

Collaboration networks and innovation in Quebec's ICT hardware cluster¹

Melik Bouhadra, Master Student, Polytechnique Montreal, melik.bouhadra@polymtl.ca

Catherine Beaudry, Professor, Polytechnique Montreal, catherine.beaudry@polymtl.ca

Polytechnique Montréal

Department of mathematics and industrial engineering

P.O. Box 6079, Downtown office Montreal, Quebec, H3C 3A7, Canada

Abstract

Over the last few decades, the importance of collaboration networks has increased in scientific research in a vast number of sectors. The ICT hardware industry is no exception and both firms and academic researchers are, for different reasons, seeking to establish partnerships. In recent literature, small-world network structure has shown optimal transmission properties. In this paper, using the Natural Sciences and Engineering Research Council of Canada data for a 10-year period (2003-2013), two sets of collaboration networks have been created: the first is composed solely of researchers while the second set adds partnering organizations, such as private firms, to the researchers' collaboration network. Social network analysis is then used to measure various structure-related indicators of the two resulting networks. Our results show the presence of small-world properties suggesting an efficient knowledge transmission through the collaboration network. The important role of firms as central connectors in the networks is also highlighted.

This is a very first draft, please do not cite without the authors' permission

1 Introduction

Many industrial sectors face challenges from emerging economies, but none more so than the ICT hardware sector in western economies. New international innovation systems emerge, elaborated partnerships are being put in place with a vast number of organizations, and new innovation and intellectual property (IP) practices are developed. Microprocessors and electronic chips, components of the ICT hardware industry, are often considered General-Purpose Technologies (GPTs). According to (Bresnahan & Trajtenberg, 1995, p. 84), “[a]s a GPT evolves and advances it spreads throughout the economy, bringing about and fostering generalized productivity gains”. As such, R&D

¹ Acknowledgements : This work is funded by the SSHRC funded partnership grant *Creating Digital Opportunity* (CDO).

investments in this particular sector are important because of their potential impact on the entire economy (society as an end user, pervasive use in other industries, etc.). This pervasiveness is a characteristic of the ICT hardware industry and makes it an important growth engine for economies. Since GPTs are connected to various segments of the economy, coordination problems has been an issue (Bresnahan & Trajtenberg, 1995). Furthermore, with the increasing complexity of products, and the necessity to accelerate the innovation process, collaboration is increasingly used to develop new applications for these technologies.

This has led to the extensive use of networks by all firms. Networks are complex structures that are needed by firms to search for various sources of knowledge (Nieto & Santamaría, 2007; Tommaso Buganza & Roberto Verganti, 2009). Recent empirical studies have shown a close relationship between network structure and actors' innovation performance (Grewal, Lilien, & Mallapragada, 2006; Phelps, 2010). Many of them have focused on the properties of *small-world* networks. Small-world networks are defined as clusters of locally dense interaction connected via occasional nonlocal bridging edges (Fleming, King, & Juda, 2007). A small-world network is typically highly clustered, yet have a small average path length (Watts & Strogatz, 1998).

This paper focuses on the impact of the collaboration network structure linking companies, universities and governmental entities in the ICT hardware cluster of the province of Quebec, in Canada. More specifically, the study aims to determine whether the network has the characteristics of a *small world* and examine the implications of such a collaborative organisation.

Two levels of networking are considered in this paper: First, we map the collaboration networks of academic researchers who raised funds from the Natural Science and Engineering Council of Canada (NSERC). Second, we add to these networks the collaboration links (from the industry/organisation-university collaborative NSERC grants) between the researcher leading the research project and the partners.

Social network analysis of the individual scientist networks, excluding firms and other organisations, shows networks composed of multiple components (i.e. highly fragmented) based on specific ICT disciplines (photonics, quantum computing, telecommunications engineering, etc.), some of which correspond to small-world structures. In other words, within these components, information should flow faster. Yet, the disconnection between the components prevents information to flow directly through the entire networks and suggests the presence of non-filled structural holes. The second type of analysis, on the researchers-organisations networks, emphasizes the role of firms and other organisations as central actors in the networks and the clear presence of a small-world structure.

The remainder of the paper is organised as follows: Section 2 reviews the relevant literature on collaboration and small worlds, Section 3 explains the methodology as well as the data available, Section 4 presents the results of the social network analysis and Section 5 discusses the main results and concludes.

2 Theoretical framework

2.1 University–industry collaboration in the ICT hardware sector

According to (Chesbrough, 2003), the ICT hardware industry, especially the semiconductor sector, is rich in terms of knowledge. This knowledge comes from various sources. It is however more and more difficult for firms to keep up with the rapid pace of innovation by tapping only into their internal resources (Santoro & Chakrabarti, 2002). Firms must use additional sources of knowledge such as research centers, governmental laboratories, universities, industrial clusters and even rival firms. For example, hardware companies typically possess their own R&D facilities but work closely with universities on new materials.

In the development of high technology products, like most of the ICT hardware products, the role of universities is crucial in the innovation process (Lee, 2000). From the university point of view, researchers have different reasons to collaborate with firms. According to (Lee, 2000), the main motivations of researchers are driven by the need to advance their research agenda. Specifically, the most significant factor is to secure funds for their graduate students and lab equipment. Second, researchers are interested in looking for insights on their research fields within companies R&D pipelines. From the firms' point of view, on the one hand, universities generate a pool of talents from which firms can recruit researchers and other employees (engineers, technology managers, etc.). On the other hand, universities often receive specific mandates from private firms to work on research projects, most of which are focused on actual product development or prototyping, and thus close to commercialisation. However another reason why firms collaborate with universities, often cited by technology managers, is to conduct exploratory blue sky research (Lee, 2000). Indeed, firms less and less use their own resources to investigate far-fetched research hypotheses. In a world where Moore's law is ruling, investing in new technology research is necessary to survive (Joe Tidd, 2002). Here, blue sky research must not be confounded with fundamental research with no specific application.

(Santoro & Chakrabarti, 2002) further observe that large corporations in this sector tend to invest in research projects that are not always linked to their core business. Since GPTs by definition involve numerous spillover effects, firms are willing to explore new applications and increase the general level of knowledge in the field to benefit from future advances. For example, semiconductor companies like Qualcomm invest in areas like mobile computing and robotics because of their potential to become growth engines for them. Successful innovative firms have this capacity to absorb external knowledge and adapt to industry changes (Cohen & Levinthal, 1990)

(Boschma, 2005) introduced the notion of proximities as an explanation of cluster formation and collaboration. It is often assumed that geographical proximity is a major factor explaining collaboration. A study conducted by (Ponds, Van Oort, & Frenken, 2007) tested the hypothesis that collaboration between different kinds of organisations (firms, universities, government entities, etc.) is more geographically localised than collaboration between similar organisations, due to institutional proximity. The authors focused on science-based industries including ICT fields such as telecommunications, optics and semiconductors. Their main finding is that geographical proximity is more

relevant for collaboration between non-academic and academic organisations, such as university-industry collaboration, than for purely academic research collaboration. As an explanation, they suggest that geographical proximity is a way of overcoming the institutional differences between organisations.

2.2 Research collaboration

Collaboration between researchers is increasingly common, if not the norm. It is widely assumed, within the scientific community, that it is beneficial and that it should be encouraged (Katz & Martin, 1997). However, the concept of collaboration itself is not always clear and many definitions exist. For the sake of brevity, we do not enunciate these definitions but consider the one elaborated by (Laudel, 2002) where collaboration is defined as a set of research activities involving multiple actors linked by a functional purpose in order to achieve a research goal where everyone will satisfy their own interests. Hence collaborators do not have to share a common goal in order to work together.

The recent rise in research collaboration can be explained by a number of motivational factors, the increasing cost of research being one. According to (Ziman, 1994), funding agencies even try to force researchers to collaborate and communicate in order to share the equipment and facilities, leading to cost reduction. The argument being that research budget has reached a limit. The increasing complexity of research, leading to specialisation and focused expertise is another reason to collaborate (Gordon, 1980). In fact, in specific fields or multidisciplinary projects, it is almost impossible, let alone highly time consuming and inefficient, for a single researcher to execute all the required activities.

Other factors listed in the literature are the decreasing cost of communication (Kraut, Egidio, & Galegher, 1988), political factors (Subramanyam, 1983) and emerging new fields where multiple disciplines are needed (Van Rijnsoever & Hessels, 2011). Nowadays, with the establishment of Internet, scientists can communicate more efficiently than ever. Moreover, affordable flights allow in-person interactions (Melin, 2000), hence removing the necessity for geographic proximity, but emphasising the importance of social and cognitive proximity (Boschma, 2005).

At a more micro level, in a study conducted by (Melin, 2000), researchers, when they look for a partnership, evoke the special competencies of potential collaborators as an important decision factor. Respondents further mention special data or equipment that fellow researchers could provide as an important consideration in this decision. Interestingly these factors come before social reasons (old friends, past collaboration, etc.) in terms of importance.

2.3 Small-world network

Watts and Strogatz introduced the small-world model in 1998. The frequent apparition of small-world in various types of networks (man-made, biological, ecological, technological, etc) has suggested that this specific structure offer a potent organizing mechanism for increasing performance (Uzzi, Amaral, & Reed-Tsochas, 2007). Scholars agree that this structure facilitates information diffusion through a network. The small-world network enables dense and clustered relationships to coexist with distant and more

diverse links. The clustered part of the graph enables trust and close collaboration, while distant edges bring new information to the cluster (Fleming et al., 2007).

(Cowan & Jonard, 2004) developed a model to study the efficiency of networks in a knowledge diffusion study and showed it was maximal when networks had small-world properties. A number of previous studies focused on the impact of a small-world structure on firms' networks, investigating topics as firms' performance and knowledge diffusion. For example, (Sullivan & Tang, 2012) mapped the inter-firm links of the American venture capital industry and evaluated the impact of its structure on the firms' productivity. They observed a positive relation between small-world properties and productivity. In another study, (Schilling & Phelps, 2004) concentrated their efforts to determine the impact of small-world property on firms' performance by looking at patents. Their work showed a positive effect due to the high clustering coefficient and short path length enabling companies to have access to new knowledge required for innovation.

In the innovation literature, it is also argued that small-world networks foster creativity and increase innovation performance. However, no consensus exists regarding its impact on performance (Uzzi et al., 2007). In fact, an equal number of studies show that there is no direct impact of the small-world structure on actors' performance (Fleming et al., 2007; Fleming & Marx, 2006).

On the individual level, many studies have also been conducted using co-authorship to characterise networks (Goyal, Van Der Leij, & Moraga-González, 2006; Newman, 2000). In these studies, small-world networks have been discovered in fields such as physics, mathematics, biology and economics. Co-authorship networks show a tendency toward a small-world structure (Ebadi & Schiffauerova, 2015). This previous work showed the important role of the best-connected actors in joining individuals and clusters in the networks. Also, the co-authorship pattern (team size, multidisciplinary, etc.) is a significant factor to obtain small-world structure. Interestingly, there is an increased probability of having a small-world network when scientific disciplines are team oriented with large team sizes (Wuchty, Jones, & Uzzi, 2007). Hence, the presence of a small-world structure is common for disciplines in which teamwork is typical.

3 Data and methodology

3.1 Data

The data used for our research is the collaboration links from the Natural Sciences and Engineering Research Council (NSERC) funding programs from 1993 to 2013. It was collected via the NSERC website. The data corresponds to collaboration information linking industrial partners with leading academic researchers. On complementary files other data on collaboration gives the links between researchers for the same projects. More specifically it links the co-applicants (researchers) with the main researcher, the one applying for the grant. However, the co-applicants data was available only from year 2003 so we will consider the 2003-2013 period for the study of research collaboration, which is the focus of this paper.

The raw data contained information on all disciplines and fields. Thus, we had to filter the projects in order to keep only those related with ICT hardware. The first filter retained

ICT projects in general and we then sorted out software and services related collaborative research projects. These filters are easily applied due to NSERC data codification. Subsequently, the 2003-2013 database contained 6738 ICT hardware research projects and 751 researchers working in this field.

3.2 Social network analysis

A social network characterises the interactions between a set of individuals or organisations (groups of individuals). Social networks consist of nodes (or vertices) and edges (also called ties, links, or connections) that connect the nodes. In the case examined in this paper, nodes represent the individual actors that compose the networks and edges are the funding relationships between the actors. Social network analysis is widely used to study complex systems in various disciplines (biology, social sciences, to name a few). The techniques employed combine mathematical analysis with the visualisation of systems that facilitate the characterisation and understanding of different interactions (Krebs, 2004). This type of analysis has as primary goal the detection and interpretation of patterns amongst social links between group members. It offers a framework to test hypotheses and theories based on structured relationships with the help of mathematical measures and network structural properties (Nooy, Mrvar, & Batagelj, 2011). Recent studies have used social network analysis to understand collaboration linkages and the influence of an innovator's network structure on its innovative performance (Bercovitz & Feldman, 2011; Rost, 2011).

The visual representation of a network is called a graph. Graph theory and social network analysis employ various measures to describe the overall structure of the network but also to determine relative importance amongst the nodes. This paper will use a number of concepts, which are defined below:

Giant component: largest connected subgraph (component), i.e. that contains the majority of nodes. The network is composed of numerous unconnected components. The largest the giant component, the less fragmented is the network.

Actor degree centrality: number of ties associated with a particular node. Thus, for a simple undirected network it is also the number of adjacent neighbours of the node (Wasserman & Faust, 1994). This type of centrality is often interpreted as the immediate risk of a node for 'catching' what is flowing through the network, in our case: knowledge. Mathematically, the degree centrality $C_D(i)$ of a node i can be expressed by the equation (1).

$$C_D(i) = \sum_j x_{ij} \quad (1)$$

Where x_{ij} is the value of the link, e.g. the number of times two nodes collaborated together, between i and j . In order to compare networks of different sizes, the degree centrality can be normalized by dividing it by the total number of ties within the network.

Betweenness centrality: is a measure calculated for every node of the network. It measures the control that nodes have over paths in the graph. Typically, it favors nodes connecting communities (dense subnetworks). The idea is that an actor is central if it lies between others actors especially if it is positioned in the shortest path linking them (Wasserman & Faust, 1994). More specifically, it is calculated with equation (2) for a node i .

$$g(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \quad (2)$$

Where σ_{st} is the total number of shortest paths from node s to node t and $\sigma_{st}(i)$ is the number of them passing by node i . The value we are using in this paper is the normalized value of betweenness centrality defined by the value obtained with equation (2) divided by the maximum value observed in the graph. Hence, we always get an actor with a value of 1 and this node represents the most central one in terms of betweenness.

Eigenvector centrality: measure the relative centrality of a node in a network. It assigns relative scores to all nodes in the network based on the principle that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes (Nooy et al., 2011). In fact, the assumption is that each node's centrality is proportional to the sum of the centrality values of the nodes connected to it (Newman, 2004).

Clustering coefficient: measure of the degree of interconnectivity in the neighbourhood of a node (Watts & Strogatz, 1998). In other words, it measures the extent to which one's friends are also friends of each other. Two versions of this measure exist: the global and the local. The global version gives an overall indication of the clustering in the network, whereas the local clustering coefficient is designed to give an indication of the embeddedness of single nodes. For the same graph G described earlier, the *local clustering coefficient* (cc_l) of a node i can be defined by the equation (3).

$$cc_l(i) = \frac{\text{number of pairs of neighbors connected by edges}}{\text{number of pairs of neighbors}} \quad (3)$$

The clustering coefficient for the entire graph G , $cc_l(G)$, is the simple average of $cc_l(i)$ for all i within V .

The second definition, the *global clustering coefficient* (cc_g), also called *transivity*, was introduced by (Newman, Strogatz, & Watts, 2001). It is calculated by using equation (4).

$$cc_g(G) = \frac{\text{number of closed 2-paths}}{\text{number of 2-paths}} \quad (4)$$

Average path length: average number of edges along the shortest paths for all possible pairs of nodes in the network. It measures the efficiency of information diffusion within a network. Let $d(i_1, i_2)$ represent the shortest distance between node i_1 and node i_2 in the graph G , where i_1, i_2 belong to V . Then, the average path length (l_G) is calculated using equation (5).

$$l_G = \frac{1}{n(n-1)} \cdot \sum_{i \neq j} d(i_1, i_2) \quad (5)$$

Small-world networks are characterised by a high clustering coefficient combined with a short average path length. In contrast, random graphs, where nodes are randomly connected, have short average path length and low clustering coefficient. Therefore, a way to determine if a graph has a small-world structure is to compare its properties to those of a random graph of the same size. Mathematically, equations (6) and (7) have to be respected.

$$\frac{l_G}{l_{rd}} \approx 1 \quad (6) \quad \text{and} \quad \frac{cc_l(G)}{cc_l(rd)} \gg 1 \quad (7)$$

Where l_{rd} and $cc_l(rd)$ are respectively the average path length and the local clustering coefficient of a random graph. We can combine the 2 equations to form the small-world variable, SW , defined by equation (8). Where, a high SW (much greater than 1) confirms the small-world structure.

$$SW = \frac{cc_l(G)}{cc_l(rd)} \bigg/ \frac{l_G}{l_{rd}} \quad (8)$$

In the second phase, Gephi software was used to construct and visualize the collaboration networks of the researchers as well as measure the structural network and small-world variables. We used the complementary files on co-applicants to establish the collaboration links. If researcher A and researcher B were co-applicants with the academic principal investigator C for a given project we then assume the collaboration links A-C, B-C and A-B. However, for the researchers-organizations networks, we only considered the links between the academic leader C and the different industrial collaborators. We used 5-year moving windows over 2003-2013 periods. Therefore, we mapped 14 distinct undirected networks, 7 researchers networks and 7 researchers-organizations networks. The structural properties of the 14 networks were measured by Gephi.

The research collaboration networks we generated are highly disconnected. They are composed of many subgraphs (components). Component of a graph, or a network, is a sub-network in which all the nodes are interconnected, there is no isolated nodes. Therefore, in order to study the small-world phenomenon we had to consider only the largest component of the networks. This limitation is largely due to the fact that the average path length can be calculated for a connected graph. The use of the largest component to determine the small-world variable has been commonly used (e.g. (Baum, Shipilov, & Rowley, 2003; Uzzi & Spiro, 2005)). The justification relies the fact that the main activities occur in the largest component, where we usually find the most influential actors. In our case, the composition of the largest components in our generated networks is shown in Figure 1.

The largest components of our networks contain between 13% (for the 2005-2009 period) and 23% (2009-2013 period) of the nodes. For the first two periods (2003-2007 and 2004-2008), the largest component represented about 55% of all the collaboration activity, i.e. the total number of edges in the network. Hence confirming that the main activities were occurring in this largest component. However, from the period 2005-2009, the proportion of collaboration in the largest component dropped to 15%. This is attributable to the fact that the second largest component has increased in size to overtake the largest component of the previous periods, as can be witnessed in Figure 2. The second largest component contains only between 5% and 7% of the researchers, but they represent up to 47% of the collaboration activity in the 2007-2011 period. A small-world analysis of the first and second largest section will be conducted in the next section.

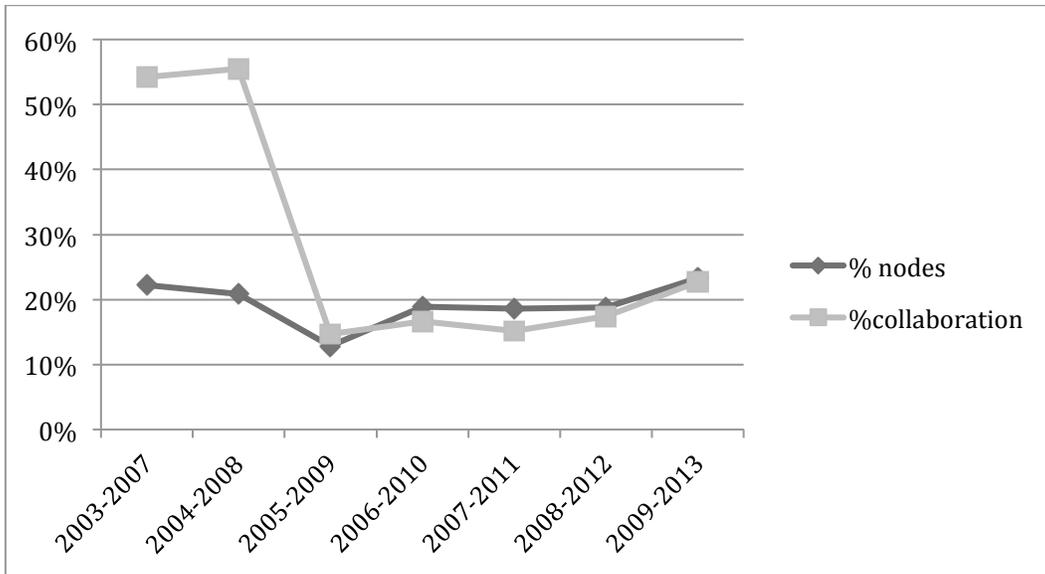


Figure 1: Evolution of the composition of the largest component

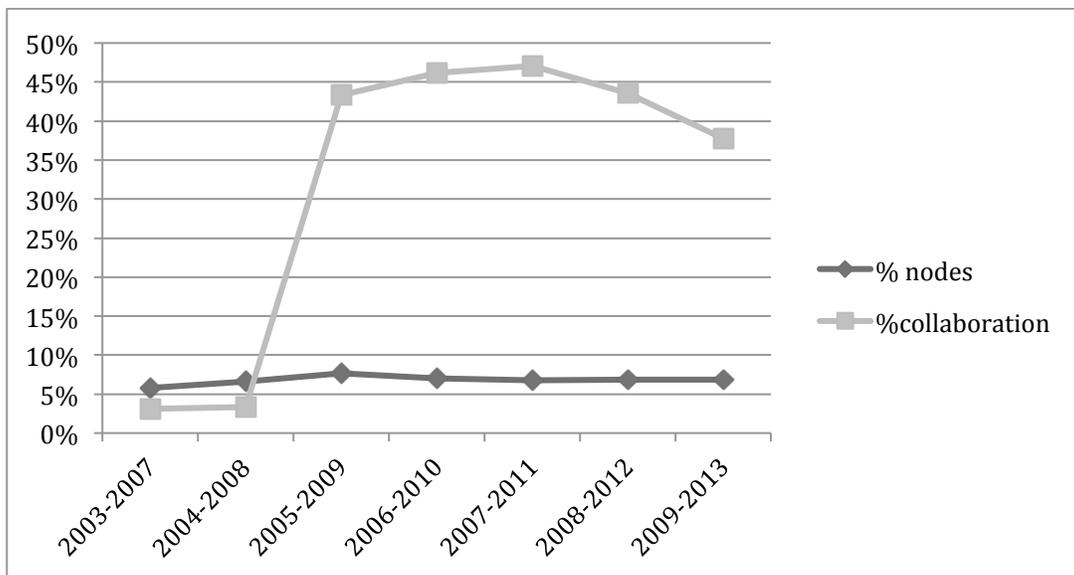


Figure 2: Evolution of the composition of the second largest component

As an example, Figure 3 presents the graphical representations of the largest and second largest components for the 2008-2012 period compared to the full network. The network also appears highly fragmented, as there are multiple disconnected components of the full graph (Figure 3a). In fact, the period with the least components possesses 74 of them. This large number is due to a considerable number of one-time projects involving small teams of researchers.

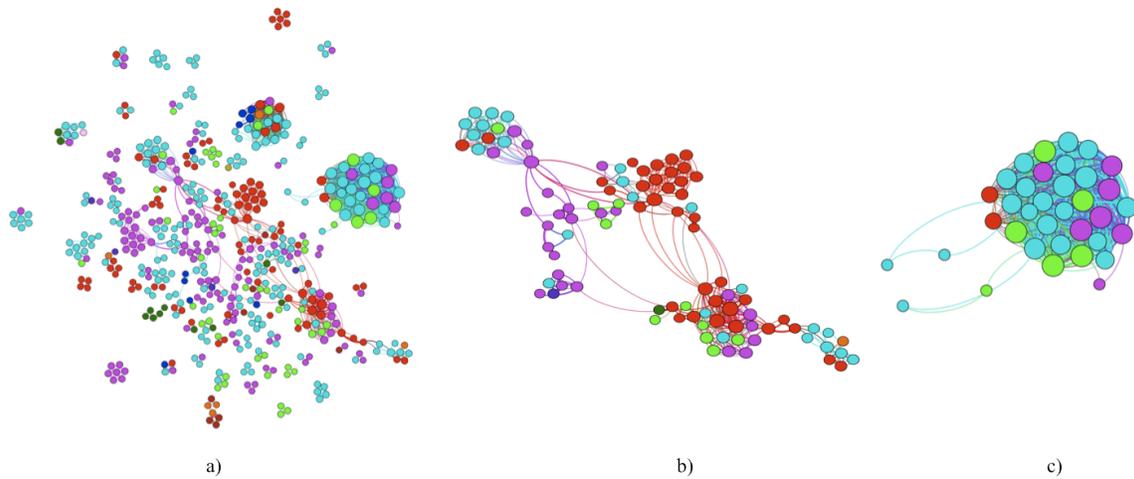


Figure 3: a) 2008-2012 full network, b) its largest component and c) its second largest component²

4 Network analysis

4.1 Network size

The size of the components is calculated by the number of actors involved in each of the 5-year moving periods. According to Figure 4, the size of the largest component is almost constant, around 100 researchers, except for the 2005-2009 where it dropped to 59. This is explained by the splitting of the largest component in two distinct parts in the 2005-2009 collaboration network. Figure 5 indeed shows that the largest component of the 2005-2009 network represents only a small part of it (13% of the nodes, see Figure 1).

² In the graphs, the size of the node representing every network actor is a function of the number of partnerships in which it is involved. In other words, it depends on the number of links connected to the node itself. And, the number of partnerships between two players determines the size of the link between them. The different colors distinguish the province of the researcher's university: Ontario (turquoise), Quebec (purple), Alberta (green), British Columbia (red), Nova Scotia (blue), Manitoba (dark green), Saskatchewan (orange), Newfoundland and Labrador (burgundy), New Brunswick (dark purple) and N/A (light pink).

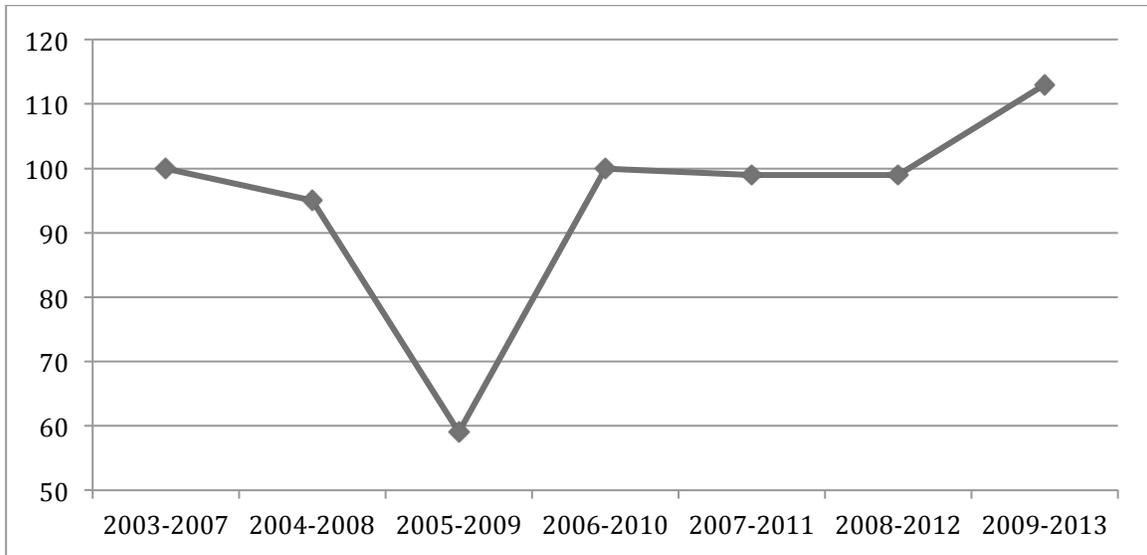


Figure 4: Evolution of the size of the largest component

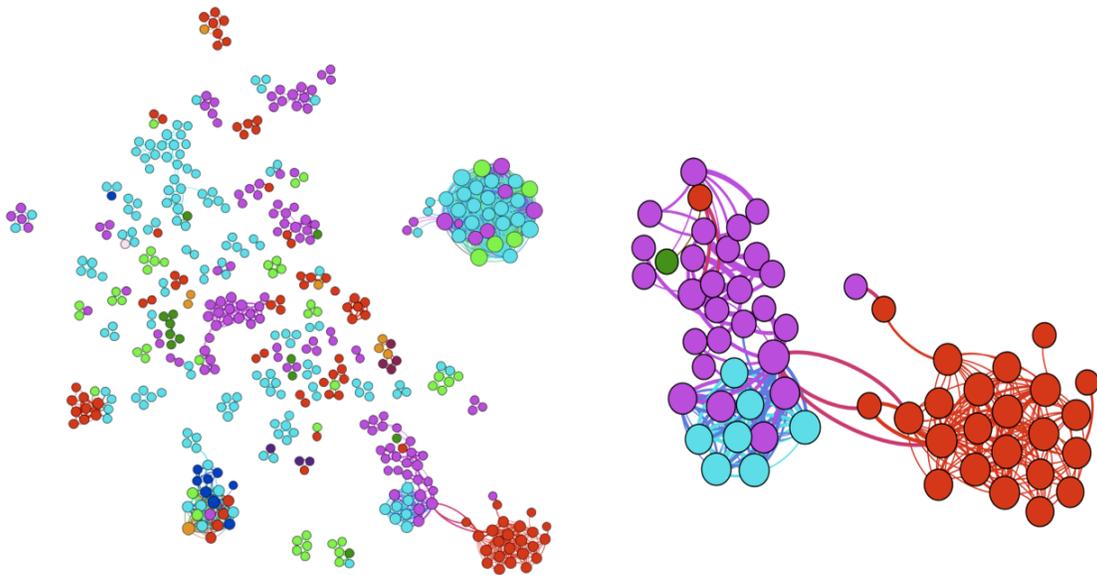


Figure 5: 2005-2009 full network (left) and its largest component (right)

Figure 6 illustrates, the evolution of the size of the second component. Starting at 26 researchers, it reaches a maximum of 37 nodes during the 2006-2010 window before decreasing slightly to end up at 33 for the last studied period. In fact, in the 2005-2009 collaboration network, the largest component of the previous network (2004-2008) split itself in two parts. The biggest part of the two became the new largest component of the 2005-2009 network while the other part, the smallest of the two, became the second largest component. Hence, this shift pushed the second largest of the 2004-2008 at the third position in importance in the subsequent graphs. By further investigating the data,

we verified that from the 2005-2009 period the two largest components (first and second) were composed principally of the same main researchers.

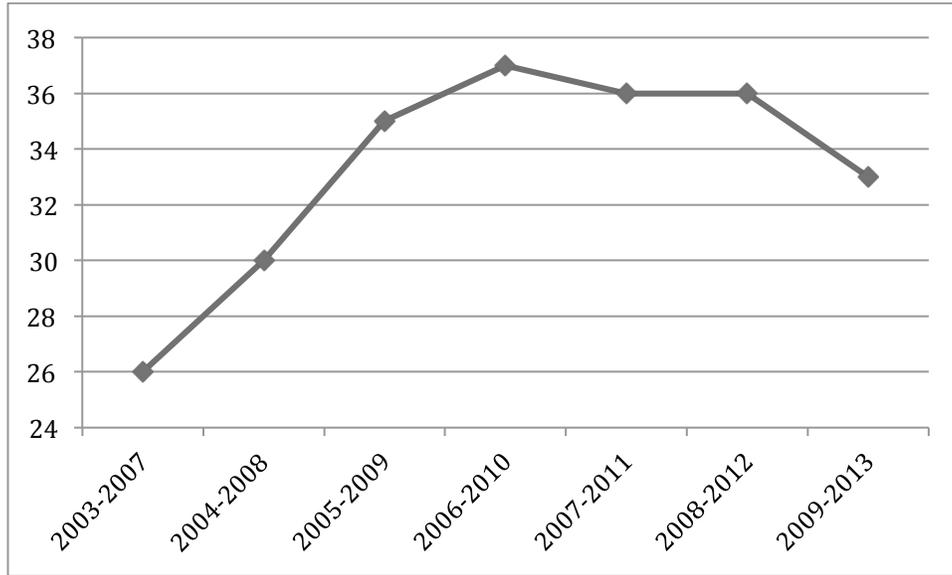


Figure 6: Evolution of the size of the second component

4.2 Small-world analysis for research collaboration networks

By definition, a network exhibits a small-world structure if it shows a higher clustering coefficient than a random network that possesses the same number of nodes while having approximately the same average path length. In order to compare our collaboration networks with random graphs, we used Gephi’s Erdos-Renyi random graph generator. Hence, a random graph the same size as the main component of the studied networks was created for each of the examined period. Then, their respective clustering coefficient and average path length were calculated and compared with those of the largest component networks. The results are showed in Figure 7 and Figure 8.

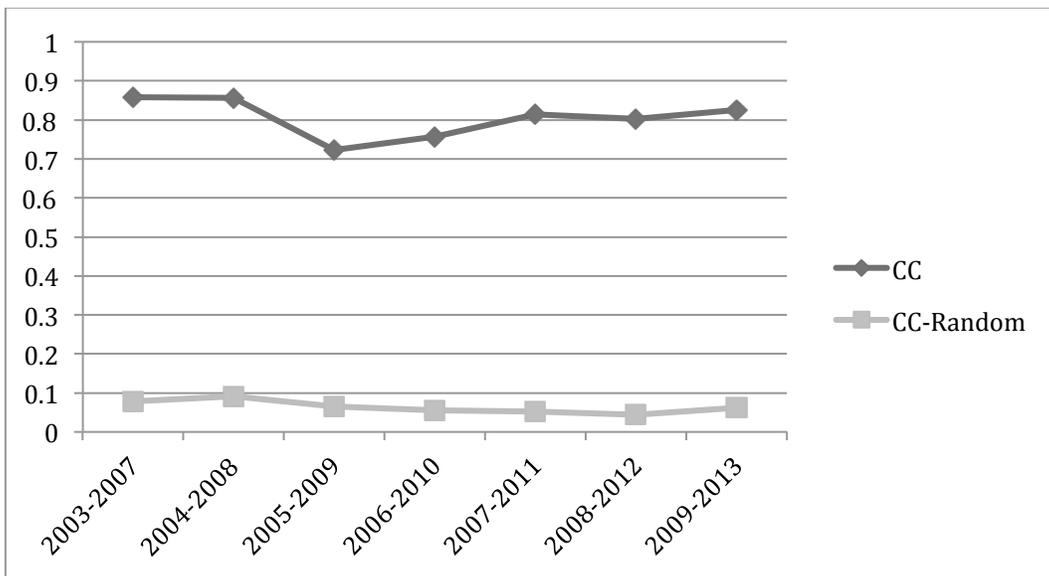


Figure 7: Clustering coefficient of the collaboration and random networks

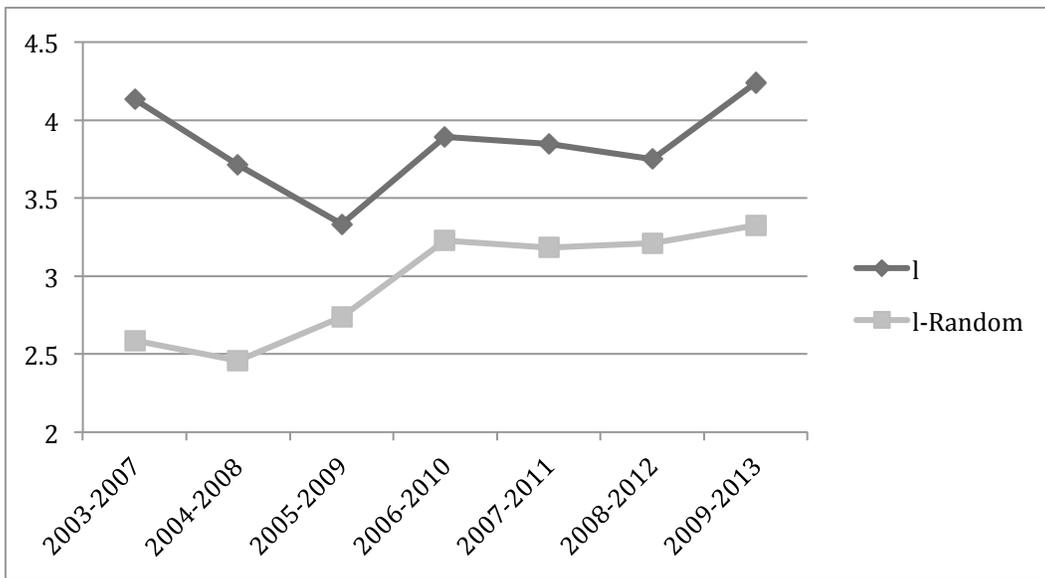


Figure 8: Average path length of the collaboration and random networks

The clustering coefficient of research collaboration networks measures the extent to which a researcher’s collaborators are also collaborating with each other. Figure 7 shows that the clustering coefficient of the researchers network is significantly higher than the one of the random network. Moreover, it is almost constant and always higher than 0.7. This represents the first characteristic of small-worlds.

According to Figure 8, the path length of the collaboration network shows a minimum during the 2005-2009 period. This is not surprising considering the smaller network size during this period (see Figure 5). With the exception of this point, the average path length for the NSERC network lies between 3.6 and 4.2 approximately, which is slightly higher than the path length of the random generated graphs. The graph also shows a decrease in the difference between the observed and random values. The main component of our collaboration network therefore seems to meet Watts and Strogatz’s small-world network criteria.

To further analyze the small-world structure, we calculated the small-world variables (SW) for each examined period (see Table 1). According to Baum et al. (2003), the SW variable increases with the network size. However, we can observe that it increases throughout the periods even when the network size drops for the 2005-2009 period. Both the average path length and the clustering coefficient show trends towards a more typical small-world structure resulting in a value of 18.356 for the small world variable for 2009-2013 period. Figure 4 showed that the network size seems to stagnate around 100 researchers. As mentioned earlier, these researchers are mostly the same during the last 4 periods, so it is coherent to think they created a more clustered environment where information flows more easily.

Table 1: Small-world properties for the largest component

Period	Network size	$l/l(\text{rd})$	$CC/CC(\text{rd})$	SW
2003-2007	100	1.597	13.438	8.413
2004-2008	95	1.511	12.478	8.260
2005-2009	59	1.217	10.955	9.000
2006-2010	100	1.206	13.518	11.208
2007-2011	99	1.208	20.450	16.925
2008-2012	99	1.168	19.048	16.309
2009-2013	113	1.274	23.382	18.356

Table 2 presents the results of performing the same analysis for the second largest component of the networks. This second component shows small-world characteristics only during the first two periods. Afterwards, from 2005-2009 the component loses these properties as indicated by the low values of SW. Again this is due to the shift explained in Section 4.1. We are not looking at the same group of researchers in the first two periods. From the period 2005-2009 onward, the component shows a smaller path length than the random graph indicating a very tight network. On the other hand, the ratio between the clustering coefficient of the collaboration network and the one of the random graph is close to 1 and decreasing.

Table 2: Small-world properties for the second largest component

Period	Network size	$l/l(\text{rd})$	$CC/CC(\text{rd})$	SW
2003-2007	26	0.774	14.850	19.193
2004-2008	30	1.039	24.458	23.546
2005-2009	35	0.894	1.932	2.160
2006-2010	37	0.918	2.014	2.194
2007-2011	36	0.894	1.696	1.896
2008-2012	36	0.894	1.738	1.943
2009-2013	33	0.835	1.543	1.848

4.3 Small-world analysis for researchers-organisations collaboration networks

In order to measure the impact of organisations within the NSERC collaboration networks, we added the relationships between the academic principal investigator (researcher) of the funded projects and the industrial partners. Once again we consider the largest component of the network for the small-world analysis. The direct effect, of adding an additional type of player in the network is an increase in the size of the main component as depicted in Table 3 and Figure 9. The addition of the links between the principal investigators and the organisations allows the connection between previously disconnected researchers sub-components, as depicted in Figure 9.

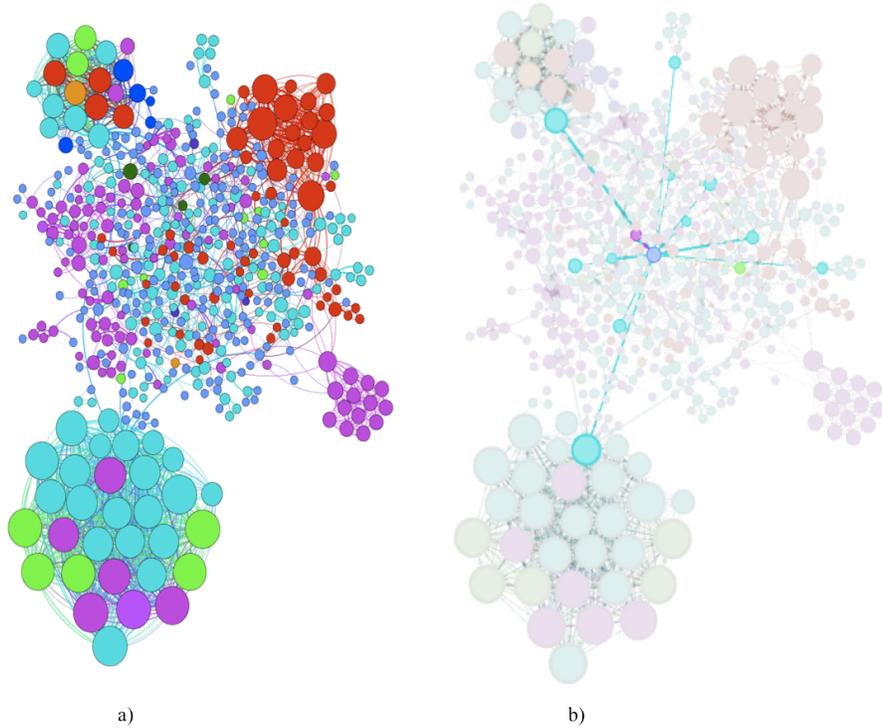


Figure 9: a) Largest component for the 2009-2013 researchers-organisations collaboration network (organisations are coloured in violet) and b) highlighted connections of an organisation within the network linking multiple subgroups of researchers

To assess the role of the organisations, we measured their betweenness centrality. On Figure 10, we can see the evolution of the normalized betweenness centrality for a few of important players in the Canadian ICT scene.

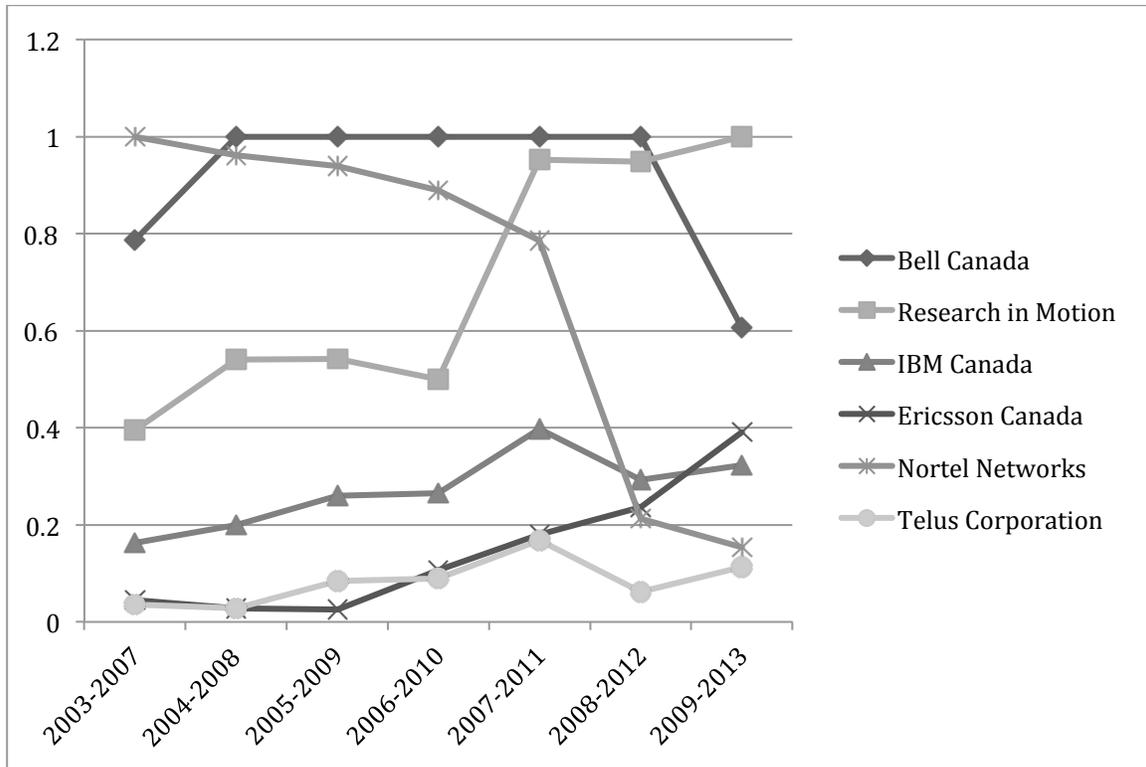


Figure 10: Evolution of normalized betweenness centrality for key firms of the researchers-organisations network

For every period, the most central node (value of 1) in terms of betweenness is a private firm, not a researcher neither a public organisation. Not surprisingly, Nortel Networks shows a decreasing value over the period attributable to its bankruptcy around 2009, being rapidly replaced in importance by Research in Motion, whose betweenness centrality increased from 0.4 for the 2003-2007 network to nearly 1 later in the period, ending as the most central node. For nearly all of the examined periods, Bell Canada is the most central actor (in terms of betweenness centrality).

Performing the same analysis for public organisations, we obtained the values shown in Figure 11. Interestingly, throughout the period Industry Canada has taken a more central position (in terms of betweenness centrality), in contrast with the National Research Council (NRC) who shows a declining betweenness centrality. As Industry Canada is neither a technology developer nor a research Institute, further investigation in this regard is required.

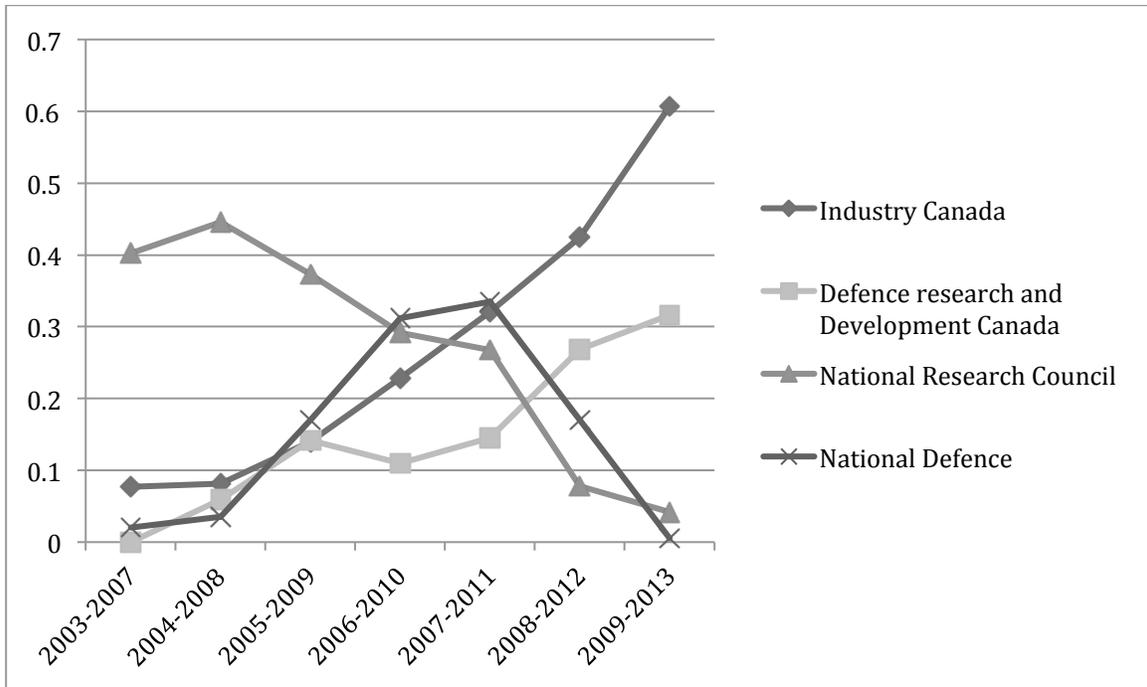


Figure 11: Normalized betweenness centrality for key public organisations in the network

Table 3 highlights the significant general increase in the value of the SW variable of the university-industry network compared to the values seen for the researchers collaboration networks (see Table 1). We can see the difference between the observed values in Figure 12. According to the small-world theory, this suggests that firms have a key knowledge transmission/integration role.

Table 3: Small-world properties for the largest component of the researchers-organisations collaboration networks

Period	Network size	CC/CC(rd)	I/I(rd)	SW
2003-2007	493	215.00	1.06	202.13
2004-2008	512	138.67	1.04	133.74
2005-2009	542	85.80	1.13	76.02
2006-2010	636	71.50	1.07	66.74
2007-2011	669	146.33	1.24	118.36
2008-2012	663	49.00	1.15	42.70
2009-2013	687	119.67	1.11	107.73

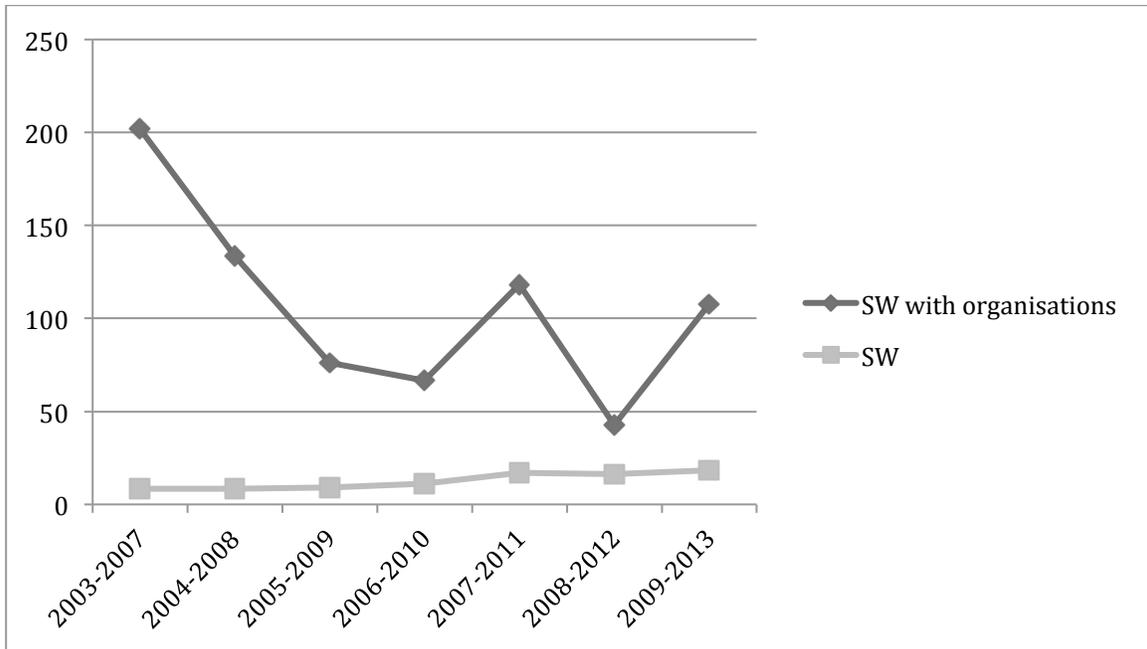


Figure 12: SW evolution for the two sets of networks (researchers only and researchers-organisations)

5 Discussion and conclusion

This paper focused on the research collaboration network of the Canadian researchers working in the ICT hardware field involved in projects funded by the Natural Sciences and Engineering Research Council of Canada. By adding the links between principal investigators and organizations, the network of researchers and firms showed a much greater cohesion. Our work investigated the existence of small-world structure in order to understand the collaboration mechanisms taking place in the network.

Our results confirm the presence of a fairly stable small-world structure for the largest components of the collaboration networks for the examined periods. Indeed, they showed a high clustering coefficient compared to random networks of the same size, yet with a similar average path length. The network of the last period studied (2009-2013) had the highest small-world variable, exhibiting an increasing trend. Hence, the network becomes more connected over time, and the short path length suggests that knowledge exchange is easier.

Our analysis also showed that the addition of the ties linking organizations to principal investigators provoked a small-world variable surge. Moreover, the largest component grew much larger and the firms established connections between various subgroups of researchers that would be otherwise stand alone components. Their role as connectors or intermediaries is highlighted by their high betweenness centrality.

Our research has many limitations. First, the ICT hardware industry is hard to define because of the transcendent nature of ICT. It has multiple application fields and major research contributions come from various disciplines. For example, advances in quantum computing are largely due to mathematical algorithms. Therefore, there is without a doubt a source of error in our filters. Some of the projects contained in our database may

not be totally related to ICT hardware and vice-versa some hardware projects were probably wrongly taken off the initial database. Further research adding publications and patents to the database and to the networks should partly remedy this limitation by allowing a better classification of ICT researchers and of their collaborators, whether other researchers or organisations.

The size of the researchers networks (the largest components) is another limitation. It is hard to determine the collaboration mechanisms of an entire network by analyzing only 20% of it. However, this is something we could explore further. For example, the full network could be formed of other sub networks (third components, etc.) that possess small-world properties and we should investigate this question. The disconnections observed in the full researchers' collaboration networks and the size of the largest components suggests a lack of interdisciplinarity, but more importantly that teams that apply for funds are rarely changing over time. It would be interesting to test this hypothesis in future work, but also to consider other means by which to measure collaboration.

Covering more years could give a better historical trend. Unfortunately, data on co-applicants was missing before 2003, but other collaboration indicators could remedy this lack of data. A longer time series would give a better understanding of the network evolution.

Finally, the collaboration networks examined in this paper contained only NSERC data. Ideally, in addition to adding various other sources of collaboration, co-publishing and co-patenting for example, but also more informal collaboration, MITACS, NCEs and other funding sources should be added to the analysis, providing we can lay our hands on them. The next research objective will be to determine quantitatively the impact of this small-world structure on innovative performance.

6 References

- Baum, J. A., Shipilov, A. V., & Rowley, T. J. (2003). Where do small worlds come from? *Industrial and Corporate Change*, 12(4), 697–725.
- Bercovitz, J., & Feldman, M. (2011). The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. *Research Policy*, 40(1), 81–93.
- Boschma, R. (2005). Proximity and innovation: a critical assessment. *Regional Studies*, 39(1), 61–74.
- Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies “Engines of growth”? *Journal of Econometrics*, 65(1), 83–108.
- Chesbrough, H. W. (2003). *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Harvard Business Press.
- Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 128–152.
- Cowan, R., & Jonard, N. (2004). Network structure and the diffusion of knowledge. *Journal of Economic Dynamics and Control*, 28(8), 1557–1575.

- Ebadi, A., & Schiffauerova, A. (2015). On the Relation between the Small World Structure and Scientific Activities. *PLoS ONE*, *10*(3).
- Fleming, L., King, C., & Juda, A. (2007). Small Worlds and Regional Innovation. *Organization Science*, *18*(6), 938–954.
- Fleming, L., & Marx, M. (2006). Managing creativity in small worlds. *California Management Review*, *48*(4), 6–27.
- Gordon, M. (1980). A critical reassessment of inferred relations between multiple authorship, scientific collaboration, the production of papers and their acceptance for publication. *Scientometrics*, *2*(3), 193–201.
- Goyal, S., Van Der Leij, M. J., & Moraga-González, J. L. (2006). Economics: An emerging small world. *Journal of Political Economy*, *114*(2), 403–412.
- Grewal, R., Lilien, G. L., & Mallapragada, G. (2006). Location, Location, Location: How Network Embeddedness Affects Project Success in Open Source Systems. *Manage. Sci.*, *52*(7), 1043–1056.
- Joe Tidd, M. J. T. (2002). Organizational and Technological Antecedents for Knowledge Creation and Learning. *R&D Management*, *27*(4), 359 – 375.
- Katz, J. S., & Martin, B. R. (1997). What is research collaboration? *Research Policy*, *26*(1), 1–18.
- Kraut, R., Egido, C., & Galegher, J. (1988). Patterns of contact and communication in scientific research collaboration. In *Proceedings of the 1988 ACM conference on Computer-supported cooperative work* (pp. 1–12). ACM. Retrieved from <http://dl.acm.org/citation.cfm?id=62267>
- Krebs, V. (2004). An introduction to social network analysis. Retrieved November, 9, 2004.
- Laudel, G. (2002). What do we measure by co-authorships? *Research Evaluation*, *11*(1), 3–15.
- Lee, Y. S. (2000). The Sustainability of University-Industry Research Collaboration: An Empirical Assessment. *The Journal of Technology Transfer*, *25*(2), 111–133.
- Melin, G. (2000). Pragmatism and self-organization: Research collaboration on the individual level. *Research Policy*, *29*(1), 31–40.
- Newman, M. E. (2000). Models of the small world. *Journal of Statistical Physics*, *101*(3-4), 819–841.
- Newman, M. E. (2004). Fast algorithm for detecting community structure in networks. *Physical Review E*, *69*(6), 066133.
- Newman, M. E., Strogatz, S. H., & Watts, D. J. (2001). Random graphs with arbitrary degree distributions and their applications. *Physical Review E*, *64*(2), 026118.
- Nieto, M. J., & Santamaría, L. (2007). The importance of diverse collaborative networks for the novelty of product innovation. *Technovation*, *27*(6–7), 367–377.

- Nooy, W. de, Mrvar, A., & Batagelj, V. (2011). *Exploratory Social Network Analysis with Pajek*. Cambridge University Press.
- Phelps, C. C. (2010). A Longitudinal Study of the Influence of Alliance Network Structure and Composition on Firm Exploratory Innovation. *Academy of Management Journal*, 53(4), 890–913.
- Ponds, R., Van Oort, F., & Frenken, K. (2007). The geographical and institutional proximity of research collaboration*. *Papers in Regional Science*, 86(3), 423–443.
- Rost, K. (2011). The strength of strong ties in the creation of innovation. *Research Policy*, 40(4), 588–604.
- Santoro, M. D., & Chakrabarti, A. K. (2002). Firm size and technology centrality in industry–university interactions. *Research Policy*, 31(7), 1163–1180.
- Schilling, M. A., & Phelps, C. C. (2004). Small world networks and knowledge creation: implications for multiple levels of analysis. Available at SSRN 385022. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=385022
- Subramanyam, K. (1983). Bibliometric studies of research collaboration: A review. *Journal of Information Science*, 6(1), 33–38.
- Sullivan, B. N., & Tang, Y. (2012). Small-world networks, absorptive capacity and firm performance: evidence from the US venture capital industry. *International Journal of Strategic Change Management*, 4(2), 149–175.
- Tommaso Buganza, & Roberto Verganti. (2009). Open innovation process to inbound knowledge: Collaboration with universities in four leading firms. *European Journal of Innovation Management*, 12(3), 306–325.
- Uzzi, B., Amaral, L. A., & Reed-Tsochas, F. (2007). Small-world networks and management science research: A review. *European Management Review*, 4(2), 77–91.
- Uzzi, B., & Spiro, J. (2005). Collaboration and creativity: The small world Problem1. *American Journal of Sociology*, 111(2), 447–504.
- Van Rijnsoever, F. J., & Hessels, L. K. (2011). Factors associated with disciplinary and interdisciplinary research collaboration. *Research Policy*, 40(3), 463–472.
- Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge University Press.
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of “small-world” networks. *Nature*, 393(6684), 440–442.
- Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, 316(5827), 1036–1039.
- Ziman, J. M. (1994). *Prometheus bound*. Cambridge University Press.