated to assets based on their expected returns, it implies that forward citations can predict future revenue streams associated with a patent. However, in no way does this link imply that firms base their appreciation of a patent on the number of forward citations that they receive. Instead, we assume that the diffusion of a patent can be sensed by its owner through indicators other than the analysis of forward citations, but that these indicators can be manifested through forward citations.

By adapting the Herfindahl-Hirschman Index, Trajtenberg et al. (1997) use the information about a patent's forward citations' US classes to measure its basicness. Given a patent with n forward citations falling into m classes, the degree B with which the patent's subsequent use spans technological disciplines is:

$$B = 1 - \sum_{i=1}^{m} \left(\frac{CLASS_i}{n} \right)^2 \tag{6.1}$$

Where $CLASS_i$ is the number of forward citations that fall within class i. As the value for equation 6.1 gets nearer to one, forward citing patents are closer to be equally spread over the m classes, which means that the patent is more basic that focused. Since patents do not have the same amount of forward citations, this measure, if taken alone, is more likely to associate basicness to patents that have higher rates of forward citations. We propose to overcome this issue by normalizing equation 6.1 (Gaur et al., 2012):

$$\hat{B} = \frac{B - \frac{1}{m}}{1 - \frac{1}{m}} \tag{6.2}$$

For each patent in our sample, we compute basicness with equation 6.2 by taking forward citations received for years 0 to 4, 5 to 8 and 9 to 12 starting from the patent's grant year. These values are represented by dependent variables *BASICNESS4*, *BASICNESS8* and *BASICNESS12* respectively.

We account for the sector of activity (private or public) by examining patent assignees. Patents are classified based on whether they are owned by corporations or public institutions, with the latter including universities. We use the dummy variable *PRIVATE* to indicate whether the assignee is a firm or a public institution.

6.3.4 Control variables

The scope of patent claims determines the monopoly power bestowed to its owner by defining the main novel features of the invention (Merges and Nelson, 1990). Applicants have an incentive to claim as much as possible while examiners must narrow down the scope of the patent before granting it (Lanjouw and Schankerman, 2004a). The number of claims can therefore be used as an indication of a patent's scope and quality (Tong and Frame, 1994). The variable *CLAIMS* is thus a measure of the number of claims granted to the patent. In a different fashion, Lerner (1994) measures scope through the number of technological classes to which a patent is assigned. Similarly, we employ the variable *SCOPE* to measure the number of distinct three-digit US classes assigned to each patent.

The increasingly complex nature of high technology products obliges teamwork (Wuchty et al., 2007). Team size can thus be viewed as a sign of commitments to greater resources, which implies a certain level of expectations from the investor's point of view. This could in turn have an impact on firms' willingness to extend their *ex post* learning period as well as their general perception about an invention. Since many advantages can be associated with being part of the inventing team, it is reasonable to assume that only those who bring distinctive skills to the table will be able to negotiate a place among the inventor list. We thus use the number of inventors listed in a patent, which is represented by *TEAMSIZE*, as a proxy for the size of the team involved in the development process.

Time can have various effects on patent renewal practices. Industries go through different stages. As they mature and innovative activities take a cumulative turn, uncertainty associated to incremental innovations, which represent the bulk of the innovative effort, is lowered. Firms are thus expected to have a higher rate of patent renewal than in the early days where many failures can occur. In emerging industries, acceleration in the introduction of novel technologies can also lead to a faster rate of obsolescence which will also impact A firm's decision to renew. We control for this factor by using patents grant years, which are represented by the year dummies *Y1991* to *Y1997*.

6.4 Analysis and Results

Tables C.1 and C.2 in the appendix show descriptive statistics for our sample. As we can see, correlation between independent variables is below the 0.5 level, and thus suppose each variable is independent. However, for the purpose of multicollinearity resulting from interaction effects, we use the grand-mean centered transformation of our continuous variables (Neter et al., 1985). Tables C.3 and C.4 in the appendix are provided for supplementary material to our main models represented by Tables 6.1 and 6.2.

Models 1, 2, 4, 5 and 8 in Table 6.1 summarize the results of simple probit models (not controling for the interaction of basicness with the sector). Models 1 and 2 show that an early spread of a patent over technological classes (*BASICNESS4*) has a positive impact on the 4^{th} year renewal decision. Hence, during the learning period where assignees try to gather *ex post* information about the private value of their patents, those that have quickly spread over different disciplines happen to be perceived to be more valuable from a private perspective. As we have specified earlier, this does not imply that firms base their decisions on the number or spread of forward citations. It is simply an indication that innovations which have a more basic feature also happen to be preferred in earlier renewal periods.

In the subsequent period, however, where *ex post* learning is complete, there is a forward looking shift in assignee renewal decisions. Indeed, we can see in models 5 and 6 that*BASICNESS12* has a positive and significant relationship with *RENEW8*. This means that, in year 8, patent holders tend to renew patents that will spread over various disciplines in the future. However, it should be noted that past spread (*BASICNESS4*) is still relevant as it is shown in model 6 of Table C.3 in the appendix. This means that the revenue stream associated with the past spread of a patent will have a long-lasting impact. Therefore, model 6 in Table 6.1 shows that the impact of future spread of a patent is more relevant in predicting renewal in the 8^{th} year, if we discount for the information about past and current spread of a patent.

In model 8 (Table 6.1), we can see that there is a significant positive relationship between *BASICNESS12* and *RENEW12*. Once again, patent basicness is associated with the renewal decision. It should be noted that to maintain the sample size, we did not take into account forward citations received after year 12 of a patent' granting as it would have restricted our sample to the 1990-1994 period. Thus, we cannot comment about whether future spread of a patent would have a stronger impact on renewal as it is observed for year 8. Nevertheless, model 8 shows that the impact of patent basicness on renewal in the final period is positive and significant. Overall, these observations give strong support for H1: present and future spread of a patent over technological disciplines will be associated with higher levels of private value.

The interaction effect between the variable *PRIVATE* and basicness for the three periods is considered in models 3, 7 and 10. Here, we can see how the sector of activity will impact renewal decisions when information regarding a patent' spread is available (H2) and when forecasting of future spread needs to be done (H3).

As we can see in model 3, the sector of activity does not have a significant moderating effect on renewal. Thus, earlier in the process, when patent holders are still sensing the market, both private and public institutions have the same perception about basic innovations. However, in subsequent periods (8^{th} and 12^{th} year), there is a shift in this perceived private value of basic innovation depending on the sector of activity. In model 7, we can see that there is a positive and significant relationship between *BASICNESS8* × *PRIVATE* and *RENEW8*, meaning that firms associate current patent basicness with higher levels of private returns. Similarly, in model 10, we can see that *PRIVATE* has a positive and significant moderating effect on *BASICNESS12*, thus indicating that when firms dispose of current information about the spread of a patents, those that are more basic are more likely to be renewed. These findings support H2: all things being equal, innovations that have proven to be useful in a multitude

Table 6.1 Probit regression results - simple and interaction effects

	RENEW4			RENEW8				RENEW12		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PRIVATE	-0.268	-0.223	-0.148	0.387**	0.493**	0.483**	0.426**	-0.0796	-0.0700	-0.217
	(0.212)	(0.212)	(0.218)	(0.186)	(0.198)	(0.200)	(0.217)	(0.229)	(0.227)	(0.243)
CLAIMS	0.0185**	0.0178*	0.0178*	0.000724	-0.00269	-0.00331	-0.00519	0.0137	0.0139	0.0181*
	(0.00929)	(0.00953)	(0.00946)	(0.00615)	(0.00622)	(0.00628)	(0.00635)	(0.00900)	(0.00891)	(0.00944)
SCOPE	0.0150	0.0106	0.00168	-0.0282	-0.0265	-0.0288	-0.0296	0.0828	0.0818	0.0724
	(0.0754)	(0.0783)	(0.0817)	(0.0754)	(0.0830)	(0.0826)	(0.0864)	(0.0892)	(0.0904)	(0.0989)
TEAMSIZE	0.0347	0.0285	0.0322	0.233***	0.244***	0.242***	0.241***	0.133*	0.133*	0.140*
	(0.0503)	(0.0508)	(0.0524)	(0.0882)	(0.0899)	(0.0890)	(0.0882)	(0.0699)	(0.0711)	(0.0738)
YEARS	yes	yes	yes	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
BASICNESS4	0.608***	0.548**	0.219			0.328	0.205		-0.114	0.793*
	(0.207)	(0.214)	(0.323)			(0.249)	(0.357)		(0.219)	(0.465)
BASICNESS8		-0.0702	0.519**	0.394*		-0.0566	-0.774		0.0683	1.011*
		(0.208)	(0.246)	(0.234)		(0.265)	(0.476)		(0.314)	(0.604)
BASICNESS12		0.289	0.0123		0.793****	0.743***	0.802**	0.509**	0.501*	-0.426
		(0.231)	(0.377)		(0.227)	(0.253)	(0.364)	(0.245)	(0.257)	(0.515)
BASICNESS4×PRIVATE			0.533				0.109			-1.439***
			(0.413)				(0.530)			(0.552)
BASICNESS8×PRIVATE			-0.848**				1.153*			-1.278*
			(0.367)				(0.595)			(0.691)
BASICNESS12×PRIVATE			0.344				-0.0458			1.394**
			(0.461)				(0.488)			(0.624)
Constant	0.778**	0.751**	0.673**	0.556	0.644	0.591	0.642	0.958*	0.957*	1.411**
	(0.312)	(0.315)	(0.281)	(0.447)	(0.448)	(0.446)	(0.490)	(0.552)	(0.564)	(0.617)
Obs.	327	327	327	270	270	270	270	224	224	224
Wald χ^2	36.15	45.22	49.33	19.00	29.46	30.52	36.37	17.30	17.72	40.78
Pseudo R^2	0.123	0.128	0.142	0.0802	0.114	0.122	0.145	0.0801	0.0811	0.142
Log likelihood	-132.7	-132.0	-129.9	-113.4	-109.2	-108.2	-105.4	-111.7	-111.5	-104.1

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 6.2 Logit regression results - simple and interaction effects

	RENEW4				RENEW8					RENEW12		
	(1)	(2)	(3)		(4)	(5)	(6)	(7)		(8)	(9)	(10)
PRIVATE	-0.476	-0.395	-0.206		0.731**	0.902**	0.897**	0.845**		-0.171	-0.161	-0.367
	(0.392)	(0.394)	(0.416)		(0.346)	(0.360)	(0.363)	(0.424)		(0.414)	(0.418)	(0.451)
CLAIMS	0.0377**	0.0365**	0.0369**		0.000315	-0.00512	-0.00654	-0.0100		0.0251	0.0255	0.0315*
	(0.0177)	(0.0183)	(0.0180)		(0.0112)	(0.0114)	(0.0116)	(0.0115)		(0.0169)	(0.0167)	(0.0179)
SCOPE	0.0309	0.0159	0.00406		-0.0454	-0.0568	-0.0676	-0.0728		0.131	0.132	0.0994
	(0.129)	(0.138)	(0.145)		(0.132)	(0.148)	(0.150)	(0.158)		(0.153)	(0.157)	(0.178)
TEAMSIZE	0.0777	0.0629	0.0679		0.466***	0.464***	0.464***	0.458**		0.234*	0.235*	0.261*
	(0.0946)	(0.0950)	(0.0997)		(0.177)	(0.177)	(0.176)	(0.182)		(0.127)	(0.131)	(0.140)
YEARS	yes	yes	yes	yes	yes		n.s.	n.s.	n.s.	n.s.		n.s.
BASICNESS4	1.069***	0.973**	0.293				0.678	0.471			-0.238	1.360
	(0.407)	(0.419)	(0.608)				(0.498)	(0.653)			(0.395)	(0.923)
BASICNESS8		-0.178	1.050**		0.700*		-0.175	-1.392			0.0675	1.698
		(0.387)	(0.473)		(0.424)		(0.494)	(0.857)			(0.546)	(1.108)
BASICNESS12		0.527	-0.0351			1.381****	1.339***	1.480**		0.926**	0.947**	-0.678
		(0.432)	(0.699)			(0.416)	(0.479)	(0.646)		(0.430)	(0.457)	(0.930)
BSICNESS4×*PRIVATE*			1.072					0.208				-2.418**
			(0.786)					(1.049)				(1.049)
BASICNESS8×*PRIVATE*			-1.717**					2.056*				-2.185*
			(0.688)					(1.123)				(1.267)
BASICNESS12×*PRIVATE*			0.729					-0.141				2.368**
			(0.846)					(0.943)				(1.120)
Constant	1.316**	1.293**	1.087**		0.856	1.046	0.979	1.013		1.735*	1.778*	2.521**
	(0.539)	(0.554)	(0.484)		(0.792)	(0.780)	(0.791)	(0.917)		(1.011)	(1.054)	(1.136)
Obs.	327	327	327		270	270	270	270		224	224	224
Wald χ^2	33.60	41.65	47.58		18.55	30.38	30.51	34.72		16.51	16.70	38.40
Pseudo R^2	0.126	0.130	0.147		0.0833	0.115	0.125	0.148		0.0827	0.0840	0.141
Log likelihood	-132.3	-131.6	-129.0		-113.0	-109.0	-107.9	-105.0		-111.3	-111.2	-104.2

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

of industries are associated with higher levels of private returns when innovators are from the private sector.

These observations, however, do not represent the whole set of phenomena that our interaction models observe. If one looks at the forward looking indicators of basicness, it is a contrasting story. For instance, models 3 shows that, at the 4^{th} year, private institutions actually dump a larger share of patents that will spread over disciplines in the subsequent period (i.e. when considering the impact of *BASICNESS8*×*PRIVATE* on *RENEW4*). As we have pointed out, the same private firms will eventually turn out to prefer a patent that has shown to be basic. But in the process, they have discarded many that would spread over disciplines later on. It should be noted that this phenomenon is visible while the learning period is not complete. Indeed, model 7 does not show any significant moderating relationship between private sector and betweenness at the subsequent period (i.e. when considering the impact of *BASICNESS12*×*PRIVATE* on *RENEW8*). Nevertheless, our results suggest that this phenomenon is widespread enough if one takes into account that most patents renewed at the final period have been mostly focused innovations during the first 8 years on the patent's life (*BASICNESS4*×*PRIVATE* and *BASICNESS8*×*PRIVATE* in model 10). Given the correlation between betweenness at one period and a subsequent one, but also that betweenness at subsequent periods is generally associated with higher perceived private returns (see model 8), it appears reasonable to ask whether a great deal of innovations that would have eventually spread over various technological disciplines aren't discarded due to a lack of vision from the private sector.

One can of course use arguments about the implacable efficiency of markets and claim that the fact that the private sector discard a patent that will spread over disciplines in the future is not a sign that it is unable to foresee its potential, but that it is simply due to the fact that the patent is no longer valuable. The analysis can be brought to the next level by claiming that it is public institutions that do not perform the correct resource allocation by renewing patents that would be discarded later on. Finally, the fact that patents that are basic and more often renewed at the 12^{th} year by the private sector were initially focused in earlier periods can be interpreted as the ultimate proof that the private sector has a tremendous vision.

While our experiment cannot refute this claim, we still find it odd to see that the private sector significantly rejects innovations that would eventually be considered basic in the future. Indeed, given that basic innovations are more relevant strategic tools in conditions of strong appropriability regime and industry dynamism, there should not be any reason for their discarding. In fact, what the literature tells us, is that routines within the private sector are geared towards short-term profits which translates into local search and the exploitation of known technological paths (Fang et al., 2010). Under such conditions, it is more reasonable to assume that private organizations select patents that they believe will have a focused area of application in the future and which give the assurance of relying on knowledge that has been accumulated so far. Later on, however, when it becomes clear that a patent can serve multiple purposes, the private sector is very capable in using its complementary assets to capture private returns from the opportunity.

6.5 Conclusion

Basic innovations are crucial from an economic perspective: they drastically change productivity ratios and serve as the basis for subsequent incremental innovations in a multitude of disciplines. With regard to their appropriability, the literature offers mixed reviews. Basic innovations are associated with knowledge spillovers which imply weak opportunities to capture private returns. However, when appropriability regimes are strong, and when firms are evolving in a dynamic industry, basic innovations should be an attractive option for private firms. One of the contributions of this paper is to bring empirical evidence regarding this statement.

Our results show that, under favorable market conditions, the expected return from a private investor's point of view appears to be significantly positive. Also, investors expect returns for longer periods from basic innovations. Obsolescence rate is slower for innovations that span technological disciplines. As inventions spread across industries, innovators develop a more optimistic view of future incomes. When firms have gathered enough *ex post* information about the value of an invention, they tend to perceive better opportunities for revenue streams in innovations that will subsequently have application in many disciplines.

A second objective of this paper was to add perspective to the debate about the involvement of public institutions commercial activities. As we have seen, an extra burden of taking part in entrepreneurial activities has been put on universities who are viewed as producers of knowledge spillovers. However, it is far from evident whether such policies will impede innovation or impact negatively research output in public institutions. We have thus asked a fundamental question: if one does not bring under question the quality of university patents, can we expect positive results with regards to technology transfer? For this purpose, we have examined how public institutions compare to private firms with regards to the allocation of resources to basic innovation.

Our results show that while public institutions are better able to forecast future spread of an innovation over disciplines, they are less capable of capturing value when information about the value of an innovation as been cumulated by players in both private and public sectors. This finding is in line with the generally reported tendency for firms to fall to the propinquity trap. In other words, while they are in a better position to profit from basic innovations, they seem to prefer those that will serve in a focused technological area. However, when the spread of an innovation is clear, private firms attempt to seize the opportunity.

These findings have important ramification with regard to the debate about the increasing entrepreneurial universities. What we can conclude from our study is that even if one does not bring under question the capacity of universities to produce basic innovations when they are asked to be active in both basic and applied research, it is not obvious that anyone wins. Indeed, universities attempting to commercialize basic innovations in favorable conditions will not accomplish much more than file for patents that they will eventually drop. The cause behind this phenomenon is in the lack of resources that universities possess with regards to the commercialization of their inventions. Given that public institutions are capable of predicting future spread of an innovation over disciplines, the skill that they appear to be missing is market orientation (Slater and Narver, 1995), the precise skill that the private sector must have.

The lack of data about incomes associated with patents is a major limitation to our research. Obtaining such data is not impossible in the case of discrete technologies because they can be more easily associated with products and thus revenue streams. However, when such data is missing, one cannot automatically conclude about whether private institutions are inefficient resource allocators when they fail to renew patents that will subsequently spread over technological classes. In fact, these patents could have been dropped anyways in the future because of lack of commercial opportunity. In such cases, firms are good resource allocators because they can pick the winners in advance. However, given a context of industry dynamism and strong appropriability regime, forecasting future spread of an invention over technological classes should to be a nice ability to have.

We have limited our experiment to the nanobiotechnology industry. We cannot thus readily expand our findings to other industries which are dynamic and offer strong appropriability regimes. Future research directions can be to expand the results of this study through a larger sample that contains multiple industries.

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CHAPTER 7

GENERAL DISCUSSION

This thesis aimed at answering two sets of hypotheses. The first consisted in identifying the conditions that lead to the creation of basic innovations and the second was to identify the conditions under which innovators can appropriate returns from basic innovations. As we have seen in Chapter 2, a methodological challenge regarding the use of patent information for grouping technologically similar patents together needed to be answered. The following sections in this chapter will discuss the results of the findings with regards to these three areas of contribution.

7.1 Patent clustering

The results of the co-citation network clusterings show that patent citations can be used to group technologically similar patents together. Although irrelevant citations can be added by patent examiners or applicants, building a co-citation network does not result in a random graph. Furthermore, subtle differences between subfields within a larger field of expertise or a very large organization can be discerned. The technological relationship or proximity between these areas of competence can be represented either by projecting clusters from a dendrogram (Barirani et al., 2011) or by collapsing community patents co-citations between fields (Barirani et al., 2012a). Citation-based unsupervised learning techniques thus allow us to obtain refined knowledge about the application domains within an emerging industry in which continuous development are ultimately defined by the collective effort of the communities of practice and for which standard classification is not yet available. The view that the examination process leads to thorough citations to prior art is thus corroborated (Meyer, 2000b). Furthermore, even if some citations can be irrelevant, the phenomenon is not widespread to the point where co-citation networks become irrelevant for analytic purposes.

Analyzing trends in multiple progress indicators for different fields of expertise, such as the number of citations (both forward and backward), claims and non-patents references can also be used as a tool to assess the stage of development of an emerging industry for which commercial data other than patents are not readily available. Our analysis of the Canadian nanotechnology patents shows that innovative activities are concentrated in three major industries: nanobiotechnology, display technologies and optics. The first is a dynamic industry which appears to be in its early days. The other two industries are dominated by a few large players, and although the use of nanotechnology appears to be relatively novel, few new entrants appear to penetrate this industry.

7.2 Distant recombination

Another major finding of this thesis is to complement literature that associates distant recombination with innovation basicness (Fleming, 2001; Kim et al., 2012). If one admits that time pressure and short-term imperatives constraints autonomous opportunity seeking agents to prefer local search over distant recombination, then there could be a tendency for markets as a whole to neglect the production of basic innovations. Moreover, the results of this thesis shows that distant recombination performed by the private sector is positively associated with the innovation's spread in multiple disciplines. In other words, the task of producing basic innovations cannot be exclusively bestowed upon public institutions, as market orientation and industry relationships are essential for successful spread of innovations.

This thesis also underlines the inherent relationship between innovation and technology diffusion. Indeed, an invention can be a technological success but be a commercial failure if it is not adopted in the marketplace. Since commercial success depends on factors other than technological prowess, effort by public institutions in providing the industry with breakthrough technologies cannot be successful unless universities, and especially faculty, become more market oriented. Also, combining distant recombination with strong linkage with basic science appears to lead to innovations that do not spread over technological disciplines. In these cases, a new technology can be intrinsically important, but fail to have adequate adoption.

Finally, the findings of this thesis seem to support the idea that distant recombination yields basic innovations in emerging and dynamic industries such as nanobiotechnology. This is, to a certain degree, due to the fact that mature industries will concentrate on focused innovations. In such fields, where a few players are dominant, innovations are cumulative in nature. R&D effort will therefore be concentrated on incremental improvement of dominant designs. Introducing radically novel ways of doing things in such industries will not spread over technological classes.

These findings are supported by both OLS and Tobit models (see Tables 5.1 and 5.2). The latter model is useful given the mass of patents for which *BASICNESS* is equal to 0 (see

Figure B.1). The results, being equivalent in both models, seem to indicate that OLS is a good approximation model in our case.

7.3 Appropriability

The third contribution of this thesis is to bring empirical evidence regarding the capacity of innovators to appropriate returns from basic innovations under conditions of strong appropriability regimes and industry dynamism. The findings show that, under favorable market conditions, innovators perceive better opportunities to capture returns from basic innovations. Also, obsolescence rate appears to be slower for basic innovation as investors expect returns for longer periods from basic innovations.

This appreciation of basic innovation, however, depends on the sector of activity. Therefore, the postulate of transaction costs theory (Williamson and Masten, 1995) which expects all profit maximizing agents to allocate resources in similar fashion under such circumstances is not apparent. Private institutions tend to perceive higher returns for innovations that have proven to be useful in a multitude of industries, while public institutions perceive higher returns for innovations that will eventually spread over technological classes in the future. This finding is in line with the generally reported tendency for firms to fall to the propinquity trap. In other words, while they are in a better position to profit from basic innovations, they seem to prefer those that will serve in a focused technological area. However, when the spread of an innovation is clear, private firms attempt to seize the opportunity. These findings support the view in evolutionary economics which states that institutional routines are better predictors of firm behavior (Nelson and Winter, 1982).

CONCLUSION AND RECOMMENDATIONS

Synthesis

The findings in this thesis have important ramification with regard to the debate about increasing the entrepreneurial role of universities and call for a review of management practices within both the private and the public sectors as far as basic innovations are concerned. So far, the literature has associated technological exploration with higher probabilities of generating breakthroughs but also of failures (Fleming, 2001; Kim et al., 2012). However, the cases, or conditioned, under which failures and successes occur were not studied.

In the private sector, the general belief that distant recombination can lead to many failures appear to be unfounded in dynamic industries. In fact, in such industries, distant recombination performed by the private sector has a higher probability of producing basic innovations. This is mostly due to the fact that firms have access to complementary skills such as production and marketing know-how. However, these resources do not appear to be used efficiently, as basic innovations are mostly produced by public institutions. Moreover, firms are better able to appropriate returns from basic innovations, but only when their spread is obvious. In fact, the private sector seems to overlook innovations that will eventually be used in multiple disciplines in the future. These practices appear to be rooted in the routines that have been shaped through constant attempts to exploit knowledge with which firms are familiar. More than the general appropriation difficulty associated with basic research, this tendency, by the private sector to perform local search appears to be the major obstacle that impacts its capacity to produce as well as appropriating returns from basic innovations.

Need for changes in management practices are also apparent in the public sector. Here, the thesis will reach both proponents and opponents of the entrepreneurial universities (Henderson et al., 1998; Etzkowitz et al., 2000). First, the lack of commitment to commercial activities seems to disfavor attempts by public institutions to successfully transfer their innovations to the market. In fact, this incapacity to ultimately appropriate returns from basic innovations appears to do nothing more than block, for a while, the use of socially useful inventions developed by public institutions. Furthermore, breakthroughs resulting from distant recombination and strong linkage to basic science cannot be successful if current customer needs are not taken into account. This disconnect between market reality and research effort by public institutions appears to be the main obstacle to successful technology transfer. The lack of production and marketing capabilities also prevents public institutions from appropriating returns from innovations that have actually found adoption. This lack of market orientation appears to be very costly if one takes into account that public institutions have a great potential for producing breakthrough innovations.

This thesis also underlines the strong relationship between basic sciences and technological progress. As it is pointed out in the analysis of trends for multiple metrics, growth in patenting activity can be associated with sourcing in basic sciences. The views of evolutionary economics about the necessity of sourcing knowledge external from a stagnating industry (Nelson, 2004) are thus corroborated. Furthermore, the rational view (Williamson and Masten, 1995) that firms have incentives in investing in basic innovations under conditions of strong appropriability regimes and industry dynamism is nuanced. Indeed, institutional routines seem to have a great impact on how opportunities are perceived and resources are allocated.

Limitations

An inherent limit of this thesis is in the exclusive use of patent data to measure innovative activity. As we have seen, patents do not represent the whole spectrum of inventive activity and are not all valuable. Patents are therefore a proxy rather than a direct measure of innovative activity. The findings in this thesis must therefore be corroborated by other metrics (whether proxies or direct measures) before they can be used to implement innovation policy. Furthermore, other qualitative or survey-based methods can be used to complement (or refute) the findings in this thesis.

Another inherent limitation resides in the choice of lexical queries to obtain the population of Canadian nanotechnology patents. As we have discussed earlier, there isn't unanimous agreement among experts in the definition of a unique lexical query. While using keywords that have been used by more than one expert leads to the extraction of the core of nanotechnology patents Huang et al. (2011), the fact that nanotechnology is an emerging and evolving discipline could lead to biased extractions.

Patent citations' US classes are used to measure the degree of basicness and distant recombination when US classification is not hierarchically organized. Also, the lack of direct economic indicators (such as incomes associated with patents) is a major limitation to our research. Such data could shed more light about innovators' decision to renew or not a patent. However, even having access to such data would not answer the question of whether a basic patent has been dropped due to lack of income or simply lack of vision, as not renewing a patent always means that income can no longer be associated with the patent. In the regression models, the presence of outliers has not been taken into consideration. Eventual use of the Pearson residuals and the appropriateness of the link function using the generalized link function suggested by (Pregibon, 1981). Analysis of scatter-plots C.1 to C.3 shows that some observations could be regarded as outliers (see variables *CLAIMS*, *TEAMSIZE* and *SCOPE*). Omitting these observations gives similar results in terms of variable significance level and model explanatory power. Finally, the experiments in this thesis are limited to the nanotechnology industry and cannot readily expand our findings to other industries.

Another limitation to this thesis is the lack of control for endogeneity in the regression models. Industry and market structure can indeed influence renewal as well as prior art forward and backward citation practices simultaneously. Although the use of dummy and control variables (such as *NANOBIO*, *TEAMSIZE*, *SCOPE*) attempts to correct for this phenomenon, it is known that replacing omitted variables with proxies can lead to biased estimators. By not using instrumental variables, the question of endogeneity remains unanswered. As a result, estimators in the regression models must not be interpreted as signs of causality. Instead, estimators must be interpreted as signs of relationship or link between two variables.

A final limitation of this thesis resides in the weak explanatory power of the regression models. While this is understandable given that proxies are used, it is important to have in mind that variables that are found to be statistically significant could very well not be the main factors that can explain success. Further studies of threshold and marginal effects as well as fixed-effects analysis can be used to complement the methods used in the thesis.

Perspectives

This thesis falls within a larger research goal of inquiring whether the assumptions of the bounded rationality perspective imply an underinvestment in basic innovations. This objective requires measuring the aggregate value of basic innovations compared to incremental innovations. Such a task is difficult to perform due to many concerns, one being that basic and incremental innovations are interrelated. Given that the latter owes its existence to the former, the task of separating the value of one from the other is not obvious.

The study can also be extended by gathering information about the economic value and costs associated with a given patent. Doing so will allow to put a price tag on distant recombination, as well as the private returns for creating basic inventions. Such experiments will allow for a better understanding of the trade-offs between exploitation and exploration. By then moderating exploration with various factors both external and internal to the firm, it can be found whether innovators are net winners when they perform distant search.

From a methodological point of view, it should be noted that agglomerative hierarchical clustering is not well suited for partitioning citation networks of more than a few thousand patents. As a result, the use of high dimensional clustering techniques (Kailing et al., 2004; Agrawal et al., 2005) can be explored as an alternative method to modularity-based community detection algorithms. Furthermore, divisive hierarchical clustering techniques can be used as they often result in more balanced dendrograms for smaller number of clusters. Complete linkage for agglomerative clustering, in which the distance between two clusters is computed as the maximum distance between a pair of objects, can be considered as an alternative to single and average linkage methods. Also, external clustering evaluation methods, such as the Rand Index, can be used as an alternative method to measure clustering quality.

The results of community detection methods can be further visualized by coloring graph vertices according to the community to which they have been assigned. A colored version of Figure 4.1 is shown in Figure A.1 and can be viewed as an instance of such visualization. Also, multi-level modularity optimization algorithms can be further explored as they are better suited for very large graphs (more than one million vertices) and are less bound to the resolution limit associated with modularity (Blondel et al., 2008).

REFERENCES

Abernathy, W. J. and Utterback, J. (1978). Patterns of industrial innovation. *Technology Review*, 80(7):40–47.

Abraham, B. and Moitra, S. (2001). Innovation assessment through patent analysis. *Technovation*, 21(4):245–252.

Acs, Z. J. and Audretsch, D. B. (1989). Patents as a Measure of Innovative Activity. *Kyklos*, 42(2):171–80.

Adams, J. D. (1990). Fundamental Stocks of Knowledge and Productivity Growth. *Journal of Political Economy*, 98(4):673–702.

Adler, E. and Haas, P. (1992). Conclusion: Epistemic Communities, World Order, and the Creation of a Reflective Research Program. *International Organisation*, 46(1):367–390.

Agrawal, A., Cockburn, I., and McHale, J. (2006). Gone but not forgotten: Knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography*, 6(5):571–591.

Agrawal, A. and Henderson, R. (2002). Putting patents in context: Exploring knowledge transfer from MIT. *Management Science*, 48(1):44–60.

Agrawal, R., Gehrke, J., Gunopulos, D., and Raghavan, P. (2005). Automatic subspace clustering of high dimensional data. *Data Mining and Knowledge Discovery*, 11(1):5–33.

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly*, 45(3):425–455.

Ahuja, G. and Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, 22(3):197–220.

Ahuja, G. and Lampert, C. (2001). Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal*, 22(6-7):521–543.

Albayrak, Y. and Erensal, Y. (2009). Leveraging technological knowledge transfer by using fuzzy linear programming technique for multiattribute group decision making with fuzzy decision variables. *Journal of Intelligent Manufacturing*, 20(2):223–231.

Albert, M., Avery, D., Narin, F., and McAllister, P. (1991). Direct validation of citation counts as indicators of industrially important patents. *Research Policy*, 20(3):251–259.

Albert, R. and Barabási, A.-L. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics*, 74(1):47–97.

Alcácer, J. and Gittelman, M. (2006). Patent citations as a measure of knowledge flows: The influence of examiner citations. *Review of Economics and Statistics*, 88(4):774–779.

Alcácer, J., Gittelman, M., and Sampat, B. (2009). Applicant and examiner citations in U.S. patents: An overview and analysis. *Research Policy*, 38(2):415–427.

Alencar, M., Porter, A., and Antunes, A. (2007). Nanopatenting patterns in relation to product life cycle. *Technological Forecasting and Social Change*, 74(9):1661–1680.

Allison, J., Lemley, M., Moore, K., and Trunkey, R. (2004). Valuable patents. *Georgetown Law Journal*, 92(3):435–479.

Amin, A. and Cohendet, P. (2004). *Architectures of Knowledge: Firms, Capabilities, and Communities*. Oxford University Press, USA.

Anand, B. and Khanna, T. (2000). Do Firms Learn to Create Value? The Case of Alliances. *Strategic Management Journal*, 21(3):295–315.

Andersen, B. (1999). The hunt for S-shaped growth paths in technological innovation: a patent study. *Journal of Evolutionary Economics*, 9(4):487–526.

Andriessen, J., Veld, H., and Soekijad, M. (2004). Communities of Practice for Knowledge Sharing. In *How to manage experience sharing: From organizational surprises to organizational knowledge*, pages 173–194. Elsevier.

Archibugi, D. (1992). Patenting as an indicator of technological innovation: a review. *Science and Public Policy*, 19(6):357–368.

Archibugi, D. and Pianta, M. (1996). Measuring technological change through patents and innovation surveys. *Technovation*, 16(9):451–468.

Argyres, N. and Liebeskind, J. (1998). Privatizing the intellectual commons: Universities and the commercialization of biotechnology. *Journal of Economic Behavior and Organization*, 35(4):427–454.

Arora, A., David, P., and Gambardella, A. (1998). Reputation and Competence in Publicly Funded Science: Estimating the Effects on Research Group Productivity. *Annales d'économie et de statistique*, (49/50):163–198.

Arrow, K. (1962). Economic Welfare and the Allocation of Resources for Invention. In *The Rate and Direction of Inventive Activity: Economic and Social Factors*, pages 609–626. National Bureau of Economic Research, Inc.

Arthur, W. (1989). Competing Technologies, Increasing Returns, and Lock-In by Historical Events. *The Economic Journal*, 99(394):116–131.

Arthur, W. B. (2007). The structure of invention. *Research Policy*, 36(2):274–287.

Audretsch, D. (1998). Agglomeration and the location of innovative community. *Oxford Review of Economic Policy*, 14(2):18–29.

Audretsch, D. and Feldman, M. (1996). R&D Spillovers and the Geography of Innovation and Production. *American Economic Review*, 86(3):630–640.

Azagra-Caro, J., Mattsson, P., and Perruchas, F. (2011). Smoothing the lies: The distinctive effects of patent characteristics on examiner and applicant citations. *Journal of the American Society for Information Science and Technology*, 62(9):1727–1740.

Balconi, M., Breschi, S., and Lissoni, F. (2004). Networks of inventors and the role of academia: An exploration of Italian patent data. *Research Policy*, 33(1):127–145.

Baptista, R. and Swann, P. (1998). Do firms in clusters innovate more? *Research Policy*, 27(5):525–540.

Barabási, A.-L. and Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286(5439):509–512.

Barirani, A., Agard, B., and Beaudry, B. (2011). Competence maps using agglomerative hierarchical clustering. *Journal of Intelligent Manufacturing*. Available from: `http://dx.doi.org/10.1007/s10845-011-0600-y`.

Barirani, A., Agard, B., and Beaudry, C. (2012a). Discovering and assessing fields of expertise in nanomedicine: a patent co-citation network perspective. *Scientometrics*. Available from: `http://dx.doi.org/10.1007/s11192-012-0891-6`.

Barirani, A., Beaudry, C., and Agard, B. (2012b). Distant Recombination and the Creation of Basic Innovations. *under review at Technovation*.

Barirani, A., Beaudry, C., and Agard, B. (2012c). What Happens to Basic Innovations? The Paradox of Technology Exit Under Conditions of Strong Appropriability Regimes and Industry Dynamism. *under review at Research Policy*.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17:99–120.

Basberg, B. (1987). Patents and the measurement of technological change: A survey of the literature. *Research Policy*, 16(2-4):131–141.

Bassecoulard, E., Lelu, A., and Zitt, M. (2007). Mapping nanosciences by citation flows: A preliminary analysis. *Scientometrics*, 70(3):859–880.

Beaudry, C. and Breschi, S. (2003). Are firms in clusters really more innovative. *Economics of Innovation and New Technology*, 12(4):325–342.

Beaudry, C. and Schiffauerova, A. (2008). Interaction between geographical and technological spaces of collaboration : The gatekeepers of Canadian biotechnology clusters. In *Annual DRUID Conference*.

Beaudry, C. and Schiffauerova, A. (2009). Who's right, Marshall or Jacobs? The localisation versus urbanisation debate. *Research Policy*, 38(2):318–337.

Bernstein, J. I. and Nadiri, M. I. (1989). Research and Development and Intra-industry Spillovers: An Empirical Application of Dynamic Duality. *Review of Economic Studies*, 56(2):249–67.

Berry, M. and Linoff, G. (2004). *Data Mining Techniques: For Marketing, Sales, and Customer Relationship Management*. John Wiley & Sons.

Bessen, J. (2008). The value of U.S. patents by owner and patent characteristics. *Research Policy*, 37(5):932–945.

Blondel, V., Guillaume, J., Lambiotte, R., and Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10):P10008.

Bogenrieder, I. and Nooteboom, B. (2004). Learning groups: What types are there? A theoretical analysis and an empirical study in a consultancy firm. *Organization Studies*, 25(2):287–313.

Boschma, R. (2005). Proximity and Innovation: A Critical Assessment. *Regional Studies*, 39(1):61–74.

Boschma, R. and ter Wal, A. (2007). Knowledge networks and innovative performance in an industrial district: The case of a footwear district in the South of Italy. *Industry and Innovation*, 14(2):177–199.

Bowles, S. and Gintis, H. (2002). Social Capital And Community Governance. *The Economic Journal*, 112(483):F419–F436.

Breitzman, A. (2005). Automated identification of technologically similar organizations. *Journal of the American Society for Information Science and Technology*, 56(10):1015–1023.

Breitzman, A. and Mogee, M. (2002). The many applications of patent analysis. *Journal of Information Science*, 28(3):187–205.

Breschi, S. and Catalini, C. (2010). Tracing the links between science and technology: An exploratory analysis of scientists' and inventors' networks. *Research Policy*, 39(1):14–26.

Breschi, S. and Lissoni, F. (2003). Mobility and Social Networks: Localised Knowledge Spillovers Revisited. Working Papers 142, Centre for Knowledge, Internationalization and Technology Studies, Universita' Bocconi, Milano, Italy.

Breschi, S., Lissoni, F., and Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. *Research Policy*, 32(1):69–87.

Bresnahan, T., Gambardella, A., and Saxenian, A. (2001). 'Old economy' inputs for 'new economy' outcomes: Cluster formation in the New Silicon Valley. *Industrial and Corporate Change*, 10(4):835–860.

Brown, J. and Duguid, P. (1991). Organizational Learning and Communities of Practice: Toward a Unified View of Working - Learning and Innovation. *Organization Science*, 2(1):40–57.

Burgelman, R., Christensen, C., and Wheelwright, S. (2008). *Strategic Management of Technology and Innovation*. McGraw-Hill Irwin.

Burt, R. (1992). *Structural Holes: The Social Structure of Competition*. Harvard University Press.

Burt, R. (2004). Structural holes and good ideas. *American Journal of Sociology*, 110(2):349–399.

Burt, R. S. (2001). Structural Holes versus Network Closure as Social Capital. In *Social Capital: Theory and Research*. Gruyter.

Börner, K., Chen, C., and Boyack, K. (2003). Visualizing knowledge domains. *Annual Review of Information Science and Technology*, 37:179–255.

Callaert, J., Van Looy, B., Verbeek, A., Debackere, K., and Thijs, B. (2006). Traces of prior art: An analysis of non-patent references found in patent documents. *Scientometrics*, 69(1):3–20.

Cantner, U. and Graf, H. (2006). The network of innovators in Jena: An application of social network analysis. *Research Policy*, 35(4):463–480.

Carpenter, M., Narin, F., and Wolf, P. (1981). Citation rates to technologically important patents. *World Patent Information*, 3(4):160–163.

Chan, L., Lakonishok, J., and Sougiannis, T. (2001). The Stock Market Valuation of Research and Development Expenditure. *The Journal of Finance*, 56(6):2431–2456.

Chan, S., Kensinger, J., Keown, A., and D., M. (1997). Do strategic alliances create value? *Journal of Financial Economics*, 46(2):199–221.

Chang, C. and Breitzman, A. (2009). Using patents prospectively to identify emerging, high-impact technological clusters. *Research Evaluation*, 18(5):357–364.

Chang, P.-L., Wu, C.-C., and Leu, H.-J. (2010). Using patent analyses to monitor the technological trends in an emerging field of technology: A case of carbon nanotube field emission display. *Scientometrics*, 82(1):5–19.

Chen, C. and Hicks, D. (2004). Tracing knowledge diffusion. *Scientometrics*, 59(2):199–211.

Chen, Y., Zhang, G., Hu, D., and Fu, C. (2007). Customer segmentation based on survival character. *Journal of Intelligent Manufacturing*, 18(4):513–517.

Cheng, Y.-H., Kuan, F.-Y., Chuang, S.-C., and Ken, Y. (2010). Profitability decided by patent quality? An empirical study of the U.S. semiconductor industry. *Scientometrics*, 82(1):175–183.

Chesbrough, H. (2006). *Open Innovation: The New Imperative for Creating And Profiting from Technology*. Harvard Business Press.

Chiaroni, D., Chiesa, V., Massis, A. D., and Frattini, F. (2008). The knowledge-bridging role of Technical and Scientific Services in knowledge-intensive industries. *International Journal of Technology Management*, 41(3/4):249–272.

Choudhary, A., Harding, J., and Tiwari, M. (2009). Data mining in manufacturing: A review based on the kind of knowledge. *Journal of Intelligent Manufacturing*, 20(5):501–521.

Christensen, C. (1997). *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*. Harvard Business Press.

Christensen, C. and Rosenbloom, R. (1995). Explaining the attacker's advantage: Technological paradigms, organizational dynamics, and the value network. *Research Policy*, 24(2):233–257.

Chryssolouris, G., Mavrikios, D., Xeromerites, S., and Georgoulias, K. (2008). The Use of Conceptual Maps for Competencies Mapping and Knowledge Formalization in a Virtual Lab. In Bernard, A. and Tichkiewitch, S., editors, *Methods and Tools for Effective Knowledge Life-Cycle-Management*, pages 213–225. Springer Berlin Heidelberg.

Clauset, A., Newman, M., and Moore, C. (2004). Finding community structure in very large networks. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, 70(6 2):066111/1–066111/6.

Cockburn, I., Henderson, R., and Stern, S. (2000). Untangling the origins of competitive advantage. *Strategic Management Journal*, 21(10-11):1123–1145.

Cockburn, I. M., Kortum, S., and Stern, S. (2002). Are All Patent Examiners Equal? The Impact of Examiner Characteristics. Working Paper 8980, National Bureau of Economic Research.

CodePlex (2011). CodePlex. Available from: `http://nodexl.codeplex.com`.

Cohen, W., Florida, R., Randazzese, L., and Walsh, J. (2001). Industry and the academy: uneasy partners in the cause of technological advance. In *Challenges to Research Universities*. Brookings Institute.

Cohen, W., Nelson, R., and Walsh, J. (2002). Links and impacts: The influence of public research on industrial R&D. *Management Science*, 48(1):1–23.

Cohen, W. M. and Levinthal, D. A. (1989). Innovation and Learning: The Two Faces of R&D. *Economic Journal*, 99(397):569–96.

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: a new perspective on learning and innovation. *Administrative Sciences Quarterly*, 35(1):128–152.

Cohen, W. M., Nelson, R. R., and Walsh, J. P. (2000). Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not). NBER Working Papers 7552, National Bureau of Economic Research, Inc.

Colyvas, J., Crow, M., Gelijns, A., Mazzoleni, R., Nelson, R., Rosenberg, N., and Sampat, B. (2002). How do university inventions get into practice? *Management Science*, 48(1):61–72.

Cowan, R., David, P., and Foray, D. (2000). The Explicit Economics of Knowledge Codification and Tacitness. *Industrial and Corporate Change*, 9(2):211–253.

Cowan, R. and Foray, D. (1997). The economics of codification and the diffusion of knowledge. *Industrial and Corporate Change*, 6(3):595–622.

Cowan, R. and Jonard, N. (2003). The dynamics of collective invention. *Journal of Economic Behavior and Organization*, 52(4):513–532.

Cowan, R. and Jonard, N. (2004). Network structure and the diffusion of knowledge. *Journal of Economic Dynamics and Control*, 28(8):1557–1575.

Criscuolo, P. and Verspagen, B. (2008). Does it matter where patent citations come from? Inventor vs. examiner citations in European patents. *Research Policy*, 37(10):1892–1908.

Czarnitzki, D., Hussinger, K., and Schneider, C. (2011). Commercializing academic research: the quality of faculty patenting. *Industrial and Corporate Change*, 20(5):1403–1437.

Dahlin, K. and Behrens, D. (2005). When is an invention really radical? Defining and measuring technological radicalness. *Research Policy*, 34(5):717–737.

Daim, T., Rueda, G., Martin, H., and Gerdsri, P. (2006). Forecasting emerging technologies: Use of bibliometrics and patent analysis. *Technological Forecasting and Social Change*, 73(8):981–1012.

Dang, Y., Zhang, Y., Fan, L., Chen, H., and Roco, M. (2010). Trends in worldwide nanotechnology patent applications: 1991 to 2008. *Journal of Nanoparticle Research*, 12(3):687–706.

Das, S., Sen, P., and Sengupta, S. (1998). Impact of strategic alliances on firm valuation. *Academy of Management Journal*, 41(1):27–41.

Dasgupta, P. and David, P. (1994). Toward a new economics of science. *Research Policy*, 23(5):487–521.

David, P. (1985). Clio and the Economics of QWERTY. *American Economic Review*, 75(2):332–37.

David, P. and Foray, D. (2002). An introduction to the economy of the knowledge society. *International social science journal*, 54(171):9–23.

David, P., Hall, B., and Toole, A. (2000). Is public R&D a complement or substitute for private R&D? a review of the econometric evidence. *Research Policy*, 29(4-5):497–529.

Debackere, K. and Veugelers, R. (2005). The role of academic technology transfer organizations in improving industry science links. *Research Policy*, 34(3):321–342.

Dechenaux, E., Goldfarb, B., Shane, S., and Thursby, M. (2008). Appropriability and commercialization: Evidence from MIT inventions. *Management Science*, 54(5):893–906.

Deng, Z., Lev, B., and Narin, F. (1999). Science and Technology as Predictors of Stock Performance. *Financial Analysts Journal*, 55(3):20–32.

Duflou, J. and Verhaegen, P.-A. (2011). Systematic innovation through patent based product aspect analysis. *CIRP Annals - Manufacturing Technology*, 60(1):203–206.

Duranton, G. and Puga, D. (2000). Diversity and Specialisation in Cities: Why, Where and When Does it Matter? *Urban Studies*, 37(3):533–555.

Easterby-Smith, M., Lyles, M., and Tsang, E. (2008). Inter-organizational knowledge transfer: Current themes and future prospects. *Journal of Management Studies*, 45(4):677–690.

Eisenhardt, K. and Martin, J. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, 21(10-11):1105–1121.

Ejermo, O. and Karlsson, C. (2006). Interregional inventor networks as studied by patent coinventorships. *Research Policy*, 35(3):412–430.

ESF (2005). Nanomedicine. Technical report, Europeen Science Foundation.

Etzkowitz, H. and Leydesdorff, L. (2000). The dynamics of innovation: From National Systems and "mode 2" to a Triple Helix of university-industry-government relations. *Research Policy*, 29(2):109–123.

Etzkowitz, H., Webster, A., Gebhardt, C., and Terra, B. (2000). The future of the university and the university of the future: Evolution of ivory tower to entrepreneurial paradigm. *Research Policy*, 29(2):313–330.

Fabrizio, K. (2007). University patenting and the pace of industrial innovation. *Industrial and Corporate Change*, 16(4):505–534.

Fang, C., Lee, J., and Schilling, M. (2010). Balancing exploration and exploitation through structural design: The isolation of subgroups and organizational learning. *Organization Science*, 21(3):625–642.

Feldman, M. (1994). Knowledge complementarity and innovation. *Small Business Economics*, 6(5):363–372.

Felin, T. and Hesterly, W. (2007). The knowledge-based view, nested heterogeneity, and new value creation: Philosophical considerations on the locus of knowledge. *Academy of Management Review*, 32(1):195–218.

Ferrary, M. and Pesqueux, Y. Y. (2006). *Management de la connaissance*. economica.

Fitzgibbons, K. and McNiven, C. (2006). Towards a nanotechnology statistical framework. In *Blue sky indicators conference II*.

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science*, 47(1):117–132.

Fleming, L. (2007). Breakthroughs and the "long tail" of innovation. *MIT Sloan Management Review*, 49(1):69–74+93.

Fleming, L. and Sorenson, O. (2001). Technology as a complex adaptive system: Evidence from patent data. *Research Policy*, 30(7):1019–1039.

Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, 486(3-5):75–174.

Freitas Jr., R. (2005). What is nanomedicine? *Nanomedicine: Nanotechnology, Biology, and Medicine*, 1(1):2–9.

Fung, M. and Chow, W. (2002). Measuring the intensity of knowledge flow with patent statistics. *Economics Letters*, 74(3):353–358.

Furman, J. L. and MacGarvie, M. J. (2007). Academic science and the birth of industrial research laboratories in the U.S. pharmaceutical industry. *Journal of Economic Behavior & Organization*, 63(4):756–776.

Furukawa, R. and Goto, A. (2006). The role of corporate scientists in innovation. *Research Policy*, 35(1):24–36.

Gallini, N. (2002). The economics of patents: Lessons from recent U.S. patent reform. *Journal of Economic Perspectives*, 16(2):131–154.

Gaur, A., Malhotra, S., and Zhu, P. (2012). Acquisition announcements and stock market valuations of acquiring firms' rivals: A test of the growth probability hypothesis in china. *Strategic Management Journal*.

Geroski, P. (2000). Models of technology diffusion. *Research Policy*, 29(4-5):603–625.

Gertler, M. (2003). Tacit knowledge and the economic geography of context, or The undefinable tacitness of being (there). *Journal of Economic Geography*, 3(1):75–99.

Girvan, M. and Newman, M. (2002). Community structure in social and biological networks. *Proceedings of the National Academy of Sciences of the United States of America*, 99(12):7821–7826.

Goerzen, A. (2007). Alliance networks and firm performance: The impact of repeated partnerships. *Strategic Management Journal*, 28(5):487–509.

Google (2011). GoogleBlog. Available from: `http://googleblog.blogspot.com/2011/04/patentsand-innovation.html`.

Gordon, R. (1999). US economic growth since 1870: one big wave? *The American Economic Review*, 89(2):123–128.

Gordon, R. J. (2000). Does the "New Economy" Measure up to the Great Inventions of the Past? *The Journal of Economic Perspectives*, 14(4):49–74.

Gordon, R. J. (2012). Is U.S. Economic Growth Over: Faltering Innovation Confronts the Six Headwinds. *NBER Working Papers 18315*.

Granovetter, M. (1973). The Strength of Weak Ties. *American Journal of Sociology*, 78(6):1360–1380.

Grant, R. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17(SUPPL. WINTER):109–122.

Grieneisen, M. (2010). The proliferation of nano journals. *Nature Nanotechnology*, 5(12):825.

Griliches, Z. (1958). Research costs and social returns: hybrid cordn and related innovations. *Journal of Political Economy*, 66(5):419–431.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics*, 10(1):92–116.

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, 28(4):1661–1707.

Hall, B., Jaffe, A., and Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics*, 36(1):16–38.

Hall, B. and Ziedonis, R. (2001). The patent paradox revisited: An empirical study of patenting in the U.S. semiconductor industry, 1979-1995. *RAND Journal of Economics*, 32(1):101–128.

Hall, B. H. (1999). Innovation and Market Value. Working Paper 6984, National Bureau of Economic Research.

Hansen, M. (1999). The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly*, 44(1):82–111.

Harel, D. and Koren, Y. (2002). Graph Drawing by High-Dimensional Embedding. In *Proceedings of the 10th International Symposium on Graph Drawing*, pages 207–219. Springer-Verlag.

Hargadon, A. and Sutton, R. (1997). Technology brokering and innovation in a product development firm. *Administrative Science Quarterly*, 42(4):716–749.

Harhoff, D., Narin, F., Scherer, F., and Vopel, K. (1999). Citation frequency and the value of patented inventions. *Review of Economics and Statistics*, 81(3):511–515.

Hegde, D. and Sampat, B. (2009). Examiner citations, applicant citations, and the private value of patents. *Economics Letters*, 105(3):287–289.

Heller, M. and Eisenberg, R. (1998). Can patents deter innovation? The anticommons in biomedical research. *Science*, 280(5364):698–701.

Henderson, R. and Clark, K. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, 35(1):9–30.

Henderson, R., Jaffe, A., and Trajtenberg, M. (1998). Universities as a source of commercial technology: A detailed analysis of university Patenting, 1965-1988. *Review of Economics and Statistics*, 80(1):119–127.

Hernández-Espallardo, M., Sánchez-Pérez, M., and Segovia-López, C. (2011). Exploitation- and exploration-based innovations: The role of knowledge in inter-firm relationships with distributors. *Technovation*, 31(5-6):203–215.

Hsu, C., Babin, G., Bouziane, M., Cheung, W., Rattner, L., Rubenstein, A., and Yee, L. (1994). The metadatabase approach to integrating and managing manufacturing information systems. *Journal of Intelligent Manufacturing*, 5(5):333–349.

Huang, C., Notten, A., and Rasters, N. (2011). Nanoscience and technology publications and patents: A review of social science studies and search strategies. *Journal of Technology Transfer*, 36(2):145–172.

Huang, Z., Chen, H., Yip, A., Ng, G., Guo, F., Chen, Z.-K., Roco, M. C., kai Chen, Z., and Roco, M. C. (2003). Longitudinal Patent Analysis for Nanoscale Science and Engineering: Country, Institution and Techonlogy Field. *Journal of Nanoparticle Research*, 5:333–363.

Hullmann, A. (2006). Who is winning the global nanorace? *Nature nanotechnology*, 1(2):81–83.

Hullmann, A. and Meyer, M. (2003). Publications and patents in nanotechnology: An overview of previous studies and the state of the art. *Scientometrics*, 58(3):507–527.

Jaffe, A. (1989). Real Effects of Academic Research. *American Economic Review*, 79(5):957–70.

Jaffe, A. (1998). The importance of “spillovers” in the policy mission of the Advanced Technology Program. *Journal of Technology Transfer*, 23(2):11–19.

Jaffe, A. (2000). The U.S. patent system in transition: Policy innovation and the innovation process. *Research Policy*, 29(4-5):531–557.

Jaffe, A., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108(3):577–598.

Jehn, K., Northcraft, G., and Neale, M. (1999). Why Differences Make a Difference: A Field Study of Diversity, Conflict, and Performance in Workgroups. *Administrative Science Quarterly*, 44(4):741–763.

Jensen, R. and Thursby, M. (2001). Proofs and prototypes for sale: The licensing of University inventions. *American Economic Review*, 91(1):240–259.

Kailing, K., Kriegel, H., and Kröger, P. (2004). Density-connected subspace clustering for high-dimensional data. In *Proceedings of the Fourth SIAM International Conference on Data Mining (SIAM)*, volume 4.

Kale, P., Dyer, J., and Singh, H. (2002). Alliance capability, stock market response, and long-term alliance success: The role of the alliance function. *Strategic Management Journal*, 23(8):747–767.

Kang, K. and Kang, J. (2009). How Do Firms Source External Knowledge For Innovation? Analysing Effects Of Different Knowledge Sourcing Methods. *International Journal of Innovation Management*, 13(1):1–17.

Katila, R. and Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, 45(6):1183–1194.

Kim, C., Song, J., and Nerkar, A. (2012). Learning and innovation: Exploitation and exploration trade-offs. *Journal of Business Research*, 65(8):1189–1194.

Kim, Y. G., Suh, J. H., and Park, S. C. (2008). Visualization of patent analysis for emerging technology. *Expert Systems with Applications*, 34(3):1804–1812.

Klepper, S. (1996). Entry, Exit, Growth, and Innovation over the Product Life Cycle. *American Economic Review*, 86(3):562–583.

Klepper, S. (1997). Industry life cycles. *Industrial and Corporate Change*, 6(1):145–181.

Kogut, B. and Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science*, 3(3):383–397.

Kogut, B. and Zander, U. (1996). What Firms Do? Coordination, Identity, and Learning. *Organization Science*, 7(5):502–518.

Kostoff, R., Koytcheff, R., and Lau, C. (2007). Global nanotechnology research metrics. *Scientometrics*, 70(3):565–601.

Krugman, P. (1991). Increasing Returns and Economic Geography. *Journal of Political Economy*, 99(3):483–499.

Lanjouw, J., Pakes, A., and Putnam, J. (1998). How to count patents and value intellectual property: The uses of patent renewal and application data. *Journal of Industrial Economics*, 46(4):405–432.

Lanjouw, J. and Schankerman, M. (2004a). Patent quality and research productivity: Measuring innovation with multiple indicators. *Economic Journal*, 114(495):441–465.

Lanjouw, J. and Schankerman, M. (2004b). Protecting intellectual property rights: Are small firms handicapped? *Journal of Law and Economics*, 47(1):45–74.

Lemley, M. and Shapiro, C. (2005). Probabilistic patents. *Journal of Economic Perspectives*, 19(2):75–98.

Lerner, J. (1994). The Importance of Patent Scope: An Empirical Analysis. *The RAND Journal of Economics*, 25(2):319–333.

Levin, R. C., Klevorick, A. K., Nelson, R. R., and Winter, S. G. (1987). Appropriating the Returns from Industrial Research and Development. *Brookings Papers on Economic Activity*, 18(3):783–832.

Levinthal, D. A. and March, J. G. (1993). The myopia of learning. *Strategic Management Journal*, 14(S2):95–112.

Levitt, B. and March, J. (1988). Organizational Learning. *Annual Review of Sociology*, 14:319–340.

Leydesdorff, L. (2008). Patent classifications as indicators of intellectual organization. *Journal of the American Society for Information Science and Technology*, 59(10):1582–1597.

Li, X., Chen, H., Huang, Z., and Roco, M. (2007a). Patent citation network in nanotechnology (1976-2004). *Journal of Nanoparticle Research*, 9(3):337–352.

Li, X., Chen, H., Zhang, Z., and Li, J. (2007b). Automatic patent classification using citation network information: An experimental study in nanotechnology. In *Proceedings of the ACM International Conference on Digital Libraries*, pages 419–427.

Li, X., Hu, D., Dang, Y., Chen, H., Roco, M., Larson, C., and Chan, J. (2009). Nano Mapper: An Internet knowledge mapping system for nanotechnology development. *Journal of Nanoparticle Research*, 11(3):529–552.

Li, X., Lin, Y., Chen, H., and Roco, M. (2007c). Worldwide nanotechnology development: A comparative study of USPTO, EPO, and JPO patents (1976-2004). *Journal of Nanoparticle Research*, 9(6):977–1002.

Lo, C.-C., Wang, C.-H., Chien, P.-Y., and Hung, C.-W. (2012). An empirical study of commercialization performance on nanoproducts. *Technovation*, 32(3-4):168–178.

Lockett, A., Wright, M., and Franklin, S. (2003). Technology Transfer and Universities' Spin-Out Strategies. *Small Business Economics*, 20(2):185–200.

Lundvall, B. (1992). *National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning*. Frances Pinter.

Lundvall, B. and Johnson, B. (1994). The learning economy. *Journal of industry studies*, 1(2):23–42.

Lynn, L., Reddy, N., and Aram, J. (1996). Linking technology and institutions: The innovation community framework. *Research Policy*, 25(1):91–106.

Maghrebi, M., Abbasi, A., Amiri, S., Monsefi, R., and Harati, A. (2011). A collective and abridged lexical query for delineation of nanotechnology publications. *Scientometrics*, 86(1):15–25.

Malakooti, B. and Raman, V. (2000). Clustering and selection of multiple criteria alternatives using unsupervised and supervised neural networks. *Journal of Intelligent Manufacturing*, 11(5):435–451.

Malerba, F. and Orsenigo, L. (1995). Schumpeterian patterns of innovation. *Cambridge Journal of Economics*, 19(1):47–65.

Malerba, F. and Orsenigo, L. (1996). Schumpeterian patterns of innovation are technology-specific. *Research Policy*, 25(3):451–478.

Malerba, F. and Orsenigo, L. (1997). Technological regimes and sectoral patterns of innovative activities. *Industrial and Corporate Change*, 6(1):83–117.

Malmberg, A. and Maskell, P. (2002). The elusive concept of localization economies: towards a knowledge-based theory of spatial clustering. *Environment and Planning A*, 34(3):429–449.

Manning, C., Raghavan, P., and Schütze, H. (2008). *Introduction to Information Retrieval*. Cambridge University Press.

March, J. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2(1):71–87.

March, J. and Simon, H. (1958). *Organizations*. Wiley.

Marshall, A. (1890). *Principles of Economics*. Macmillan and Company.

Martin, B. (1995). Foresight in science and technology. *Technology Analysis & Strategic Management*, 7(2):139–168.

Maskell, P. and Malmberg, A. (1999). Localised learning and industrial competitiveness. *Cambridge Journal of Economics*, 23(2):167–185.

Matlab (2009). Matlab. Available from: `http://www.mathworks.com/products/matlab/`.

Mazzoleni, R. and Nelson, R. (1998). The benefits and costs of strong patent protection: A contribution to the current debate. *Research Policy*, 27(3):273–284.

McDonough III, J. F. (2006). The Myth of the Patent Troll: An Alternative View of the Function of Patent Dealers in an Idea Economy. *Emory Law Journal*, 56:189–228.

McGrath, R. (2001). Exploratory learning, innovative capacity, and managerial oversight. *Academy of Management Journal*, 44(1):118–131.

Mensch, G. (1979). *Stalemate in technology: innovations overcome the depression*. Ballinger Pub. Co.

Merges, R. and Nelson, R. (1990). On the Complex Economics of Patent Scope. *Columbia Law Review*, 90(4):839–916.

Meyer, M. (2000a). Patent citations in a novel field of technology - What can they tell about interactions between emerging communities of science and technology? *Scientometrics*, 48(2):151–178.

Meyer, M. (2000b). What is special about patent citations? differences between scientific and patent citations. *Scientometrics*, 49(1):93–123.

Meyer, M. and Persson, O. (1998). Nanotechnology - Interdisciplinarity, patterns of collaboration and differences in application. *Scientometrics*, 42(2):195–205.

Meyer, P. (1994). Bi-logistic growth. *Technological Forecasting and Social Change*, 47(1):89–102.

Mogoutov, A. and Kahane, B. (2007). Data search strategy for science and technology emergence: A scalable and evolutionary query for nanotechnology tracking. *Research Policy*, 36(6):893–903.

Mokyr, J. (1990). Punctuated Equilibria and Technological Progress. *American Economic Review*, 80(2):350–354.

Moore, K. A. (2005). Worthless Patents. *Berkeley Technology Law Journal*, 20(4):1521–1552.

Morone, P. and Taylor, R. (2004). Knowledge diffusion dynamics and network properties of face-to-face interactions. *Journal of Evolutionary Economics*, 14(3):327–351.

Morrison, A. (2008). Gatekeepers of knowledge within industrial districts: Who they are, how they interact. *Regional Studies*, 42(6):817–835.

Mowery, D., Nelson, R., Sampat, B., and Ziedonis, A. (2001). The growth of patenting and licensing by U.S. universities: An assessment of the effects of the Bayh-Dole act of 1980. *Research Policy*, 30(1):99–119.

Mowery, D. and Rosenberg, N. (1999). *Paths of Innovation: Technological Change in 20th-Century America*. Cambridge University Press.

Mowery, D., Sampat, B., and Ziedonis, A. (2002). Learning to patent: Institutional experience, learning, and the characteristics of U.S. University patents after the Bayh-Dole Act, 1981-1992. *Management Science*, 48(1):73–89.

Mowery, D. C. (1998). The changing structure of the US national innovation system: implications for international conflict and cooperation in R&D policy. *Research Policy*, 27(6):639–654.

Mowery, D. C. and Ziedonis, A. A. (2002). Academic patent quality and quantity before and after the Bayh-Dole act in the United States. *Research Policy*, 31(3):399–418.

Murray, F. (2002). Innovation as co-evolution of scientific and technological networks: Exploring tissue engineering. *Research Policy*, 31(8-9):1389–1403.

Murray, F. and Stern, S. (2007). Do formal intellectual property rights hinder the free flow of scientific knowledge?: An empirical test of the anti-commons hypothesis. *Journal of Economic Behavior & Organization*, 63(4):648–687.

Nahapiet, J. and Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *Academy of Management Review*, 23(2):242–266.

Narin, F. (1994). Patent bibliometrics. *Scientometrics*, 30(1):147–155.

Narin, F. and Hamilton, K. (1996). Bibliometric performance measures. *Scientometrics*, 36(3):293–310.

Narin, F., Hamilton, K., and Olivastro, D. (1997). The increasing linkage between U.S. technology and public science. *Research Policy*, 26(3):317–330.

Nelson, R. (2004). The market economy, and the scientific commons. *Research Policy*, 33(3):455–471.

Nelson, R. and Winter, S. (1982). *An Evolutionary Theory of Economic Change*. Belknap Press of Harvard University Press.

Nemet, G. and Johnson, E. (2012). Do important inventions benefit from knowledge originating in other technological domains? *Research Policy*, 41(1):190–200.

Nerkar, A. and Shane, S. (2007). Determinants of invention commercialization: An empirical examination of academically sourced inventions. *Strategic Management Journal*, 28(11):1155–1166.

Nesta, L. and Saviotti, P. P. (2005). Coherence of the Knowledge Base and the Firm's Innovative Performance: Evidence from the U.S. Pharmaceutical Industry. *Journal of Industrial Economics*, 53(1):123–142.

Neter, J., Wasserman, W., and Kutner, M. (1985). *Applied linear statistical models: regression, analysis of variance, and experimental designs*. R.D. Irwin.

Newman, M. and Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, 69(2 2):026113–1–026113–15.

Newman, M. E. J. (2003). The structure and function of complex networks. *SIAM REVIEW*, 45:167–256.

Nieto, M. and Santamaría, L. (2007). The importance of diverse collaborative networks for the novelty of product innovation. *Technovation*, 27(6-7):367–377.

Nonaka, I. and Takeuchi, H. (1995). *The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation*. Oxford University Press, USA.

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., and van den Oord, A. (2007). Optimal cognitive distance and absorptive capacity. *Research Policy*, 36(7):1016–1034.

Noyons, E., for Science, L. U. C., Studies, T., ISI., F., and Commission, E. (2003). *Mapping Excellence in Science and Technology Across Europe: Nanoscience and Nanotechnology : Final Report*. Centre for Science and Technology Studies, Leiden University.

O'Connor, G. and Veryzer, R. (2001). The nature of market visioning for technology-based radical innovation. *Journal of Product Innovation Management*, 18(4):231–246.

Owen-Smith, J. and Powell, W. (2003). The expanding role of university patenting in the life sciences: Assessing the importance of experience and connectivity. *Research Policy*, 32(9):1695–1711.

Owen-Smith, J. and Powell, W. (2004). Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community. *Organization Science*, 15(1):5–21.

Pakes, A. and Schankerman, M. (1984). The Rate of Obsolescence of Patents, Research Gestation Lags, and the Private Rate of Return to Research Resources. In *R & D, Patents, and Productivity*, pages 73–88. National Bureau of Economic Research, Inc.

Pavitt, K. (1985). Patent statistics as indicators of innovative activities: Possibilities and problems. *Scientometrics*, 7(1-2):77–99.

Pei, R. and Porter, A. (2011). Profiling leading scientists in nanobiomedical science: Interdisciplinarity and potential leading indicators of research directions. *R and D Management*, 41(3):288–306.

Penin, J. (2005). Patents versus ex post rewards: A new look. *Research Policy*, 34(5):641–656.

Penner-Hahn, J. and Shaver, J. (2005). Does international research and development increase patent output? An analysis of Japanese pharmaceutical firms. *Strategic Management Journal*, 26(2):121–140.

Perkel, J. (2004). The ups and downs of nanobiotech. *Scientist*, 18(16):14–18.

Podolny, J., Stuart, T., and Hannan, M. (1996). Networks, knowledge, and niches: Competition in the worldwide semiconductor industry, 1984-1991. *American Journal of Sociology*, 102(3):659–689.

Porter, A., Youtie, J., Shapira, P., and Schoeneck, D. (2008). Refining search terms for nanotechnology. *Journal of Nanoparticle Research*, 10(5):715–728.

Powell, W., Koput, K., and Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly*, 41(1):116–145.

Powell, W. and Snellman, K. (2004). The knowledge economy. *Annual review of sociology*, pages 199–220.

Prahalad, C. K. and Hamel, G. (1990). The Core Competence of the Corporation. *Harvard Business Review*, 68(3):79–91.

Pregibon, D. (1981). Logistic regression diagnostics. *The Annals of Statistics*, 9(4):705–724.

Rapid-I (2011). Rapid-I. Available from: `http://rapid-i.com`.

Reagans, R. and Zuckerman, E. (2001). Networks, Diversity, and Productivity: The Social Capital of Corporate R&D Teams. *Organization Science*, 12(4):502–517.

Reitzig, M., Henkel, J., and Heath, C. (2007). On sharks, trolls, and their patent prey-Unrealistic damage awards and firms' strategies of "being infringed". *Research Policy*, 36(1):134–154.

Rosenberg, N. (1990). Why do firms do basic research (with their own money)? *Research Policy*, 19(2):165–174.

Rosenberg, N. (1994). *Exploring the Black Box: Technology, Economics, and History.* Cambridge University Press.

Rosenkopf, L. and Nerkar, A. (2001). Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*, 22(4):287–306.

Sainio, L.-M., Ritala, P., and Hurmelinna-Laukkanen, P. (2012). Constituents of radical innovation - Exploring the role of strategic orientations and market uncertainty. *Technovation*, 32(11):591–599.

Sammarra, A. and Biggiero, L. (2008). Heterogeneity and specificity of inter-firm knowledge flows in innovation networks. *Journal of Management Studies*, 45(4):800–829.

Sampat, B. (2010). When do applicants search for prior art? *Journal of Law and Economics*, 53(2):399–416.

Sampat, B., Mowery, D., and Ziedonis, A. (2003). Changes in university patent quality after the Bayh-Dole act: A re-examination. *International Journal of Industrial Organization*, 21(9):1371–1390.

Sampat, B. N. (2005). Determinants of Patent Quality: An Empirical Analysis. *Working Papers*.

Sawnhey, M. and Prandelli, E. (2000). Communities of Creation: Managing Distribution Innovation in Turbulent Markets. *California Management Review*, 42(4):24–54.

Saxenian, A. (1996). *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Harvard University Press.

Schilling, M. and Phelps, C. (2005). Interfirm collaboration networks: The impact of small world connectivity on firm innovation. In *Academy of Management 2005 Annual Meeting: A New Vision of Management in the 21st Century, AOM 2005*.

Schoenmakers, W. and Duysters, G. (2010). The technological origins of radical inventions. *Research Policy*, 39(8):1051–1059.

Schotchmer, S. (1996). Protecting Early Innovators: Should Second Generation Products be Patentable? *Rand Journal of Economics*, 27(2):322–331.

Schumpeter, J. (1934). *The Theory of Economic Development: An Inquiry Into Profits, Capital, Credit, Interest, and the Business Cycle*. Transaction Books.

Schumpeter, J. (1939). *Business cycles: a theoretical, historical, and statistical analysis of the capitalist process*. McGraw-Hill Book Company, inc.

Schumpeter, J. (1942). *Capitalism, Socialism, and Democracy*. HarperCollins.

Slater, S. and Narver, J. (1995). Market orientation and the learning organization. *Journal of Marketing*, 59(3):63–74.

Small, H. (1973). Co-citation in the Scientific Literature: A New Measure of the Relationship Between Two Documents. *Journal of the American Society for Information Science*, 24(4):265–269.

Small, H. (1999). Visualizing science by citation mapping. *Journal of the American Society for Information Science*, 50(9):799–813.

Steiner, M. and Ploder, M. (2008). Structure and strategy within heterogeneity: Multiple dimensions of regional networking. *Regional Studies*, 42(6):793–815.

Stephan, P. E. (1996). The Economics of Science. *Journal of Economic Literature*, 34(3):1199–1235.

Stonemann, P. and Diederen, P. (1994). Technolohy Diffusion and Public Policy. *Economic Journal*, 104(425):918–30.

Stuart, T. (1998). Network positions and propensities to collaborate: An investigation of strategic alliance formation in a high-technology industry. *Administrative Science Quarterly*, 43(3):668–698.

Takeda, Y., Mae, S., Kajikawa, Y., and Matsushima, K. (2009). Nanobiotechnology as an emerging research domain from nanotechnology: A bibliometric approach. *Scientometrics*, 80(1):23–38.

Tanriverdi, H. and Venkatraman, N. (2005). Knowledge relatedness and the performance of multibusiness firms. *Strategic Management Journal*, 26(2):97–119.

TaşKin, H., Adali, M., and Ersin, E. (2004). Technological intelligence and competitive strategies: An application study with fuzzy logic. *Journal of Intelligent Manufacturing*, 15(4):417–429.

Teece, D. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15(6):285–305.

Teece, D., Pisano, G., and Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7):509–533.

Thomas, P. (1999). The effect of technological impact upon patent renewal decisions. *Technology Analysis and Strategic Management*, 11(2):181–197.

Thursby, J., Fuller, A., and Thursby, M. (2009). US faculty patenting: Inside and outside the university. *Research Policy*, 38(1):14–25.

Thursby, J. and Kemp, S. (2002). Growth and productive efficiency of university intellectual property licensing. *Research Policy*, 31(1):109–124.

Thursby, J. and Thursby, M. (2004). Are faculty critical? Their role in university-industry licensing. *Contemporary Economic Policy*, 22(2):162–178.

Thursby, J. and Thursby, M. (2007). University licensing. *Oxford Review of Economic Policy*, 23(4):620–639.

Thursby, J. and Thursby, M. (2011). Has the Bayh-Dole act compromised basic research? *Research Policy*, 40(8):1077–1083.

Tong, X. and Frame, J. (1994). Measuring national technological performance with patent claims data. *Research Policy*, 23(2):133–141.

Trajtenberg, M. (1990). A Penny for Your Quotes: Patent Citations and the Value of Innovations. *RAND Journal of Economics*, 21(1):172–187.

Trajtenberg, M. R., Henderson, R., and Jaffe, A. B. (1997). University versus corporate patents: a window on the basicness of invention. *Economics of Innovation and New Technologies*, 5(19):19–50.

Tripsas, M. (1997). Unraveling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry. *Strategic Management Journal*, 18(SPEC. ISS.):119–142.

Tseng, Y.-H., Lin, C.-J., and Lin, Y.-I. (2007). Text mining techniques for patent analysis. *Information Processing and Management*, 43(5):1216–1247.

USPTO (2009). United States Patent and Trademark Office. Available from: `http://uspto.gov`.

Van Wijk, R., Jansen, J., and Lyles, M. (2008). Inter- and intra-organizational knowledge transfer: A meta-analytic review and assessment of its antecedents and consequences. *Journal of Management Studies*, 45(4):830–853.

Von Wartburg, I., Teichert, T., and Rost, K. (2005). Inventive progress measured by multistage patent citation analysis. *Research Policy*, 34(10):1591–1607.

Wallace, M., Gingras, Y., and Duhon, R. (2009). A new approach for detecting scientific specialties from raw cocitation networks. *Journal of the American Society for Information Science and Technology*, 60(2):240–246.

Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications.* Cambridge University Press.

Watts, D. and Strogatz, S. (1998). Collective dynamics of 'small-world' networks. *Nature*, 393(6684):440–442.

Watts, R. and Porter, A. (1997). Innovation Forecasting. *Technological Forecasting and Social Change*, 56(1):XIV–47.

Webster, E. and Jensen, P. (2011). Do patents matter for commercialization? *Journal of Law and Economics*, 54(2):431–453.

Weiss, S., Indurkhya, N., Zhang, T., and Damerau, F. (2004). *Text Mining: Predictive Methods for Analyzing Unstructured Information*. Springer.

Wenger, E. (1999). *Communities of Practice: Learning, Meaning, and Identity*. Cambridge University Press.

Westphal, I., Thoben, K.-D., and Seifert, M. (2010). Managing collaboration performance to govern Virtual Organizations. *Journal of Intelligent Manufacturing*, 21(3):311–320.

Wijnhoven, F. (2008). Manufacturing Knowledge Work: The European Perspective. In Bernard, A. and Tichkiewitch, S., editors, *Methods and Tools for Effective Knowledge Life-Cycle-Management*, pages 23–44. Springer Berlin Heidelberg.

Williamson, O. and Masten, S. (1995). *Transaction cost economics: Theory and concepts*. Edward Elgar.

Wink, R. (2008). Gatekeepers and proximity in science-driven sectors in Europe and Asia: The case of human embryonic stem cell research. *Regional Studies*, 42(6):777–791.

Wright, M., Lockett, A., Clarysse, B., and Binks, M. (2006). University spin-out companies and venture capital. *Research Policy*, 35(4):481–501.

Wuchty, S., Jones, B., and Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, 316(5827):1036–1039.

Yoshikane, F., Suzuki, Y., and Tsuji, K. (2012). Analysis of the relationship between citation frequency of patents and diversity of their backward citations for Japanese patents. *Scientometrics*, 92(3):721–733.

Zitt, M. and Bassecoulard, E. (2006). Delineating complex scientific fields by an hybrid lexical-citation method: An application to nanosciences. *Information Processing and Management*, 42(6):1513–1531.

Zucker, L. and Darby, M. (1996). Star scientists and institutional transformation: Patterns of invention and innovation in the formation of the biotechnology industry. *Proceedings of the National Academy of Sciences of the United States of America*, 93(23):12709–12716.

Zucker, L., Darby, M., and Armstrong, J. (1998). Geographically localized knowledge: Spillovers or markets? *Economic Inquiry*, 36(1):65–86.

APPENDIX A

COMMUNITY DETECTION

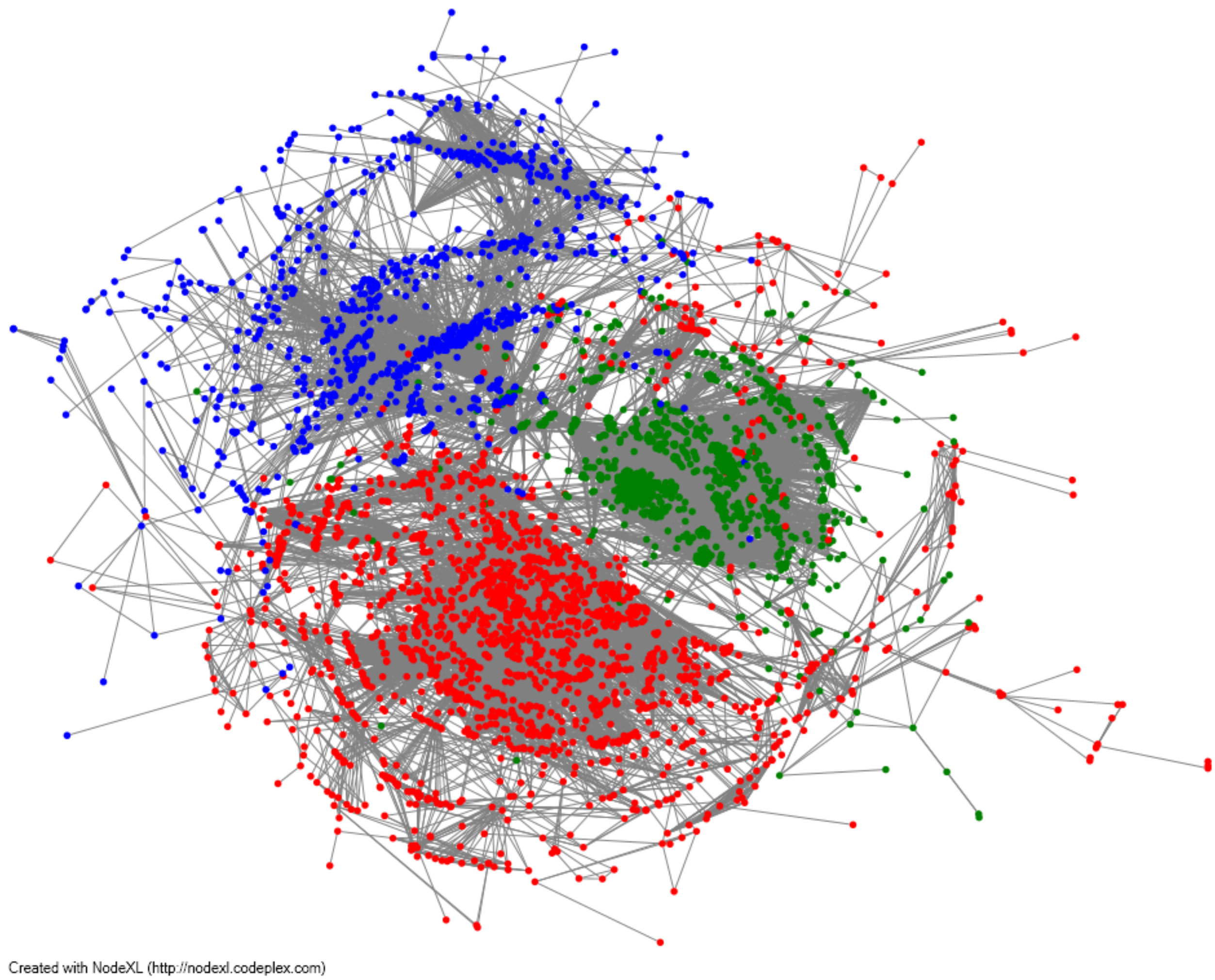

Figure A.1 Colored projected graph of the Canadian nanotechnology patent citation network. Blue vertices represent optics patents, green vertices represent print technologies patents and red vertices represent nanobiotechnology patents.

APPENDIX B

DISTANT RECOMBINATION

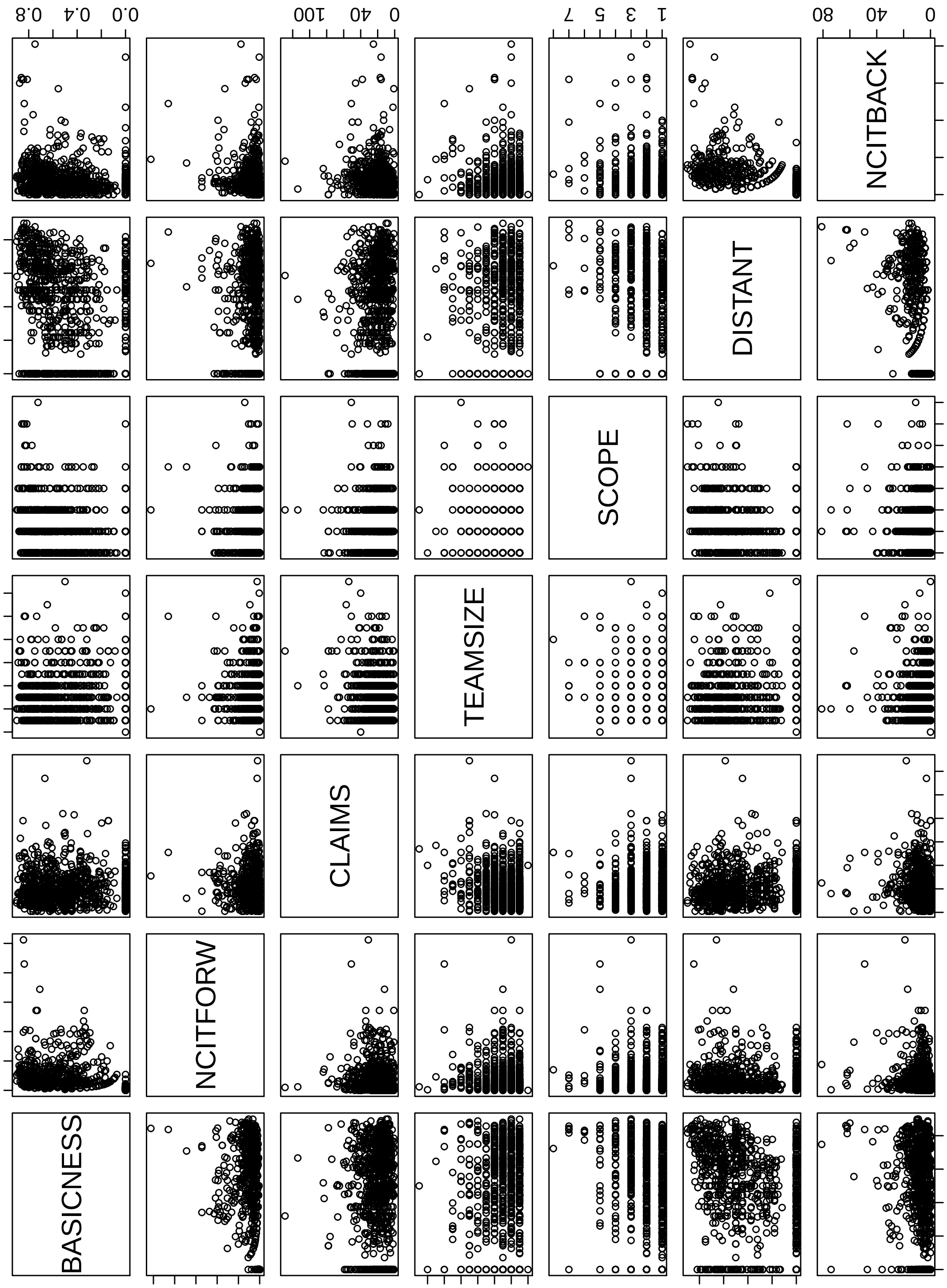

Figure B.1 Scatter-plot matrix.

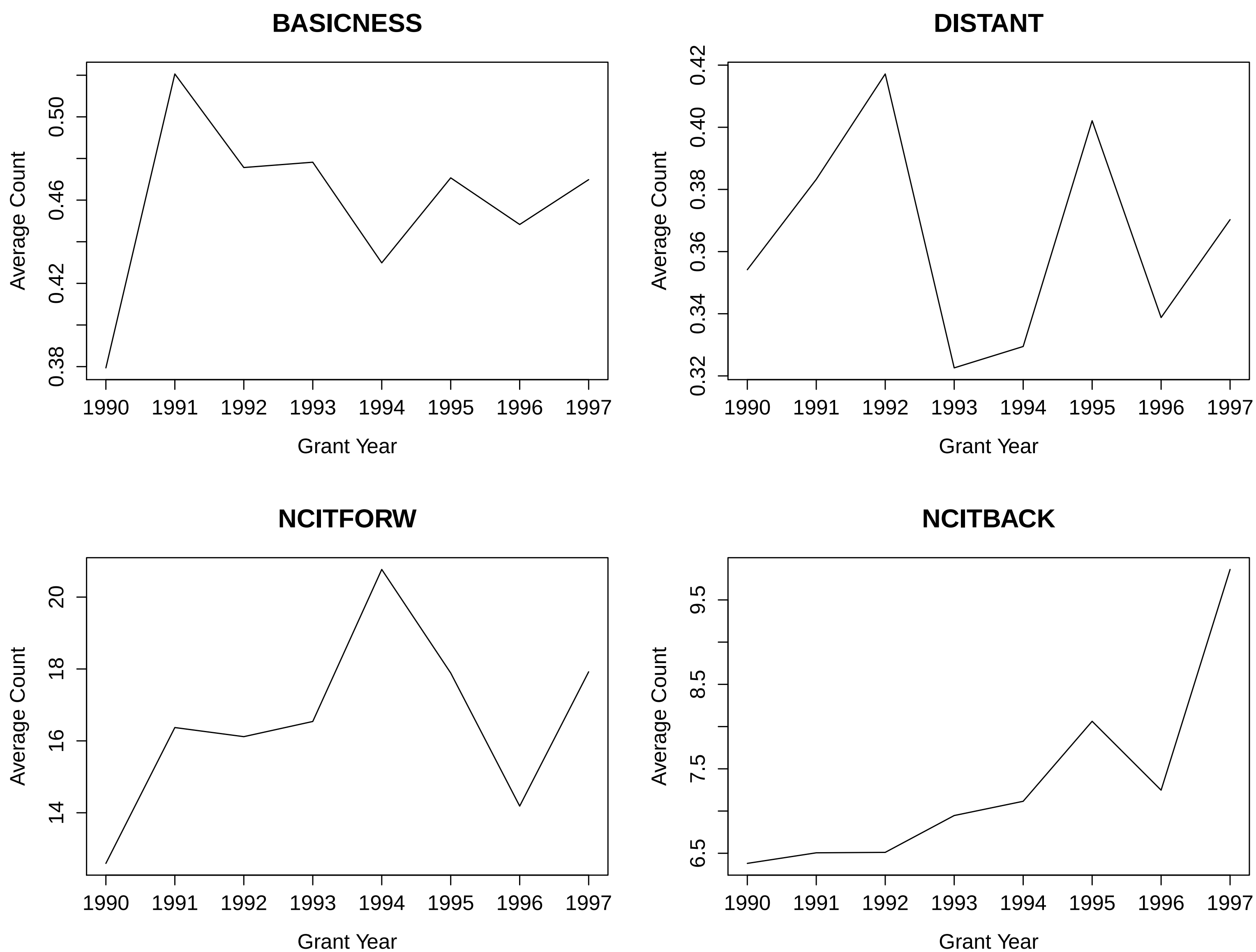

Figure B.2 Trends for average basicness, distant recombination, number of backward citations, number of forward citations.

Table B.1 Descriptive statistics

	Obs.	Mean	Std. dev.	Min.	Max.
BASICNESS	1031	.4615361	.2770533	0	.8994083
NCITFORW	1031	16.68962	23.42019	0	256
SCOPE	1031	1.980601	1.0783	1	8
CLAIMS	1031	19.72745	14.01111	1	129
NCITBACK	1031	7.727449	8.3957	0	81
DISTANT	1031	.3643925	.2890768	0	.8984375
TEAMSIZE	1031	2.895247	1.853018	0	13
NPRS	1031	7.731329	17.41594	0	181
EXPERIENCE	1031	181.3501	264.4116	1	621
PRIVATE	1031	.8234724	.3814535	0	1
NANOBIO	1031	.3753637	.4844517	0	1

Table B.2 Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11
BASICNESS	1	1										
NCITFORW	2	0.258***	1									
SCOPE	3	0.231***	0.138***	1								
CLAIMS	4	0.00721	0.125***	0.0340	1							
NCITBACK	5	0.144***	0.177***	0.177***	0.148***	1						
DISTANT	6	0.340***	0.117***	0.290***	0.0116	0.421***	1					
NPRS	7	0.0305	0.0532	0.0798*	0.0821**	0.129***	0.0332	1				
TEAMSIZE	8	-0.0214	0.0977**	0.129***	0.195***	0.0765*	0.0109	0.0714*	1			
EXPERIENCE	9	-0.160***	0.0468	-0.153***	0.223***	0.0540	-0.0877**	-0.245***	0.222***	1		
PRIVATE	10	-0.108***	0.0533	-0.0225	0.0529	0.168***	0.0382	-0.193***	-0.0207	0.251***	1	
NANOBIO	11	0.0395	-0.0584	0.124***	-0.0812**	-0.0856**	-0.0542	0.358***	-0.0329	-0.445***	-0.230***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX C

WHAT HAPPENS TO BASIC INNOVATIONS

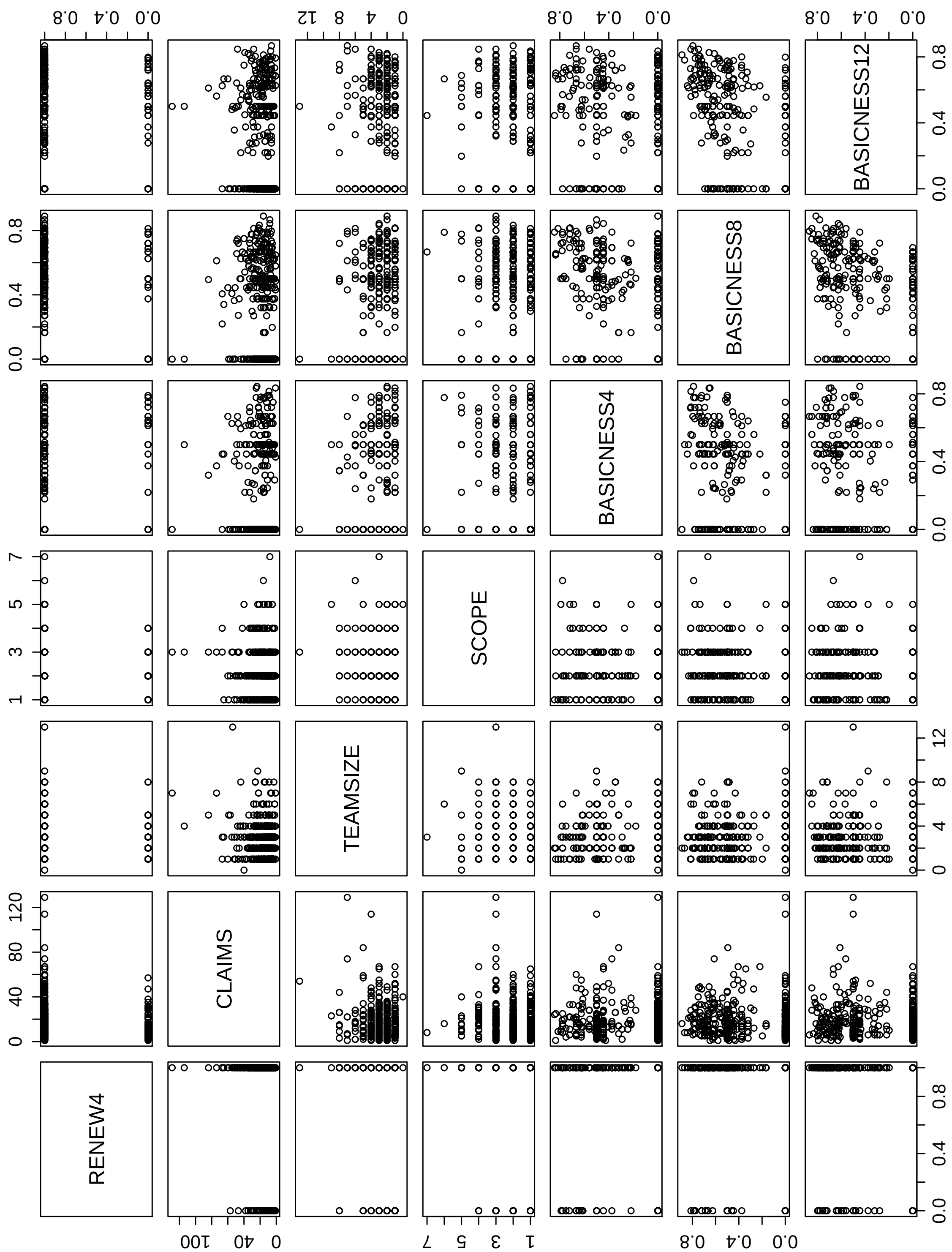

Figure C.1 Scatter-plot matrix (*RENEW4* as dependent variable)

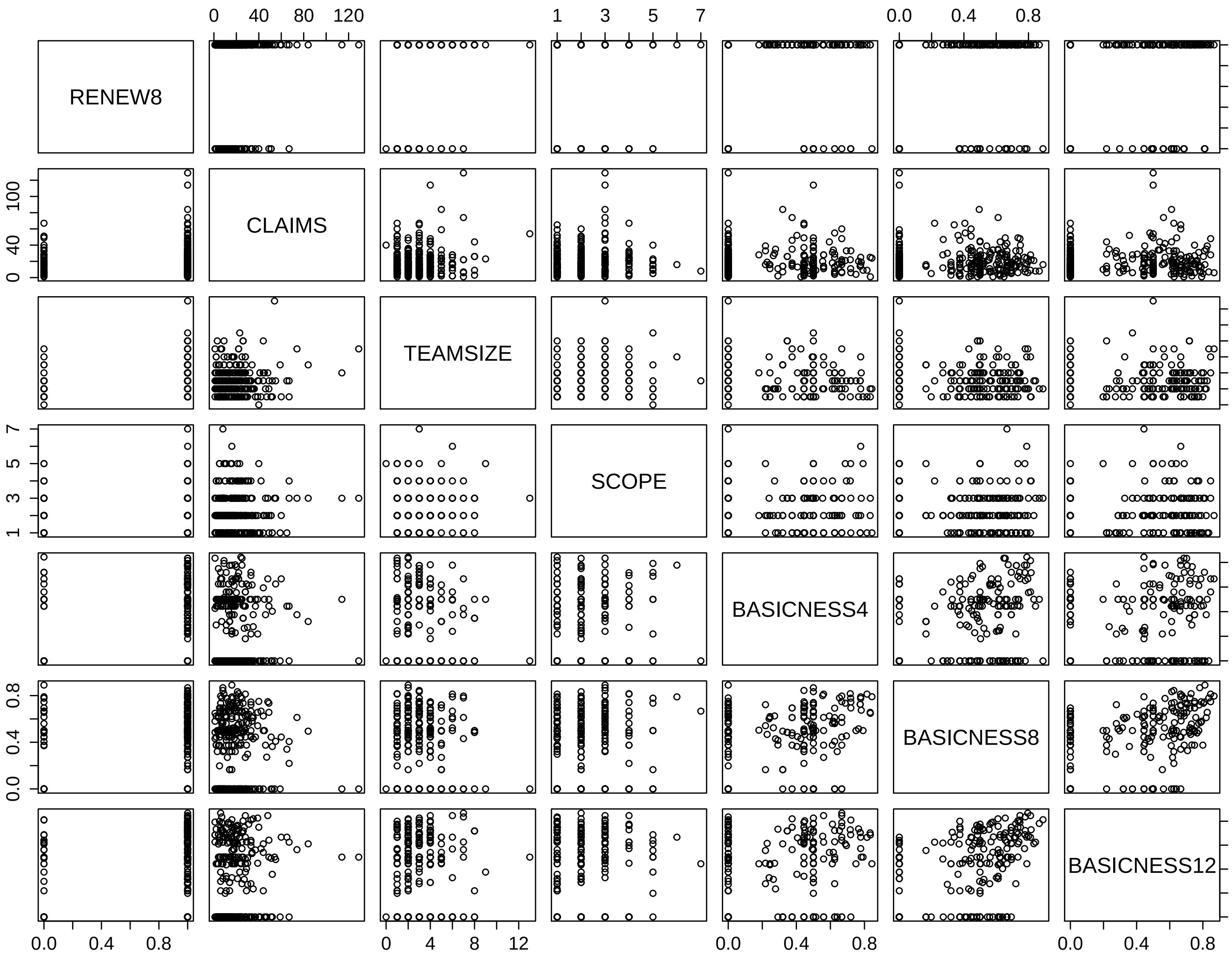

Figure C.2 Scatter-plot matrix (*RENEW8* as dependent variable)

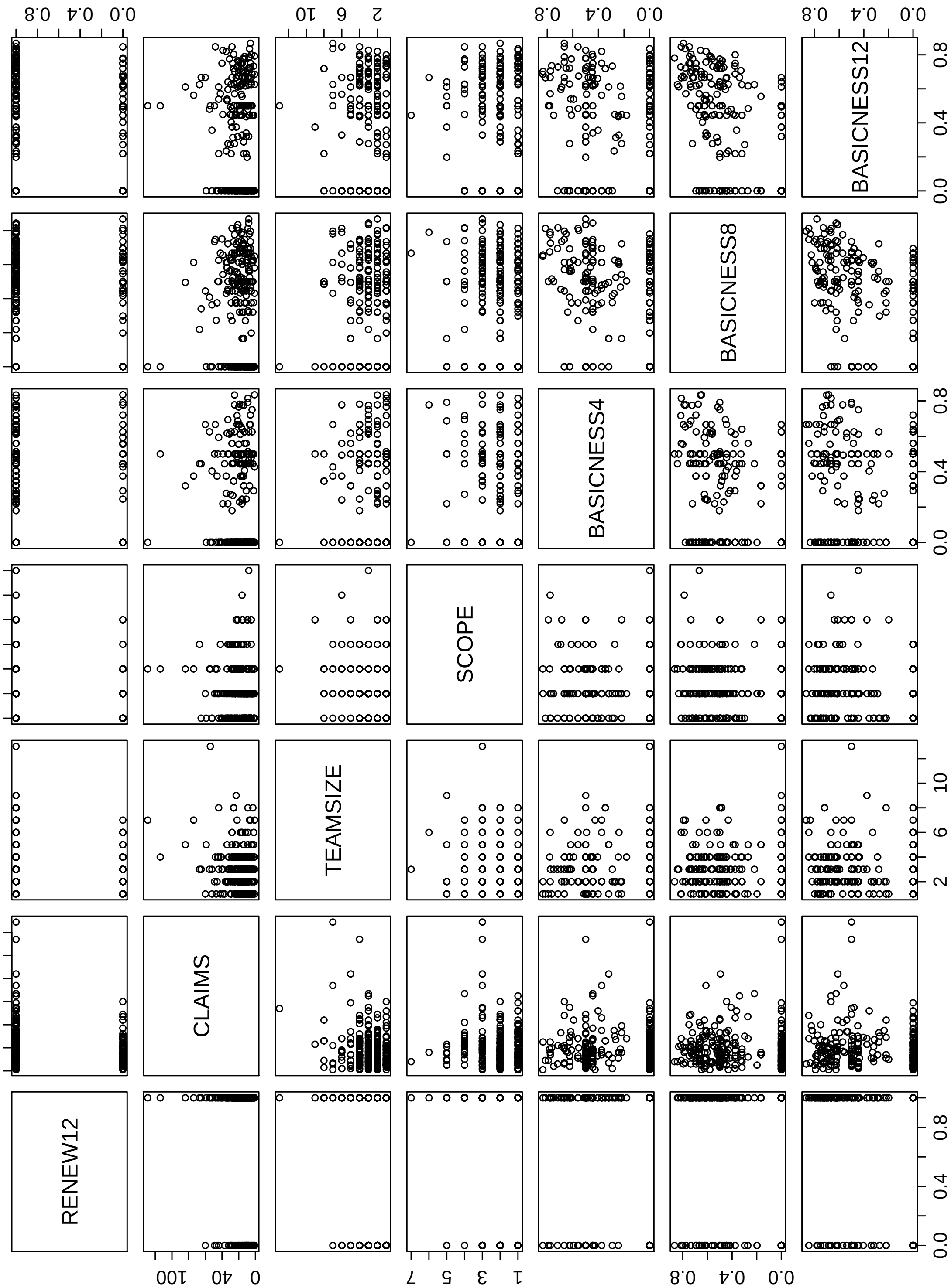

Figure C.3 Scatter-plot matrix (*RENEW12* as dependent variable)

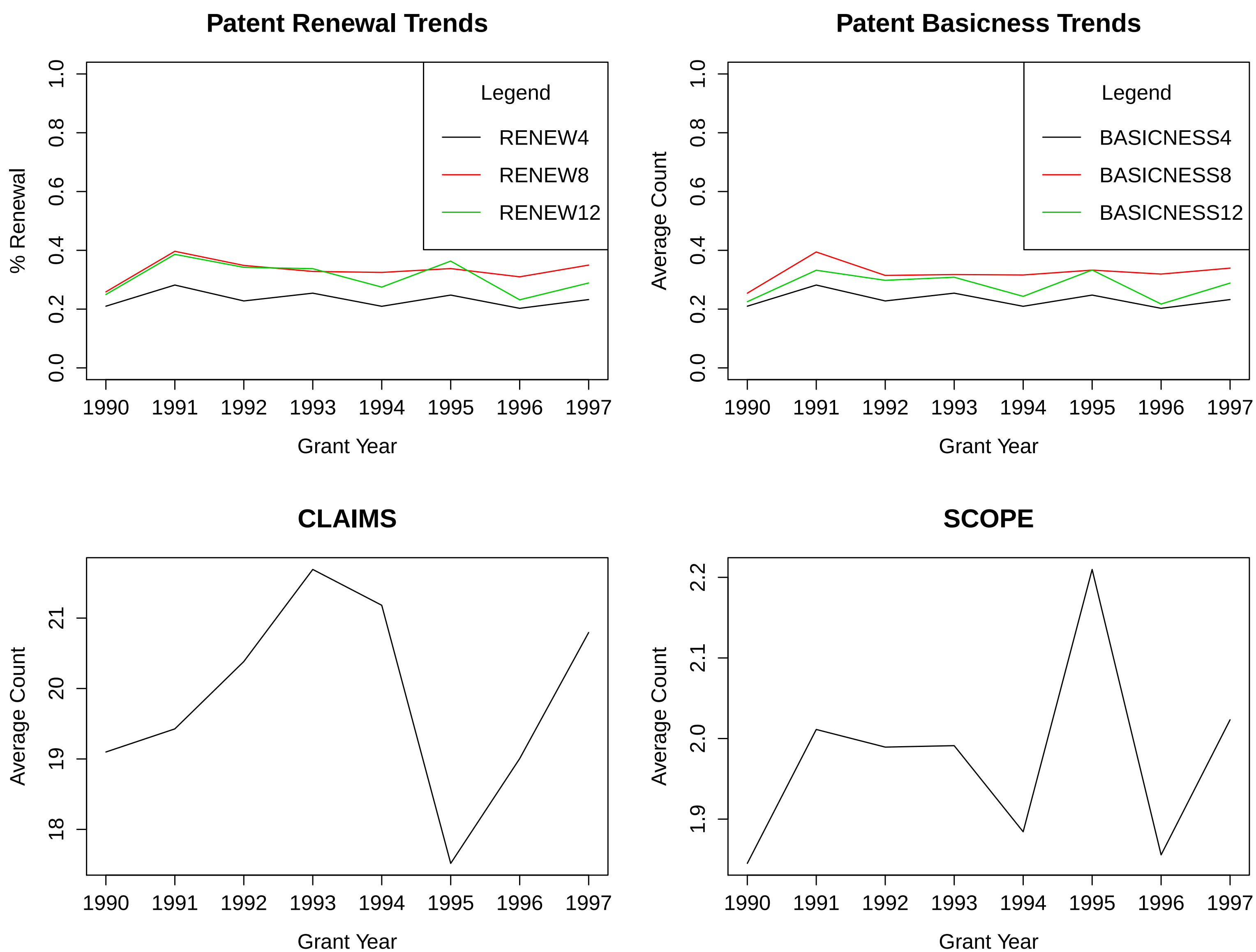

Figure C.4 Trends for average renewal, basicness, claims and scope.

Table C.1 Descriptive statistics

	Obs.	Mean	Std. dev.	Min.	Max.
RENEW4	393	.8320611	.3742885	0	1
RENEW8	393	.6819338	.466319	0	1
RENEW12	393	.5038168	.5006228	0	1
BASICNESS4	393	-.0099145	.4407094	-.3816322	.6183678
BASICNESS8	393	.0305867	.4321949	-.4893455	.5106545
BASICNESS12	393	.0354618	.4426002	-.4164254	.5835746
PRIVATE	393	.7175573	.4507614	0	1
CLAIMS	393	-1.610428	15.41351	-18.88269	109.1173
SCOPE	393	.1658519	1.031939	-.9817308	5.018269
TEAMSIZE	393	-.0765928	1.719424	-2.908654	10.09135

Table C.2 Correlation matrix

		1	2	3	4	5	6	7	8	9	10
RENEW4	1	1									
RENEW8	2	0.658***	1								
RENEW12	3	0.453***	0.688***	1							
BASICNESS4	4	0.0965	0.134**	0.0878	1						
BASICNESS8	5	-0.0329	0.0367	0.0618	0.262***	1					
BASICNESS12	6	0.0973	0.162**	0.180***	0.303***	0.413***	1				
PRIVATE	7	-0.0551	-0.00371	-0.0574	0.0236	-0.0837	-0.151**	1			
CLAIMS	8	0.139**	0.124*	0.151**	0.0871	-0.00119	0.151**	-0.0484	1		
SCOPE	9	0.00489	0.00768	0.0582	0.0807	0.0836	0.106*	0.0350	0.0818	1	
TEAMSIZE	10	0.0869	0.197***	0.232***	0.0224	-0.0733	0.0745	-0.124*	0.150**	0.119*	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.3 Probit regression results - simple and interaction effects (single period)

			RENEW4				*RENEW8*			*RENEW12*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CLAIMS	0.0179*	0.0200**	0.0200**	0.0187**	0.0189**	-0.000658	-0.000746	-0.00152	-0.00236	0.0168*
	(0.00924)	(0.00929)	(0.00937)	(0.00945)	(0.00939)	(0.00616)	(0.00614)	(0.00627)	(0.00613)	(0.00871)
SCOPE	0.0154	0.00469	0.000114	0.00342	0.00196	-0.0135	-0.00553	-0.0352	-0.0277	0.102
	(0.0759)	(0.0750)	(0.0756)	(0.0753)	(0.0763)	(0.0790)	(0.0786)	(0.0766)	(0.0836)	(0.0777)
TEAMSIZE	0.0384	0.0466	0.0470	0.0338	0.0324	0.227***	0.227***	0.233***	0.252***	0.134*
	(0.0498)	(0.0524)	(0.0539)	(0.0547)	(0.0546)	(0.0879)	(0.0879)	(0.0889)	(0.0890)	(0.0701)
YEARS	yes	yes	yes	yes	yes	n.s.	n.s.	n.s.	n.s.	n.s.
PRIVATE	-0.201	-0.239	-0.222	-0.188	-0.192	0.322*	0.346*	0.314	0.491**	-0.243
	(0.212)	(0.219)	(0.221)	(0.219)	(0.220)	(0.193)	(0.196)	(0.204)	(0.201)	(0.228)
BASICNESS4	0.227					0.472**	0.166			0.972**
	(0.311)					(0.232)	(0.305)			(0.482)
BASICNESS4×PRIVATE	0.552						0.520			-1.389**
	(0.405)						(0.462)			(0.559)
BASICNESS8		0.176	0.558**					-0.343		
		(0.196)	(0.279)					(0.451)		
BASICNESS8×PRIVATE			-0.546					1.194**		
			(0.374)					(0.536)		
BASICNESS12				0.401*	0.270				0.460	
				(0.209)	(0.348)				(0.343)	
BASICNESS12×PRIVATE					0.192				0.586	
					(0.419)				(0.445)	
Constant	0.687**	0.750**	0.741**	0.725**	0.736**	0.545	0.452	0.632	0.669	1.246**
	(0.299)	(0.336)	(0.334)	(0.340)	(0.332)	(0.433)	(0.453)	(0.479)	(0.457)	(0.507)
Obs.	327	327	327	327	327	270	270	270	270	224
Wald χ^2	38.76	35.58	35.60	32.72	33.11	20.43	18.84	24.06	29.02	20.15
Pseudo R^2	0.127	0.0984	0.104	0.108	0.109	0.0866	0.0917	0.105	0.120	0.0909
Log likelihood	-132.0	-136.4	-135.6	-135.0	-134.9	-112.6	-111.9	-110.3	-108.4	-110.3

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table C.4 Logit regression results - simple and interaction effects (single period)

	RENEW4					*RENEW8*				*RENEW12*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CLAIMS	0.0369**	0.0416**	0.0421**	0.0395**	0.0398**	-0.00202	-0.00274	-0.00384	-0.00479	0.0290*
	(0.0177)	(0.0183)	(0.0184)	(0.0186)	(0.0185)	(0.0114)	(0.0113)	(0.0114)	(0.0111)	(0.0160)
SCOPE	0.0347	0.0237	0.0150	0.00753	0.00529	-0.0284	-0.0145	-0.0592	-0.0648	0.161
	(0.131)	(0.126)	(0.127)	(0.129)	(0.131)	(0.141)	(0.142)	(0.135)	(0.149)	(0.132)
TEAMSIZE	0.0816	0.0981	0.0989	0.0742	0.0724	0.454**	0.451**	0.467**	0.467***	0.247*
	(0.0937)	(0.102)	(0.106)	(0.105)	(0.105)	(0.176)	(0.178)	(0.181)	(0.176)	(0.132)
YEARS	yes	yes	yes	yes	yes	n.s.	n.s.	n.s.	n.s.	n.s.
PRIVATE	-0.318	-0.412	-0.388	-0.329	-0.325	0.631*	0.707*	0.669*	0.947**	-0.460
	(0.399)	(0.402)	(0.405)	(0.401)	(0.406)	(0.355)	(0.374)	(0.391)	(0.373)	(0.422)
BASICNESS4	0.332					0.870*	0.327			1.707*
	(0.593)					(0.448)	(0.557)			(0.940)
BASICNESS4 × *PRIVATE*	1.056						0.985			-2.417**
	(0.776)						(0.917)			(1.073)
BASICNESS8		0.256	1.068**					-0.532		
		(0.365)	(0.537)					(0.816)		
BASICNESS8 × *PRIVATE*			-1.134					2.132**		
			(0.695)					(1.005)		
BASICNESS12				0.691*	0.449				0.851	
				(0.388)	(0.646)				(0.587)	
BASICNESS12 × *PRIVATE*					0.352				1.025	
					(0.773)				(0.840)	
Constant	1.129**	1.279**	1.256**	1.274**	1.284**	0.867	0.678	0.950	1.069	2.131**
	(0.516)	(0.594)	(0.584)	(0.604)	(0.596)	(0.759)	(0.807)	(0.879)	(0.802)	(0.929)
Obs.	327	327	327	327	327	270	270	270	270	224
Wald χ^2	36.38	32.35	32.20	29.80	30.38	19.30	17.38	22.05	29.12	18.56
Pseudo R^2	0.130	0.102	0.109	0.112	0.112	0.0900	0.0953	0.108	0.121	0.0903
Log likelihood	-131.6	-135.8	-134.8	-134.4	-134.3	-112.2	-111.5	-109.9	-108.3	-110.4

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$