Research collaboration in co-inventor networks: combining closure,bridging and proximities

Cassi, Lorenzo and Plunket, Anne

CES, University of Paris 1 Sorbonne, Observatoire des Sciences et des Techniques, ADIS Paris sud

May 2012

Research Collaboration in Co-inventor Networks:

Combining Closure, Bridging and Proximities

Lorenzo Cassi
lorenzo.cassi@univ-paris1.fr
Université Paris 1, CES - Centre d'Economie de la Sorbonne &
OST - Observatoire des Sciences et des Techniques, Paris

Anne Plunket
anne.plunket@u-psud.fr
Université Paris Sud 11, ADIS

May 2012

Abstract

This paper investigates the determinants of co-inventor tie formation using micro-data on genomic patents from 1990 to 2006 in France. In a single analysis, we consider the relational and proximity perspectives that are usually treated separately. In order to do so, we analyse various forms of proximity as alternative driving forces behind network ties that occur within existing components (i.e. closure ties) *as well as those* between two distinct components (*i.e.* bridging ties). In doing so, we contrast network and proximity determinants of network formation and we investigate to what extent social networks allow economic actors to cross over geographical, technological and organizational boundaries.

Keywords: Social networks, relational perspective, proximity, co-patenting, network formation.

JEL codes: D85, O31, R12, Z13

1. Introduction

The significance of social networks in relation to innovation is now widely acknowledged, and even considered a truism (Lobo and Strumsky, 2008). A growing body of literature convincingly argues that knowledge is far from being “in the air” and accessible to all actors but rather follows specific channels between socially and personally linked individuals (Breschi and Lissoni, 2005, 2009; Knoben, 2009). These “social proximity” arguments strongly contrast with previous studies on geographical proximity that investigate agglomeration economies and argue that knowledge circulates more or less freely among co-located industrial and academic actors, suggesting that they benefit from a premium depending upon their location (Jaffe, 1989; Jaffe et al. 1993; Audretsch and Feldman, 1996; Aharonson et al. 2008; Boufaden and Plunket, 2008; Knoben, 2009).

Although social networks suggest that innovation and diffusion of knowledge do not simply depend upon location, the strong link cannot be ignored (Boschma, 2005; Torre et Rallet, 2005). Networks and proximity appear as highly interrelated phenomena since the formation of networks is highly spatially localized, at least in its earliest stages (Ponds et al. 2010), and mainly found within organizational and cognitive boundaries (Singh, 2007). The dynamics of network formation are a major research objective for the geographical analysis of innovative networks (Boshma and Frenken, 2009). These debates raise a number of questions: first, to what extent are geographical and social proximity overlapping phenomena? Second, to what extent do networks enable to reduce geographical, organizational and cognitive boundaries and offer the opportunity to access non-local knowledge (Gluckler, 2007)?

The aim of this paper is to investigate these questions by analysing the determinants of scientific and technological network collaborations, namely inter-individual co-inventions. We address this issue through the formation of network ties using a longitudinal analysis of French co-patenting data in the field of genomics between 1990 and 2006.

In order to disentangle network and proximity effects, we consider the impact of various forms of proximity in establishing two different types of network ties. In the first case, individuals are at least indirectly linked *within the* same *network* component; they share some level of social proximity and form a closure tie. This enables them to increase the cohesion of a group of individuals, favour trust and facilitate the sharing of resources (Coleman, 1988). In the second case, actors belong to distinct components and they have no network connection. They form a bridging tie that allows for the connection of distinct groups of individuals, thus establishing a channel across networks, which facilitates access to different resources or assets (Burt, 1992). This distinction allows us to account for network effects explicitly through social proximity and preferential attachment relative to geographical, technological and organizational proximity (Boschma, 2005) as driving forces behind network formation. Considering both of these determinants in the same framework allows investigating not only their respective impacts on collaborations, but also how they overlap, interact, and possibly act as substitutes or complements.

Our findings support the idea that within-network effects (i.e. closure ties) occur among actors that share a strong organizational proximity and technological similarity. Moreover, social, geographical and organizational proximity act as substitutes, in the sense that geographical proximity is less important when individuals are already connected through common acquaintances or act under similar governance. In this sense, social connections allow actors to cross over geographical and organizational boundaries. In contrast, across-network effects (i.e. bridging ties) occur rather when individuals seek some level of variety and diversity in collaboration, and this occurs mainly through inter-organizational ties for which technological distance is more important.

The paper is organized as follows: Section 2 presents the theoretical framework and stresses the element of novelty in our work relative to the existing literature. Section 3 provides a description of data and an explanation of how networks have been built up. Section 4 describes the estimation design and discusses the results of the econometric analysis. Section 5 concludes.

2. The Determinants of Network Tie Formation

An increasing body of literature investigates innovation networks considering clusters of firms within regions and their impact on performance. Since networks are crucial for innovation, it seems important to consider the conditions under which these networks are formed and the relative importance of factors acting as network drivers. The dynamics of network formation have only recently begun to be empirically investigated and most existing studies run some form of *pairwise regression* (Bramoullé and Fortin, 2010), in which case the variable to be explained is represented by the links themselves.

Within existing studies, the formation of network ties are explained by different bodies of literature that offer two distinct perspectives: (a) the *relational perspective* assumes that trust and knowledge access and control of information are conferred through the actors' position within the network; (b) the *proximity perspective* focuses on the relative position of economic actors in space, however defined[1].

These two perspectives rely on different mechanisms. However, they highly interact in shaping the evolution of observable social networks. The proximity determinants explain the contexts in which people meet and may become connected. For instance, two individuals are located in the same region. Once connected, they are part of a network that offers opportunities to form new ties and, in doing so, to cross organisational and geographic boundaries. While different streams of literature rely on two distinct perspectives and have been developed more or less independently, researchers are increasingly concerned with how both patterns overlap and interact.

2.1. The Relational Perspective

The relational perspective focuses on direct and indirect connections among individuals; it is sometimes referred to as a 'within-the-network' approach, since the "focal predictor of network change is hypothesized to be the shape and structure of the network in a prior time period" (Rivera et al., 2010, p. 97).

Two main explanations are identified: *closure and preferential attachment*. The former concerns the tendency of actors to form clusters, the latter deals with the actors' propensity to link to the most connected individuals.

One of the characteristics that distinguish social from biological or technological networks is clustering (Newman and Park, 2003). Coleman (1988), and many others after him, have argued that being embedded in a very dense, interconnected, "cliquish" network generates benefits by enhancing the trust among individuals and thereby encouraging joint activities and the sharing of tacit and complex knowledge. Consequently, the effect of sharing a mutual acquaintance increases the likelihood of forming a dyad between indirectly connected actors. Said differently, open triads tend to close over time. These so-called "triadic closures" occur when an actor becomes connected to one's partner's partner, that is, when they share some level of social proximity. As will be discussed later, this social proximity strongly interacts with other forms of proximities since prior ties are highly localized and strongly embedded in kinship, professional and friendship networks (Boschma, 2005, Breschi and Lissoni, 2009, Ter Wal, 2011). For the sake of analytical clarity, social proximity is defined in a very restricted manner; it refers to direct or indirect inter-personal connections between any two actors. It is different from other forms of proximity such as being located in the same region, working for the same company or being part of the same technological community. The fact that individuals are proximate in those dimensions does not necessarily mean that they share inter-personal relationships.

However, being embedded in very dense and strongly cohesive networks may also harm individuals in their search of new knowledge and their learning processes. In fact, Burt (1992) argues that knowledge accessing is more efficient when individuals occupy structural holes that enable the link up of unconnected actors. Individuals positioned in structural holes are able to broker knowledge flows across unconnected groups (e.g. Gargiulo and Benassi, 2000). In sum, if clustering seems to be quite a general tendency, some strategic reasons may lead actors to avoid these configurations and, instead, seek out structural holes by forming bridging ties. As Baum et al. (2012) argue, “(…) closure is about fostering cooperation and integration within close-knit groups, bridging is about seeing variation in ideas and practices across groups […] Bridging positions afford timely access to diverse information and resources from non-redundant contact, and opportunities to broker this novel information and resources between unconnected partners (Burt, 1992)”. Individuals may form bridging ties in order to gain access to different or complementary resources outside their close network.

Skewed degree (*i.e.* the number of links per node) distribution is another recurring feature of networks. The main explanation initially proposed by Barabási is the *preferential attachment model* (Barabási and Albert, 1999); the rate at which actors acquire new ties is a function of the number of ties they already have. This is explained by the fact that actors looking for new partners consider the other agents’ number of existing ties as a factor of, for instance, productivity.

However, in some cases, establishing and maintaining a partnership could require a non-negligible (opportunity) cost, which can limit the number of partners an actor can efficiently collaborate with. Thus, the relationship between degree centrality and tie-accumulation could be weaker in those networks where certain actor’s constraints (e.g. time or resources) are important. Moreover, Newman and Park (2003) have noticed that social networks, as opposed to biological or technological ones, display a specific characteristic: a tendency for the most connected actors to connect amongst themselves. Popular actors tend to attach to popular actors; likewise, low degree actors do so with their peers.

2.2. The Proximity Perspective

Geographical proximity is at the heart of the network formation issue and often appears as one of its main drivers, since many ties take place between actors located within a short distance (Boschma and Frenken, 2009). Moreover, we know that knowledge creation and innovation are spatially concentrated activities for mainly two reasons. First, geographical proximity facilitates information and knowledge sharing through frequent interactions, especially when knowledge is tacit, complex and sticky (Bathelt et al., 2004). This close proximity also contributes to solving coordination problems through trust building and inter-organisational learning. Second, the concentration of firms and universities in industrial clusters and large agglomerations offer a wide range of potential partners and more opportunities to meet and share knowledge. These reasons largely explain why i) individuals, firms and universities collaborate primarily on a local basis, ii) networks are locally embedded and iii) knowledge spillovers are spatially bounded (Maggioni et al. 2007). Networks and network ties are locally embedded to the extent that economic actors are geographically concentrated. However, geographical proximity, *per se*, does not seem to be a necessary or sufficient condition for knowledge sharing and interactive learning (Boschma, 2005), as opposed to being part of these networks (Ter Wall, 2011; Breschi and Lissoni, 2009). In explaining knowledge flows, Agrawal et al. (2008) as well as Breschi and Lissoni (2009) show that patent citations are more likely to occur among inventors who share social proximity, held through co-ethnicity or labour mobility. In summary, geography seems more important for promoting initial connections. Once these connexions exist, they enable one to overcome geographical boundaries, and spatial proximity ultimately plays little or no role in the formation of collaborations (Maggioni et al. 2007; Autant-Bernard et al. 2007).

Besides geography, the proximity literature highlights other forms of proximity such as cognitive and organisational proximity (Boschma, 2005). Cognitive proximity means that actors share the same knowledge base or technology. On the one hand, actors are more likely to collaborate when they have very similar knowledge bases, since it makes communication, learning processes and knowledge sharing easier (Jaffe, 1989). On the other hand, too much cognitive proximity may harm collaboration and innovation because of possible redundancy of knowledge. The process of innovation requires some level of dissimilarity and complementarity in the knowledge base. Network tie formation may also result from a technological brokerage strategy whose aim is to connect previously separated technological communities (Stuart and Podolny, 1999; Burt, 2004) thus leading to cross-disciplinary fertilization (Fleming and Marx, 2006). Therefore, it is difficult to predict the impact of cognitive distance on network tie formation, unless we consider the types of ties, as will be discussed below (Section 2.3).

Organisational proximity refers to the fact that “relations are shared in an organizational arrangement, either within or between organizations” (Boschma, 2005, p. 65). Organizational proximity is high when individuals share the same affiliation, in our case, when they patent for the same company or university (prior to tie formation). These ties are believed to be beneficial for innovation collaborations because they reduce uncertainty and opportunism. They are also more manageable when individuals share similar routines and processes, and they ease confidentiality requirements (Singh, 2005). Thus, organizational proximity facilitates knowledge production, diffusion and exploitation as shown by Fleming and Marx (2006). They highlight IBM Almaden Valley Labs' structural role as IBM highly invested in research and offered a doctoral program for Stanford University students, thus favouring the connection between IBM and their doctoral students' future appointments. Similarly, in his study on patent citations, Singh (2005) shows that citations are three times larger when they happen within the same firm, whereas they are only 66% more likely when there is spatial proximity, that is, when they emanate from the same region.

Despite uncertainty and the risks of opportunism, different organizations find advantages in collaboration as they share knowledge and financial resources. Collaboration may be facilitated when they cooperate under similar organizational types (either between private companies or between research institutions) because they have a common language, similar incentives and coordination routines, especially between academics. For private companies, collaboration may nevertheless be hampered by a number of difficulties, such as potential competition, risk of opportunism and other conflicting interests. When cooperation occurs between different organizational types, that is, between private companies and research institutions, a number of problems, such as different routines and incentive schemes, and difficulties in coordinating labour and accessing funds (Ponds et al. 2007) may also hamper collaboration. Nevertheless these arrangements are increasingly implemented and encouraged in regional and European innovation programs, especially in science-based industries such as genomics. In summary, while high organizational proximity clearly increases the likelihood of any tie, the impact of inter-organizational relations is less easy to predict, and presumably depends on the type of tie, as is discussed in the following section.

2.3. Closure, Bridging and Proximity Interactions

Following Amburgey et al. (2008), it is possible to classify each new link according to the connectivity to the overall network. Taking two individual inventors as our focal point, they may become connected through four categories of links, as represented in Figure 1: (1) a link bridging two components; (2) a link determining the creation of a new component; (3) a pendant to an existing component; or (4) an intra-component link.

[Figure 1]

The formation of each type of link has different implications for the overall network structure, as summarised in Table 1.

[Table 1]

Bridging and intra-component ties have very different consequences on network structure. The former allows for the linking of separate groups of inventors and establishing channels that facilitate the access to resources or other assets. The latter type allows for the establishment of a direct link between actors already (indirectly) connected and the increase of the cohesion of a group, favouring trust and enabling the sharing of resources. In the data, most of intra-component ties occur between inventors that are at very close social distance prior to the tie formation. More precisely, 84% of intra-component ties are formed between individuals that are indirectly linked at a geodesic distance (i.e., the shortest path between two individuals within a network) smaller or equal to 3. This means that the formation of these ties allows individuals to make their local network denser, closing triangle (geodesic distance equal to 2, namely “triadic closure”) or square relations (geodesic distance equal to 3 – hereinafter labelled “quadratic closure”). Finally, for simplicity, we label all intra-component ties as *closure* ties.

By construction, network ties differ in the sense that social proximity only plays a role for establishing closure ties. This may have two consequences that we test in this article: first, bridging ties enable actors to gain access to different organizations and knowledge resources; second, social proximity may act as a moderator for geographical, technological and organizational proximity, as has already been discussed in the previous section.

Concerning geographical proximity, we expect physical propinquity to explain the formation of network links, whether bridging or closure ties. However, as Torre and Rallet, (2005) argue, face-to-face and frequent contacts do not require permanent proximity, in the sense that agents do not need to be located in the same region. As a consequence, geographical proximity is not a necessary condition for collaboration and learning since other forms of proximity may be as important. Since networks and geography are strongly overlapping phenomena, and since they endorse similar roles of reinforcing the bonds of trust, reducing uncertainty and finally facilitating knowledge sharing and interactive learning (Boschma, 2005), we expect social proximity and geography to act as substitutes (Agrawal et al. 2008; Breschi and Lissoni, 2009). In other words, the impact of geography may be less important for triadic and quadratic closure, i.e. when social proximity is very close.

As discussed earlier, the impact of technological and cognitive proximity on collaboration is difficult to predict, since two different mechanisms of opposite sign are at work. As explained by Nooteboom et al. (2007), cognitive distance creates opportunities for innovation by combining distinct and complementary bodies of knowledge, and at the same time, cognitive distance must not be too large, because of a lack of absorptive capacity. As a consequence, we expect actors looking for similar bodies of knowledge, to search for partners in their close networks and rather form closure ties. However, when they search for complementary and dissimilar types of knowledge, they may be inclined rather to look for partners outside their close networks, and form bridging ties. "Because there is a limit to the ideas and opportunities that can be created using a given knowledge base, bridging ties also increase a firm's potential for finding new combinations by exposing it to novel variations" (Baum et al., 2012). However, if cognitive distance increases and if there is no social proximity (as in bridging ties), actors may need to rely on other forms of proximity, such as being part of the same organization or being located in the same region. We expect their interaction to be complementary.

Finally, we expect the likelihood of forming any tie to be greater when two actors have a high organizational proximity (i.e. they have already patented for the same organization). In this case, organizational and geographical proximity may act as substitutes, as already discussed in the previous section. When actors have previously patented for different organizations, we expect the likelihood of collaboration to be smaller for closure ties and larger for bridging ties, especially for actors belonging to different organizational types, namely company-research institution collaborations. We also expect the role of geography to be more important in order to compensate for the lack of organizational proximity as argued by Ponds et al. 2007.

3. Patent Networks in Genomics

3.1. Description of the Data and Network Formation

The dataset under investigation is composed of all the genomic patents published at the European Patent Office between 1990 and 2006, with at least one inventor reporting a French postal address and their co-inventors, whatever their location within or outside France.

The database was built during a recent research project carried out by ADIS-Paris Sud, LERECO-INRA and the OST – *Observatoire des Sciences et des Techniques* - supported by the French National Research Agency (ANR – *Agence National pour la Recherche*). The EPO Worldwide Patent Statistical Database (PATSTAT) was searched using a specific strategy involving genetics and genomics keywords in order to define the genomic field (Laurens, Zitt and Bassecoulard, 2010). “Genetics *stricto sensu* is the science of gene heredity and variation of organisms by looking at single genes… in contrast, genomics typically looks at all the genes or at least at large fractions of a genome as a dynamic system, over time, to determine how they interact and influence biological pathways, networks and physiology, in a much more global sense” (ibid, p.649). A number of experts were asked to validate the lexical query for filtering genomics out of genetics and ultimately the field delineation and the border areas.

Our final database is a sub-sample of 2104 patents filed by 496 applicants and 4456 inventors. These represent 7976 patent-inventor couples among which 6034 report a French postal address and 1942 a foreign address.

Every patent provides information on the inventors, their name and postal address, which enables the definition of their geographical location at the NUTS 3 level for European inventors and the geographical distance between them. The patent also offers information on applicants, for which we have determined whether they are private companies, research institutes and universities, non-profit organizations or individuals. For each patent, we also know their IPC – International Patent Classification – codes, which identify their technological fields. We use all of this information in order to define the inventor's individual characteristics, such as geographical location, technological specialization and affiliation. The affiliation is, in this case, the organization for which the patent is filed and not necessarily the employer. For instance, it may happen in a number of cases that academic inventors file patents for a private company instead of their own university.

In order to build the network,[2] we assign a link (edge) between any two inventors (nodes) who file a patent together. The actors that co-patent form small components that increase over time and eventually connect to other components through new co-patenting activities. Networks may thus be described as bundles of actors that are connected, but all the actors within a network are not necessarily linked.

The aim of our paper is to understand the formation of dyads between co-inventors. These new links are explained by the network structure and the inventors' individual characteristics. In order to avoid simultaneity biases, we consider all determinants with a lag of one period. For this reason, we may only investigate links among already active actors, that is, bridging and closure ties. Another reason for investigating these links comes from the specificity of patents as compared to publications (Fafchamps et al., 2010, Ponds et al., 2007); co-inventors of a given patent have, by definition, the same affiliation[3] and technological field (IPC codes). For this reason, this information cannot be used to highlight organizational or technological determinants.

Finally, since ties may die out after a certain period of time, we use a five-year moving window to get a more realistic picture of the network for any given year. So, for instance, the network in 1994 comprises all the patents published between 1990 and 1994. Accordingly, an inventor is considered as active (e.g. in 1994), if he/she has at least one patent over the 1990-1994 period. The observed co-patents and the potential co-patents actually used for the regressions as controls start in 1996 and go through 2006.

3.2. Networks Structural and Dynamic Properties

Figure 2 displays the number of active inventors over time. At the beginning of 2000, the number of inventors clearly grows and then stabilizes around 2004.

[Figure 2]

More striking is the time-varying pattern depicted by the giant component: first, it appears to be relatively small throughout the period compared to the size in similar studies (e.g. Fleming and Frenken, 2007). Second, it reaches its maximum in the year 2002, and starts decreasing before reaching a plateau.

While previous analyses focus on the giant component, our paper tracks the network dynamic by considering all sub-components (Baum et al., 2003; Fleming and Marx, 2006; Fleming and Frenken, 2007). It is interesting to consider the formation of the giant component over time and understand why some network subparts become connected and grow over time whereas others do not. The formation of the largest component may be the result of two scenarios that are not necessarily mutually exclusive. In the first, the largest component may result from the connection of relatively large existing components that increase over time, have their own dynamics and finally become connected in a larger one. In the second scenario, the largest component may result from an incremental process wherein small components become connected, within a short time period, to a single relatively large component. In the former scenario, bridging ties would play a pivotal role for network connectivity, while such would not be the case in the latter scenario.

[Figure 3]

Figure 3 illustrates the evolution of the first four largest components in the 1998 network. The first component (137 inventors in 1998, around 13% of active inventors) is mainly composed of inventors located in the Paris region, Ile-de-France (the same holds for the second and partially for the fourth component), while the bulk of the third component is located in the Rhône-Alpes region. The components also differ in terms of patent applicants. The first component includes several big corporations (e.g. Aventis and Centillion) and foreign universities; the second mainly includes public actors such as CNRS, INSERM and certain Parisian universities as well as biotechnological firms (e.g. Neurotech SA). Finally, the third component revolves around one main applicant, Bio Merieux, while the fourth one is mainly composed of inventors working for a spin-off of CSIRO, the Australian government research agency and for a French firm located in the central region of Auvergne. Most striking is that the 'public' component, i.e. the second one, breaks up during the first years (which is represented in Figure 3, by the fact that line 2 disappears in 2001), while the other components converge into a giant component. Finally, in the most recent years (2005), the size of the giant component decreases with its members splitting into three subgroups. In summary, examination of the giant component formation confirms the usefulness of analysing the specific role of bridging ties and their determinants.

Table 2 reports the number and share of new links relative to the period we intend to explain, i.e. 1995-2006.

[Table 2]

Most ties happen to involve new inventors either through the formation of new components or through pendant links. Indeed, the most adopted strategy to enter into a network is forming a new component. The corollary is that one should already have patented (i.e. sent a signal), before attaching to some active inventor.

[Table 3]

A fortiori, this implies a more central role for bridging ties. If the majority of inventors enter into a network establishing a new component, the overall network's connectivity depends mainly upon actors' ability to link already existing components (i.e. bridging link) rather than inventors' ability to attach themselves *directly* to already active inventors (i.e. pendant link).

Moreover, descriptive statistics (Table 3) suggest that intra-component ties are to a large extent formed within the same applicant or with subsidiaries, whereas bridging ties are formed by different types of applicants, namely between academia and private companies.

4. Estimation Design and Variables

How do network configuration, proximity and their interactions affect the formation of network ties? Do they explain differences between bridging and closure tie formation? To address these questions econometrically, we use two different estimation procedures.

First, we use a conditional logit specification to test the impact of relational and proximity factors on the likelihood of forming a network tie, whether closure or bridging, as compared to the non-formation of any tie. Second, we use a multinomial logit specification to predict the likelihood of forming a bridging versus a closure tie, that is, forming a link across separate components rather than within one's component. The differences between the two types of ties may thus be considered regarding their specific network dynamic and configuration.

4.1. Dependent Variable and Estimation

4.1.1 The Conditional Logit Approach

For two inventors i and j, the probability of forming a tie p_{ij} follows a conditional logit distribution given by (Cameron and Trivedi, 2005):

$$p_{ij} = \frac{\exp(\mathbf{x}'\beta)}{\sum_m \exp(\mathbf{x}'\beta)} \text{ with } m = B, C, \text{No Tie}$$

$\mathbf{x}$ represents a vector of covariates whereas β is a vector of parameters to be estimated. If the tie is observed, the dependent variable takes the value of 1 and it is 0 otherwise. Three cases are considered whether we distinguish between closure (C), bridging (B) or No tie.

Therefore, the estimations subsequently consider the likelihood of forming a closure tie or a bridging tie versus no tie.

In order to estimate this model, we first compute all existing and potential ties between any two pairs of inventors. All of the possible and realized dyads generate around four million observations and the realized links represent only a marginal portion of all possible ties. Since this gap raises important difficulties of estimation, we adopt a case-control approach (Sorenson et al., 2006). For any realized tie and its related co-inventors, we randomly select five possible but not realized co-inventors that have filed a patent in the same year as the observed tie, which provide five controls for each co-inventor. In summary, for each realized tie, we have ten controls. Each realized tie and its controls represent a group and the estimation is realized within this group; we use a cluster robust procedure to adjust standard errors for intra-group (matched case-control) correlation. The corollary is that variables characterized by constant within-group effects, such as year dummies, cannot be estimated. We begin with a sample that has 2684 (i.e. 244 observed dyads + 244*10 controls) and 2123 (i.e 193*(10+1)) observations respectively for the bridging and intra-component cases. But, since we estimated geographical distance for European inventors only, we could not obtain kilometre distances for European and non-European inventors and, for this reason, a number of observations have been dropped and we end up with a sample of 2421 and 1604 observations respectively. The same sample is then used for the multinomial estimations[4].

4.1.2. The Multinomial Logit and Probit Approach

The multinomial logit model is equivalent to a series of pairwise Logit regressions, except that the whole sample is used in order to reduce the potential biases that may arise from dropping part of the observations. In this framework, it is supposed that inventors choose between three outcomes, forming a bridging tie (B), a closure tie (C) or not forming any tie (No tie). In our case, we choose "closure tie" as the "reference category" or comparison group, in order to estimate if proximity and relational variables explain differences between closure and bridging ties.

Let y_{ij} be the dependent variable with J nominal outcomes that are not ordered. p_{ij} is the probability of observing outcome B given explanatory variables vector $\mathbf{x}$.

The probability may be written as follows (Cameron and Trivedi, 2005):

$$p_{ij} = \frac{\exp(\mathbf{x}'\beta)}{\sum_m \exp(\mathbf{x}'\beta)} \text{ with J} = B, \text{No Tie}$$

In the Multinomial framework, the assumption of independent and identically distributed error terms in the specification of each alternative (IIA) must hold. To test the assumption of the independence-of-irrelevant-alternatives, we compute and report in the appendix the Hausman-McFadden and Small-Hsiao tests. The results are in favour of the IIA assumptions. However, one test is not conclusive and provides little guidance to the violation of the IIA assumption (Long and Freese, 2003). Since errors may be correlated among alternatives, we finally estimate a multinomial probit specification, which enables to relax the IIA assumption; we obtain very similar results to the multinomial logit estimations. As is often the case, these tests give inconsistent results and. However, the tests are

4.2. Independent Variables

Two sets of variables are considered according to the relational and proximity perspectives.

The relational perspective is tested using *social proximity and degree centrality* measures in order to grasp the closure effects. S*ocial proximity* is computed as the inverse of the geodesic distance d_{ij} between two inventors i and j, that is, the shortest path connecting them in the network. This measure is only appropriate for closure ties since the geodesic distance between unconnected nodes is infinity, which is the case for all bridging ties by definition. *Social proximity* increases the likelihood of forming a tie since inventors may collaborate more easily with their partners' partners because "knowing" them facilitates trust and collaboration. The impact of social proximity is estimated by computing two dummy variables to account for triadic and quadratic closure: "*social proximity (=2)"* is equal to 1 when the geodesic distance is 2 and 0 otherwise and likewise, "*social proximity (=3*)" in the case geodesic distance is equal to 3. These variables are then interacted with geographical and organizational proximity to estimate to what extent they may be substitutable or complementary (see Appendix A for a table with all the variables' definitions).

Social proximity is expected to increase the likelihood of forming a tie; however inventors cannot manage an increasing number of collaborations. For this reason we expect that the likelihood of forming a tie increases with the number of common partners up to a certain threshold, and after that it may decrease. In other words, we expect an inverted U-curve relation between collaboration and the number of common partners. In order to test this relationship, we compute four dummy variables ("common (= 1, 2, 3 and 4)) according to the fact that co-inventors have 1, 2, 3 or 4 common partners with a geodesic distance of 2.

To account for preferential attachment, we consider the *degree centrality measure*. Since the study considers the likelihood of two inventors in forming a tie, we must examine this measure for both inventors and consider the average $\overline{n}_{ij}$ and the difference Δn_{ij} of both inventors' degrees (Fafchamps et al. 2010).

$$\overline{n}_{ij} = \frac{(n_i + n_j)}{2}$$

$$\Delta n_{ij} = \left| n_i - n_j \right|$$

For each type of tie, we expect a different sign. In particular, we expect the average measure to be positive and the difference to be negative for closure ties and *vice versa* for bridging ties. When actors belong to the same sub-network, individuals tend to link to partners similar to themselves in terms of degree: thus the difference in the number of partners should tend to zero. This is even more important for individuals with a greater number of collaborations since they are more visible within the network. When individuals are searching for an effective collaboration that enables them to access new and different resources, it is likely that similarity is less important or even plays a negative role. In this case, a greater difference would have a positive effect on tie formation and, consequently, we should expect a negative effect of the average degree as well.

The proximity perspective is assessed through geographical, technological and organizational proximity. In order to calculate the "*geographical proximity"* in kilometres, we locate each inventor at the NUTS 3 level based on its postal address. All European inventors are identified this way; the non-European inventors have been dropped from the regressions[5]. The distance is calculated using the latitude and longitude coordinates of each NUTS 3 centroïd.[6] We calculate the distance in kilometres divided by 100[7]. Geographical proximity is thought to have a positive impact on the likelihood of forming a tie since proximity decreases transaction costs.

Collaboration is easier among inventors that share similar technological interests and specializations. For this reason, we suppose that "*technological proximity" increases* the likelihood of collaboration. It is computed as the Jaffe's (1989) index t_{ij}, which is a proximity measure ranging between zero and one, depending on the degree of overlap between the co-inventors' prior patent IPC codes.

$$t_{ij} = \frac{\sum_{k=1}^{K} f_{ik} f_{jk}}{\sqrt{\sum_{k=1}^{K} f_{ik}^2 \sum_{k=1}^{K} f_{jk}^2}}$$

f_{ik} and f_{jk} represent each inventor *i* and *j* technological position.

We then consider the impact of organizational proximity. Organizational proximity occurs when two inventors file a patent for the same applicant. When inventors file a patent for different organizations, two inventors may work for similar types of organizations, either among academia and public research centres or among private companies (Ponds et al. 2007). We suppose that inventors are more likely to form ties within their own organizational boundaries or with inventors belonging to similar organizational types. In order to account for different organizational settings, we consider three occurrences: "Same applicant" takes the value of 1 when inventors have patented for the same organization prior to tie formation and 0 otherwise; "Same type" takes the value of 1 when inventors have patented for the same organizational type (firms or companies) and 0 otherwise; and "Different type, different applicant" as the last occurrence, in our case university – industry relationships.

We interact these variables with geographical and social proximity in order to test if they may have substitutable or complementary impacts on network tie formation. Our hypothesis is that inventors will choose closure ties when they require similar competences that may be found in a close neighbourhood. They will choose bridging links when they need distinct skills that may not be found in their own environments.

We introduce two types of controls. We first control for the distinction between French located inventors and foreigners. Since being a foreigner is strongly correlated with geographical distance, we prefer to consider the specific case of foreigners located in border countries by introducing a dummy for inventors located in one of the French border countries, that is, Spain, Germany, Italy, Switzerland, and Belgium. We expect the impact to be positive.

We also consider the number of years since the first tie in order to control for experience with the patent process. Again, in order to account for the symmetric relation, we introduce the difference and average value of both inventors' experiences, namely *Experience – absolute difference* and *Experience –average difference.*

All variables are considered and computed for the period prior to the tie formation for which we estimate the likelihood. We cannot control for year fixed effects in the conditional logit model since by definition it includes group fixed effects for the inventors and their controls[8]. In order to control for changes through time, we have introduced year fixed effects in the multinomial probit estimation. However, introducing year fixed effects does not change the overall results.

5. Estimation Results and Discussion

5.1. Explaining Network Tie Formation

Table 4 presents the results from a series of conditional logit models with cluster robust standard errors. Models 1-5 demonstrate the impact of relational and proximity variables on the likelihood of forming closure ties, and 6-8 test the same variables on bridging ties. Across models, variables and controls remain consistent overall in sign and magnitude, suggesting that they are rather robust to the introduction of additional variables.

Since social proximity is infinite by definition in the case of separate components, and in order to enable comparison between closure and bridging ties, we first test the impact of networks through degree centrality in all models. The results for the absolute difference and average for the inventors' prior degrees show distinct patterns of dissimilarity between both types of ties. As expected, the inventors' relative position within the network explains closure tie formation. The difference in degrees has a negative impact whereas average degree has a positive impact in this case. This confirms that the likelihood of forming such ties decreases when inventors are more dissimilar and it increases when they have high degrees, namely when they are more visible and attractive within the network. Yet, these impacts are only slightly significant as opposed to the bridging ties for which the signs are opposite but highly significant, suggesting that bridging ties are driven by a search for diversity. The corollary is found in the negative sign for the averages. The attractiveness is not a question of visibility for bridging ties; inventors are apparently looking for other characteristics and resources.

The absolute number of years since the first patent does not seem to play an important role in the formation of network ties, as opposed to average years of experience. This impact is especially strong for closure ties, which depend on within-network relationships that are built over time.

Regarding the *proximity mechanisms*, all the sources of similarity impact collaborations, as expected. The likelihood of forming a tie is larger when co-inventors share similar technological fields and work in close spatial distance. The impact is even twice as large for the closure ties in the case of technological proximity. This is not very surprising given that 84% of closure ties occur within a short social proximity with geodesic distance of 2 (66% of cases) and 3 (18%); given that they occur within such a short social distance, knowledge bases are highly overlapping, or even redundant. Organizational proximity is also strongly significant and positive; the likelihood of forming a tie increases when inventors patent for the same applicant, even in the case of bridging ties. This confirms the fact that inventors patent first of all with individuals that belong to their own organization (Singh, 2005).

In summary, collaborations mainly occur when inventors are located in close geographical distance to each other, work in similar technological areas and presumably patent for the same organization. However, the interaction term *Geographical proximity x Same applicant* is strongly negative for closure ties. This suggests that combining geographical and organizational proximity reduces the likelihood of forming a closure tie, which means that that geographical proximity matters less for collaborations when inventors already patent for the same organization. The interaction is negative although non significant for bridging ties which implies that the facilitating role of geographical proximity is as important for inventors patenting for the same or for a different organization, presumably to compensate for the lack of social proximity.

[Table 4]

In contrast, proximity in organizational type has a negative impact. Since the large majority of collaborations between similar types of organizations occur between private companies (see Table 3), this result is not very surprising if we consider the risks due to opportunism and competition. This negative sign also means that science-industry relations are most likely to occur among inter-organizational collaborations. The interaction of “Same type” with geographical proximity is positive, confirming Ponds et al. (2007) findings that geographical proximity compensates for organizational distance.

Finally, forming a tie with a foreigner located in countries bordering France has a positive impact on network tie formation, although slightly less positive for bridging ties.

When introducing dummies for the number of common partners, previous results remain consistent overall in sign and significance, although the magnitude of coefficients is reduced for all proximity variables. Since these dummy variables represent the number of common partners, they explicitly account for triadic closure, and it appears that social proximity and other proximity variables partly overlap. This aspect will be further developed in the next section when social proximity is explicitly introduced in the regression. We expected an inverted U-shape for the number of common partners. The results do not confirm this hypothesis. Signs remain positive overall; coefficients first become larger for two partners in common, they subsequently become smaller for three partners in common and finally insignificant after four common partners.

[Table 5]

Table 5 further explores the impact of social proximity on closure ties. Most of these ties (84%) occur within a geodesic distance of 2 or 3, and regressions show that social proximity is a strong determinant of network tie formation. Once it is accounted for, all other network and proximity variables become less important, technological proximity becoming even insignificant. In a sense this confirms that closure ties occur among a close community of inventors that share similar knowledge bases, and at least as regards technology, ties appear as rather redundant when they occur at such a close social distance. The interactions with geographical and organizational proximity are very negative and highly significant for very close social proximity (i.e. geodesic distance = 2). This means that social, geographical and organizational proximity act as substitutes in facilitating collaborations. Geographical and organizational proximity matter less for collaboration when inventors have one partner in common.

The opposite impact occurs among similar organizations; only very close social proximity will facilitate collaboration among similar types of organizations. This result is explained by the fact that for the 165 closure ties, only 21 occur among similar organizations, and all but one concern private and distinct companies. This supports the view that having a partner in common creates sufficient trust to compensate for the risk of opportunism. Social propinquity and similar organizational types appear as complements since the former moderates the negative sign of the latter when explaining collaborations.

5.2. Bridging Versus Closure Ties

Until now we have considered the determinants of bridging and closure ties as opposed to not forming any tie. The previous regression tables have revealed that behaviours are rather similar as regards geographical, technological and organizational proximity. Some differences appear in the coefficients that are slightly smaller for bridging than for closure ties, but this does not enable us to infer any clear conclusion regarding differences between both ties.

In order to further investigate these differences, we estimate a multinomial probit presented in Table 6. These results provide direct evidence for the argument that bridging ties occur outside organizational boundaries with some technological diversity. Geographical, technological and organizational proximity have all negative signs, which means that more proximity leads to closure ties rather than bridging ties. We may infer from this result that bridging ties occur when inventors cross local networks (no social distance), organizational and technological boundaries. The interaction term is positive, which confirms that geographical proximity is more important when individuals have no social proximity. In other words, when there is no social proximity as in bridging ties, geographical and organizational proximity complement each other.

[Table 6]

Finally, it is specifically worth considering the interaction between geographical, technological and organizational proximity to fully understand how bridging ties allow individuals and firms to cross over different types of boundaries. Figure 4 displays the probabilities of forming bridging and closure ties for three levels of technological distance, that is, none, average and large technological distances given the co-inventors geographical and organisational distances.

[Figure 4]

It appears that closure ties are preferred when inventors belong to the same organization and share the same research area. Within organizational boundaries and with no technological distance, geographical distance can be overcome (Figure 4, upper left). When technological distance reaches an average level, closure ties are still preferred whatever the geographical distance. For greater geographical distances, even within organizational boundaries, inventors will use bridging ties, but the differences in probability are marginal. The picture becomes sharper when technological distance becomes larger as well. Bridging ties appear to be dominant when there is organizational distance, namely for academia-firm linkages, whatever the level of technological distance. The probability of forming closure ties, in this case, decreases as technological distance increases, and it becomes nearly null when there is no technological overlap between inventors. These results are somewhat counterintuitive because we would expect social proximity to facilitate crossing over geographical boundaries, but this does not seem to be the case. On the contrary, social proximity seems very much correlated to geographical, technological and organizational boundaries. The likelihood of inter-regional bridging ties increases with technological distance and different applicants. These ties are formed outside one's component and in other regions in order to find different technological skills that are not easily found in close technological, geographical and organizational neighbourhoods.

If the likelihood of forming a tie is increased within one's organization for bridging as well as for closure ties, interregional collaboration offers the opportunity to find new partners outside organizational boundaries.

5.3. Robustness Check

Since the proportion of ties in the sample (11%) is much higher than the proportion of ties in the population (less than 0.005%), logistic regressions may be biased (King and Zeng, 2001; Sorenson et al., 2006). For this reason, rare event logistic models may be more appropriate to estimate models based on a case-control design, as discussed by these authors. As a robustness check to the conditional logit model implemented in this paper, we have also estimated a rare event logistic model using the method proposed by King and Zeng (2001) and implemented through the ReLogit Stata routine proposed by Tomz (1999). The strategy is to select all the "cases" for which the event is realized (p_{ij}=1, we observe a realized tie in the population as well as in the sample) and we consider a random selection of controls (p_{ij} =0, the tie is potential but not realized). Using this sampling method, we know the fractions of ones in the population; in our case, we know that we have 244 bridging ties and 193 closure ties. To estimate the rare event logit, we implement the prior correction procedure, which involves computing the usual logistic regression and correcting the estimates using prior information about the fraction of ones in the population. In doing so it is possible to correct the estimation, taking in account the difference between the probability of a positive case observed in the sample and the *rarity* of the event actually observed in the population. In our case, we compute the fraction of ones in the population by dividing the number of realized ties by the number of potential ties[9], which corresponds to .005425% for bridging ties and .00429% for closure ties. The number of realized dyads in the sample is 11% since we have for each observed dyad, ten controls, i.e., five for each inventor.

These regressions are similar as regards signs, magnitude of coefficients and statistical significance to the conditional logit procedure discussed in the previous section. In particular, regarding the interaction terms between geographical and organizational proximity, we end up with similar results. They are presented in the appendix (Table 7).

6. Conclusion

The aim of the paper was to investigate the dynamics of network formation using data on research collaborations identified through co-patenting in the field of genomics in France over the last two decades. Two main questions have been raised. First, to what extent are geographical and social proximity overlapping phenomena? Second, to what extent do networks enable the reduction of geographical, organizational and cognitive boundaries and offer the opportunity to access non-local knowledge? In order to answer these questions, we have considered two distinct network configurations as whether these collaborations occur within the same network through closure ties or across separate network components through bridging ties. The fundamental difference between both situations is the existence of social proximity. Considering both of these determinants in the same framework enables to investigate not only their respective impact on collaborations, but also how they overlap, interact, and possibly act as substitutes or complements.

Our findings contribute to identifying the extent to which networks and proximity strongly overlap. Geographical, technological and organizational proximity strongly determine the likelihood of forming network ties. However, once network ties are established, social proximity becomes predominant, in the sense that it acts as a substitute for geographical and organizational proximity for further tie formation. When there is social proximity, geographical and organizational proximity are less important. This confirms previous studies analysing the link between networks and geography (Maggioni et al. 2007, Autant-Bernard et al. 2007, Agrawal et al. 2008 and Breschi and Lissoni, 2009) and means that social proximity, once established, enables one to cross geographical and organizational boundaries. However, this result is only valid for triadic closure when geodesic distance is 2, that is, when collaboration occurs with once partner's partner. For higher geodesic distances and for inter-organizational relationships, geographical proximity is again more important because it allows for compensation of risk and uncertainties (Ponds et al. 2007). This is the overall picture when collaborations occur within networks and especially for triadic closure, for which trust and reputation seem to play a prominent role. However, this happens only when technological distance is rather reduced, and apparently the advantages of closure disappear as technological distance increases.

When technological distance increases, individuals may have to cross over their close networks through bridging ties. These bridging ties are explained by a different dynamic, mainly driven by organizational and technological diversity. These ties are mainly inter-firm and firm-university collaborations. As illustrated by the figure 4, bridging ties enable the crossing-over of organizational boundaries in search of some technological variety, but they mainly occur within a certain geographical proximity, at least when they occur. This result may be explained by the two facts. First, our data are mainly composed by dyads among French inventors, thus geographical distances are overall limited. Second, in France, genomics has benefited from large public and private funding that has enabled the creation of five regional-based Genopoles in France. This has largely favoured the development of public research, private spin-offs and ultimately science-university research projects.

The role of bridging versus closure ties as it appears in this analysis may also advance some explanations regarding industrial clustering and specialization effects. It appears that local clustering is mainly based on within-network closure ties that facilitate collaborations between academic and non-academic organisations within similar technological fields, thus contributing to the increase of local specialisation effects. While the cluster increases over time, different technological resources are needed, and these are brought to the network through bridging ties, which enable the bringing together of communities that are technologically separate. This is clearly related to the debate on 'local buzz and global pipelines' (Bathlelt et al. 2004).

The main limitations of our study fall under three categories. The first concerns how time is taken into account. Although the impact of time is considered through the path-dependent effect of prior network connections and network structural position, the impact of time itself is not explicitly considered. Yet, it could be interesting to analyse in future studies the effects of interplay of the different forms of proximities and networks, that is, how the substitution or complementary effects changes over time through the different stages of development, and how the role of geographical proximity evolves over time (Boschma, 2005).

The second limitation is related to our definition of social proximity, which is reduced to the geodesic distance between inventors in a network of patent collaborations. In other words, we capture only a subset of relevant interpersonal relations. An extension could be to supplement social proximity with additional data such as collaborations through publications. This way we could have a broader picture of network connections (Breschi and

Catalini, 2010).

The third limitation is related to the motivation of individuals. Our framework does not allow accounting explicitly for the motivation nor for the strategies of individuals in establishing their collaboration. For this reason, our analysis proposes to disentangle the effect of different dimensions of proximity in establishing one type of tie rather than the other. We could not infer anything from this analysis in terms of individuals' strategic behaviour, nor did we analyse the effect of this collaboration on individuals' productivity. However, the former topic has been analysed in a different theoretical context (see for instance Carayol and Roux, 2009 who explicitly model individuals' choice and test their arguments using similar micro-data on co-invention). Concerning the second issue, we intend to address the effect of different type of ties on individuals' performance in a further analysis.

References

Agrawal, A. & Kapur, D. & McHale, J., (2008), How do spatial and social proximity influence knowledge flows? Evidence from patent data, *Journal of Urban Economics*, 64(2), 258-269.

Aharonson, B. S., Baum, J. A. and Plunket, A. (2008), Inventive and uninventive clusters: The case of Canadian biotechnology, *Research Policy* **37**(6-7), 1108 - 1131.

Amburgey, T., Al-Lahan, A., Tzabbar, D. and Aharonson, B. (2008), The structural evolution of multiplex organizational networks: research and commerce in biotechnology, *Advances in Strategic Management,* **25**, 171-209.

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

Autant-Bernard C., Billand P., Frachisse D. and Massard N. (2007), Social distance versus spatial distance in R&D cooperation: Empirical evidence from European collaboration choices in micro and nanotechnologies, *Papers in Regional Science*, 86(3), pages 495-519

Barabasi, A.-L. and Albert, R. (1999), Emergence of Scaling in Random Networks, *Science* **286**(5439), 509-512.

Bathelt H., Malmberg A. and Maskell P. (2004), Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation *Progress in Human Geography, 28: 31-56*

Baum, J. A. C., Shipilov, A. V. and Rowley, T. J. (2003), Where do small worlds come from?, *Ind Corp Change* **12**(4), 697-725.

Baum J.A.C, McEvily B., and Rowley T.J. (2012), Better with Age? Tie Longevity and the Performance Implications of Bridging and Closure, *Organization Science,* 23:529-546

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

Boschma, R. and Frenken, K. (2009), The spatial evolution of innovation networks. A proximity perspective, *in* Ron A. Boschma & Ron Martin, (ed.), Handbook of Evolutionary Economic Geography, Edward Elgar

Boufaden, N. and Plunket, A. (2008), Proximity and innovation: Do biotechnology firms located in the Paris Region benefit from localized technological externalities?, *Les Annales d'Economie et Statistique* **87/88**, 198-220.

Bramoullé, Y. and Fortin, B. (2009), The Econometrics of Social Networks, CIRPEE.

Stefano Breschi, Christian Catalini, (2010), Tracing the links between science and technology: An exploratory analysis of scientists' and inventors' networks, *Research Policy*, 39(1), 2010, Pages 14-26,

Breschi, S. and Lissoni, F. (2009), Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows, *Journal of Economic Geography* **9**(4), 439-468.

Breschi, S. and Lissoni, F. (2005), Cross-firm and Social Networks: Localized Knowledge Spillovers Revisited, *Les Annales d'Economie et de Statistique*, **79/80**, 189--209.

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

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

Cameron, A. C. and Trivedi, P. K. (2005), *Microeconometrics: Methods and Applications*, Cambridge University Press, N. Y

Carayol N., Roux P. (2008), The strategic formation of inter-individual collaboration networks. Evidence from co-invention patterns, *Annales d'Economie et de Statistiques,* 87-89, 275-302

Coleman, J. S. (1988), Social Capital in the Creation of Human Capital, *The American Journal of Sociology* **94**, S95--S120.

Fafchamps, M., Goyal, S. and van der Leij, M. J. (2010), Matching and Network Effects, *Journal of the European Economic Association* **8**(1), 203--231.

Fleming L., and Matt M. (2006), Managing Innovation in Small Worlds. *MIT Sloan Management Review,* 48(1): 8-9.

Fleming, L. and Frenken, K. (2007), The Evolution Of Inventor Networks In The Silicon Valley And Boston Regions, *Advances in Complex Systems (ACS)* **10**(01), 53-71.

Gargiulo, M. and Benassi, M. (2000), Trapped in Your Own Net? Network Cohesion, Structural Holes, and the Adaptation of Social Capital, *Organizational Science* **11**(2), 183-196.

Gluckler, J. (2007), Economic geography and the evolution of networks, *Journal of Economic Geography* **7**(5), 619--634.

Jaffe, A. B. (1989), Real Effects of Academic Research, *The American Economic Review* **79**(5), 957-970.

Jaffe, A. B., Trajtenberg, M. and Henderson, R. (1993), Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations, *The Quarterly Journal of Economics* **108**(3), 577-598.

King, G., Zeng, L., 2001. Logistic regression in rare events data. *Political Analysis* 9, 137–163

Knoben, J. (2009), Localized inter-organizational linkages, agglomeration effects, and the innovative performance of firms, *The Annals of Regional Science* **43**(3), 757-779.

Laurens, P., Zitt, M. and Bassecoulard, E. (2010), Delineation of the genomics field by hybrid citation-lexical methods: interaction with experts and validation process, *Scientometrics*

82(3), 647-662.

Lobo, J. and Strumsky, D. (2008), Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects, *Journal of Urban Economics* **63**(3), 871-884.

Long J.S. and Freese J. (2003), *Regression Models for Categorical Outcomes Using Stata*, Stata Press

Maggioni, M. A. Nosvelli, M. and Uberti, T.E. (2007), Space versus networks in the geography of innovation: A European analysis, *Papers in Regional Science*, 86(3), 471-493

Moody, J. (2000), *SPAN: SAS Programs for Analyzing Networks.* University of North Carolina at Chapel Hill

Newman, M.E. J. and Park, J. (2003), Why social networks are different from other types of networks, *Phys. Rev. E* **68**(3).

Nooteboom B., Van Haverbeke W., Duysters G., Gilsing V. van den Oord A (2007), Optimal cognitive distance and absorptive capacity, *Research Policy*, 36 (7),

Ponds, R., Van Oort, F. and Frenken, K. (2007), The geographical and institutional proximity of research collaboration, *Papers in Regional Science* **86**(3), 423-443.

Powell, W. W., White, D. R., Koput, K. W. and Owen-Smith, J. Network (2005), Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences, *The American Journal of Sociology,* **110**, 1132-1205

Rivera, M. T., Soderstrom, S. B. and Uzzi, B. (2010), Dynamics of Dyads in Social Networks: Assortative, Relational, and Proximity Mechanisms, *Annual Review of Sociology* **36**(1), 91-115.

Singh, J. (2007), External Collaboration, Social Networks and Knowledge Creation: Evidence from scientific publications, DRUID Summer Conference 2007.

Singh, J. (2005), Collaborative Networks as Determinants of Knowledge Diffusion Patterns, *Management Science* **51**(5), 756-770.

Sorenson, O., Rivkin, J. W. and Fleming, L. (2006), Complexity, networks and knowledge flow, *Research Policy* **35**(7), 994-1017.

Stuart, T. and Podolny, J. (1999), Positional Causes and Correlates of Strategic Alliances in the Semiconductor Industry, *Research in the Sociology of Organizations*, 161-182.

Ter Wal A. (2011), The Dynamics of the Inventor Network in German Biotechnology: Geographical proximity and Triadic Closure, Papers in Evolutionary Economic Geography, 11.02

Torre, A. and Rallet, A. (2005), Proximity and localization, *Regional Studies* **39(1)**, 47-59.

Tomz, M., 1999. Relogit (Stata ado file). Available at http://www.stanford.edu/~tomz/software/software.shtml

[1] Sociologists identify a further perspective related to compatibilities and complementarities between actors' attributes (e.g. race) – the so-called assortative perspective (Rivera et al., 2010)

[2] Social Network Analysis computation has been programmed by the authors themselves with SAS. The SPAM modules developed by James Moody (2000) have been extremely helpful.

[3] Even for industry-university collaborations, usually there is only one affiliation for a given patent. For this reason, inventors of a given patent have the same affiliation even if the applicant designated in the patent does not employ them.

[4] We limit our estimations to bridging and closure ties since we are not able to estimate geographical, or organizational and institutional distances for the pendant and new component ties, because these ties are formed by new inventors for which we have no information about their characteristics in t-1.

[5] In order to ensure that dropping all non-European inventors do not affect regressions, we have estimated all models with a proxy of the geographical distance to non-Europeans by introducing a geographical distance of 6000 km for all North-American inventors. Observations are substantially increased with 1999 observations for closure ties and 2671 for bridging ties. Results remain overall similar in signs, magnitude and significance.

[6] We adjust the latitude and longitude coordinates for the earth curvature; thus the distance in km between two points A and B is computed as:

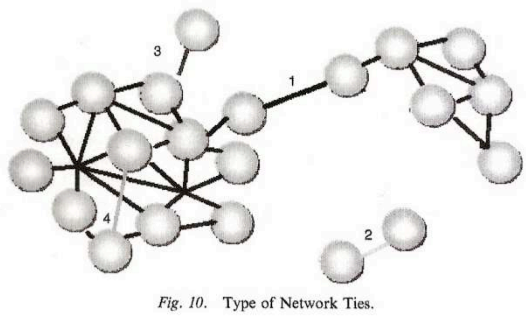
$$d(A,B) = 6371 \times \arccos[\sin(\text{latitude}(A)) \times \sin(\text{latitude}(B)) + \cos(\text{latitude}(A)) \times \cos(\text{latitude}(B)) \times \cos(|\text{longitude}(A) - \text{longitude}(B)|)]$$

[7] We also calculated the Euclidean distance and we obtained similar results.

[8] We have also estimated a logit model with cluster robust errors and year fixed effects, and we obtain similar results to the conditional logit. These tables can be provided upon request.

[9] If n is the number of active inventors, n*(n-1) is the number of potential ties between these inventors. We estimate this number to be approximately 3000.

Fig. 1 Type of network ties



Source: Fig. 10, Amburgey et al. (2008)

Fig. 2 Size of the network (active inventors) and of the giant component

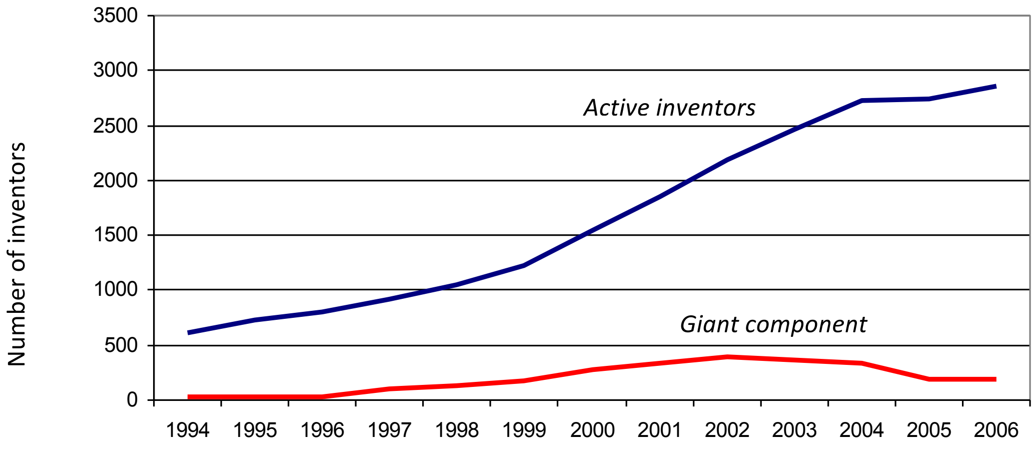
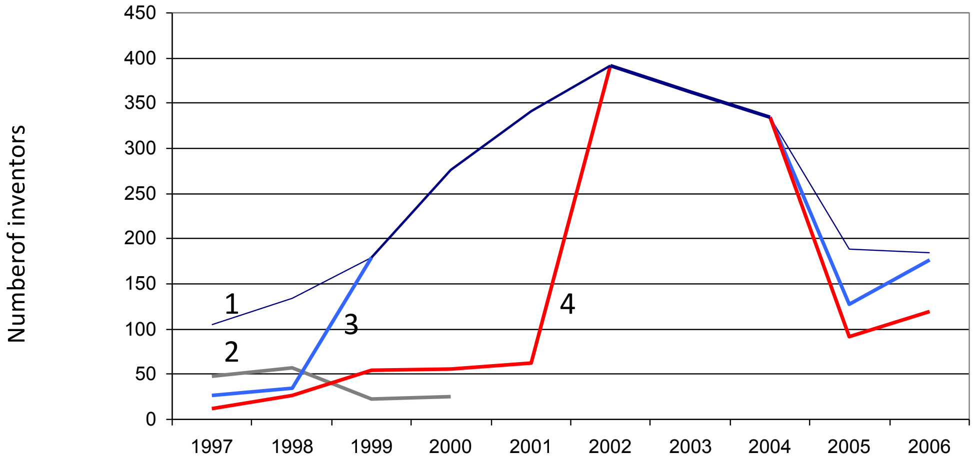
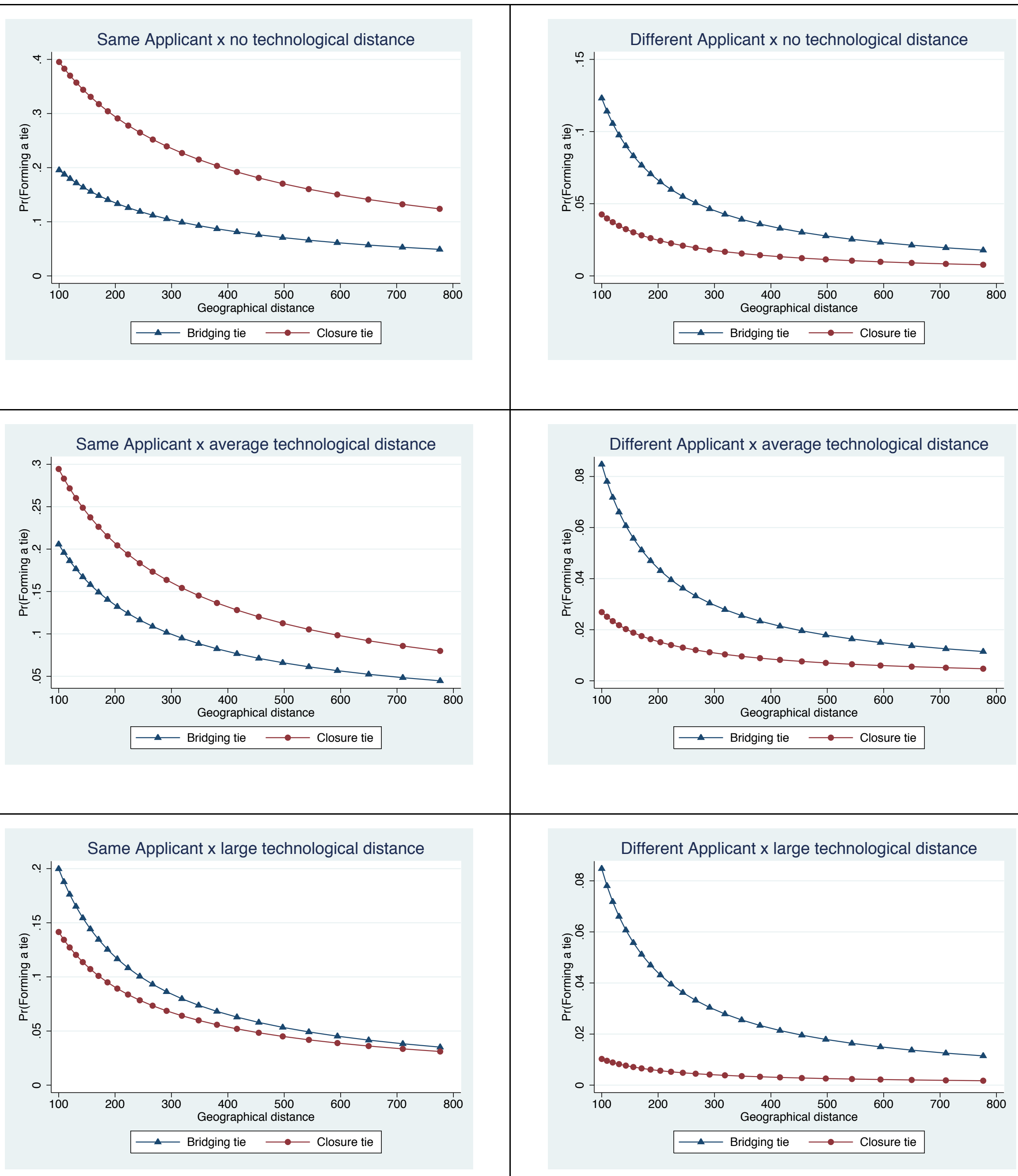


Fig. 3 Evolution of the first four 1998 components



Note: The figure displays the evolution of the first four components in terms of size as measured in 1998. The fact that two lines converge (as line 2 and 3 in 1999) means that two components have been merged by a bridging link.

Fig. 4 Relative probabilities of forming bridging versus closure ties given different technological distances



These probabilities correspond to a multinomial logit estimation with all the variables set at their mean except for geographical distance which ranges from 0 to 800 km and the technological distance which is set to zero, its average and its extreme value depending on whether we consider no, average or large technological distances.

Tab. 1 Consequence of tie formation

Type of link	Size of the network	Number of components	Size of components
1. Bridging links	$\leftrightarrow$	$\downarrow$	$\uparrow$
2. New component links	$\uparrow$	$\uparrow$	$\uparrow$
3. Pendant links	$\uparrow$	$\leftrightarrow$	$\uparrow$
4. Intra-component links	$\leftrightarrow$	$\leftrightarrow$	$\leftrightarrow$

Tab. 2 New link: type of networks ties

Links	Total number	%
1. Bridging links	244	1,88
2. New component links	8723	67,03
3. Pendant links	3853	29,61
4. Intra-component links	193	1,48
Total	13013	100

Tab 3. Organizational relationships among types of ties[1]

	Bridging ties				Closure ties			
	Whole sample		Regressions		Whole sample		Regressions	
	Total	%	Total	%	Total	%	Total	%
Organizational proximity								
Within the same applicant	77	31,56	74	32,03	148	76,68	121	73,33
Among academics	12	4,92	12	5,19	1	0,52	1	0,61
Among firms	43	17,62	38	16,45	21	10,88	20	12,12
Organizational distance								
Between firms and academics	112	45,90	107	56,32	23	11,92	23	13,94
Total	244	100	231	100	193	100	165	100

Note : The definition and coding of variables are explained in the next section and summarized in Appendix A

[1] The definition and coding of variables are explained in the next section and summarized in the appendix A.

Tab. 4 Conditional logit – Determinants of network ties

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Closure	Closure	Closure	Closure	Closure	Bridge	Bridge	Bridge
Geographical proximity	1.205***	2.031***	1.783***	0.969***	0.847***	1.334***	1.308***	1.339***
	(0.187)	(0.258)	(0.325)	(0.205)	(0.226)	(0.143)	(0.156)	(0.162)
Technological proximity	2.704***	2.678***	1.753+	2.529***	1.779*	1.430**	1.427**	1.430**
	(0.770)	(0.771)	(0.916)	(0.751)	(0.905)	(0.456)	(0.458)	(0.457)
Same applicant	2.221***	1.470***	1.164**	2.289***	1.870***	1.306***	1.402***	1.304***
	(0.307)	(0.327)	(0.396)	(0.312)	(0.363)	(0.210)	(0.281)	(0.213)
Geographical proximity x Same applicant		-1.789***	-1.674***				0.191	
		(0.326)	(0.418)				(0.276)	
Same type	-0.575+	-0.342	0.011	0.053	0.303	-0.678***	-0.678***	-0.691*
	(0.348)	(0.356)	(0.389)	(0.429)	(0.500)	(0.194)	(0.193)	(0.302)
Geographical proximity x Same type				0.872**	0.737+			-0.016
				(0.329)	(0.395)			(0.264)
Border	1.487***	0.898*	0.408	1.414***	0.897+	0.637*	0.649**	0.638*
	(0.396)	(0.454)	(0.547)	(0.403)	(0.518)	(0.251)	(0.248)	(0.251)
Degrees - Abs.diff.	-0.254+	-0.281*	-0.212	-0.233	-0.145	0.288*	0.290*	0.288*
	(0.146)	(0.143)	(0.180)	(0.146)	(0.185)	(0.130)	(0.131)	(0.131)
Degrees - Avrg	0.383	0.417+	0.014	0.337	-0.066	-0.504**	-0.501**	-0.505**
	(0.239)	(0.237)	(0.342)	(0.242)	(0.333)	(0.188)	(0.189)	(0.189)
Experience - Abs.diff	0.163	0.238	0.268	0.191	0.159	-0.048	-0.045	-0.049
	(0.285)	(0.294)	(0.365)	(0.286)	(0.355)	(0.191)	(0.194)	(0.191)
Experience - Avrg	-0.365*	-0.396*	-0.400+	-0.369*	-0.342+	-0.170	-0.167	-0.169
	(0.169)	(0.176)	(0.205)	(0.173)	(0.207)	(0.114)	(0.115)	(0.114)
# common partners (= 1)			2.454***		2.513***			
			(0.410)		(0.399)			
# common partners (= 2)			3.103***		3.257***			
			(0.646)		(0.648)			
# common partners (= 3)			2.171**		2.220**			
			(0.679)		(0.731)			
# common partners (= 4)			-0.875		-0.815			
			(1.177)		(1.225)			
Observations	1604.000	1604.000	1604.000	1604.000	1604.000	2421.000	2421.000	2421.000
Log Likelihood	-185.703	-173.642	-124.896	-183.211	-130.087	-393.782	-393.597	-393.780
Pseudo R-Square	0.504	0.536	0.666	0.510	0.652	0.273	0.274	0.273

Cluster Robust standard errors in parentheses + p<0.10, * p<0.05, ** p<0.01, *** p<0.001 - Dependent variable: closure tie (model 1 to 5) or bridging tie (model 6 and 8) versus no tie

Tab. 5 Conditional logit – Determinants of network ties with social proximity

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Closure	Closure	Closure	Closure	Closure	Closure	Closure
Social proximity (= 2)	3.432***	2.214***	5.138***	3.828***	2.226***	3.045***	1.975***
	(0.431)	(0.480)	(0.583)	(0.634)	(0.478)	(0.460)	(0.517)
Social proximity (= 3)	2.189***	1.680**	2.727***	1.986*	1.667**	2.032***	1.632**
	(0.436)	(0.557)	(0.734)	(0.844)	(0.556)	(0.482)	(0.594)
Technological proximity	1.366	1.010	1.283	0.966	1.030	1.030	0.966
	(0.995)	(1.001)	(1.056)	(1.074)	(0.993)	(1.040)	(1.008)
Geographical proximity	0.889***	1.968***	0.731**	1.854***	2.016***	0.921***	2.009***
	(0.210)	(0.499)	(0.233)	(0.559)	(0.506)	(0.216)	(0.529)
Social proximity (= 2) x Geographical proximity		-3.939**		-3.500**	-3.898***		-3.471**
		(1.203)		(1.300)	(1.175)		(1.224)
Social proximity (= 3) x Geographical proximity		-0.877		-0.624	-0.902		-0.843
		(0.697)		(0.689)	(0.694)		(0.688)
Same applicant	1.136**	1.031**	2.651***	2.333***	1.178***	1.703***	1.441***
	(0.395)	(0.369)	(0.645)	(0.588)	(0.300)	(0.359)	(0.343)
Social proximity (= 2) x Same applicant			-3.164***	-2.837***			
			(0.808)	(0.839)			
Social proximity (= 3) x Same applicant			-1.587+	-0.977			
			(0.918)	(0.898)			
Same type	-0.227	-0.297	-0.271	-0.268			
	(0.397)	(0.429)	(0.556)	(0.568)			
Social proximity (= 2) x Same type						2.121**	1.472*
						(0.733)	(0.707)
Social proximity (= 3) x Same type						-0.304	-0.636
						(0.943)	(0.949)
Degrees - Avrg	-0.311	-0.380	-0.207	-0.398	-0.431	-0.352	-0.448
	(0.374)	(0.383)	(0.400)	(0.398)	(0.384)	(0.384)	(0.383)
Degrees - Abs.diff.	0.044	0.149	-0.079	0.080	0.163	0.049	0.169
	(0.197)	(0.217)	(0.198)	(0.219)	(0.215)	(0.215)	(0.227)
Border	1.177**	-0.267	1.331**	0.186	-0.183	1.343**	0.230
	(0.446)	(1.065)	(0.468)	(1.168)	(1.030)	(0.458)	(1.088)
Experience - Abs.diff	-0.040	0.431	0.285	0.826+	0.475	0.141	0.556
	(0.357)	(0.380)	(0.411)	(0.462)	(0.370)	(0.366)	(0.386)
Experience - Avrg	-0.391+	-0.470*	-0.360	-0.396	-0.479*	-0.429*	-0.454*
	(0.205)	(0.216)	(0.237)	(0.246)	(0.214)	(0.210)	(0.220)

Observations	1604.000	1604.000	1604.000	1604.000	1604.000	1604.000	1604.000
Log Likelihood	-121.052	-106.132	-110.711	-98.367	-106.311	-116.141	-103.903
Pseudo R-Square	0.677	0.716	0.704	0.737	0.716	0.690	0.722

Tab. 6 Multinomial probit – Bridging and no tie versus closure ties

	(1)		(2)		(3)		(4)	
	Network tie		Network tie		Network tie		Network tie	
	Bridge	No tie	Bridge	No tie	Bridge	No tie	Bridge	No tie
Geographical proximity	-0.068	-0.804***	-0.397**	-1.140***	-0.068	-0.804***	0.039	-0.690***
	(0.126)	(0.111)	(0.149)	(0.132)	(0.126)	(0.111)	(0.146)	(0.131)
Technological proximity	-0.707	-1.356***	-0.690	-1.343**	-0.707	-1.356***	-0.689	-1.340***
	(0.460)	(0.407)	(0.463)	(0.411)	(0.460)	(0.407)	(0.459)	(0.407)
Same applicant	-1.149***	-2.002***	-0.871***	-1.681***	-1.149***	-2.002***	-1.177***	-2.030***
	(0.178)	(0.159)	(0.205)	(0.184)	(0.178)	(0.159)	(0.182)	(0.163)
Geographical proximity x same applicant			0.715**	0.765***				
			(0.234)	(0.202)				
Same type	-0.366+	0.048	-0.428*	-0.016	-0.366+	0.048	-0.594*	-0.201
	(0.198)	(0.167)	(0.205)	(0.176)	(0.198)	(0.167)	(0.271)	(0.221)
Geographical proximity x Same type							-0.352	-0.369+
							(0.237)	(0.197)
Border	-0.156	-0.593**	0.122	-0.311	-0.156	-0.593**	-0.083	-0.518*
	(0.248)	(0.210)	(0.283)	(0.252)	(0.248)	(0.210)	(0.255)	(0.218)
Experience - Abs.diff	-0.175	-0.256+	-0.176	-0.254+	-0.175	-0.256+	-0.177	-0.257+
	(0.177)	(0.145)	(0.179)	(0.147)	(0.177)	(0.145)	(0.178)	(0.145)
Experience - Avrg	0.149	0.297**	0.169	0.319**	0.149	0.297**	0.159	0.307**
	(0.112)	(0.099)	(0.115)	(0.102)	(0.112)	(0.099)	(0.114)	(0.100)
Degrees - Abs.diff.	0.204*	0.058	0.211*	0.068	0.204*	0.058	0.205*	0.060
	(0.100)	(0.075)	(0.102)	(0.077)	(0.100)	(0.075)	(0.100)	(0.075)
Degrees - Avrg	-0.608***	-0.172	-0.623***	-0.192	-0.608***	-0.172	-0.615***	-0.180
	(0.171)	(0.131)	(0.174)	(0.134)	(0.171)	(0.131)	(0.171)	(0.131)
Constant	2.411***	3.809***	2.211***	3.598***	2.411***	3.809***	2.452***	3.857***
	(0.523)	(0.447)	(0.525)	(0.451)	(0.523)	(0.447)	(0.526)	(0.450)
Observations	4025.00		4025.00		4025.00		4025.00	
Log Likelihood	-1174.32		-1167.20		-1174.32		-1172.81	
LR Chi Square	699.08		602.98		699.08		682.21	

Robust standard errors are in parentheses. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001 – Comparison group : Closure ties – Year dummies included

Appendix:
A1. Variables: definitions

Variables	Definitions
Dependant variables	
Closure tie	Takes value 1 if two inventors already in the network form an intra-component tie
Bridging tie	Takes value 1 if two inventors already in the network form a bridging tie
Network variables	
Common (= 1) (=2) (=3) or (=4)	Four categorical variables take the value 1 if two inventors have respectively 1, 2, 3 or 4 partners in common with a geodesic distance of 2.
Absolute difference in degree	Absolute value of the differences between the co-inventors' respective degree centrality
Average degree	The average value of the co-inventors' respective degree centrality
Social proximity (= 2) or (=3)	Social proximity takes the value 1 if two inventors have a geodesic distance of 2 or 3
Proximity variables	
Geographical proximity	The inverse of the distance in km/100 between NUTS3 regions prior to attachment (in logs) – very similar to the Euclidean distance
Technological proximity	The Jaffe's index using IPC codes for each co-inventor's patents prior to attachment
Same applicant	Takes the value of 1 when inventors have patented for the same organization prior to tie formation and 0 otherwise; it is a proxy for close organizational proximity
Same type	Takes the value of 1 when inventors have patented for the same organizational type (firms or companies) and 0 otherwise. It is a proxy for proximity in organizational type.
Other Controls	
Absolute difference in experience	Absolute value of the differences between each co-inventors' number of years since first patent
Average experience	The average value
Border	Takes value 1 if one of the co-inventors belong to a border country to France, 0 otherwise

A.2. Variables: descriptive statistics

	Variables	Observations	Mean	Std. Dev.	Min	Max
1.	Geographical proximity	4069	-1.148249	.7218783	-2.584302	0
2.	Technological proximity	4069	.7295127	.1953041	0	1
3.	Border	4069	.1162448	.3205576	0	1
4.	Same applicant	4069	.1162448	.3205576	0	1
5.	Same type	4069	.4885721	.4999308	0	1
6.	Absolute difference in degree	4069	1.654726	.8848728	0	4.025352
7.	Average degree	4069	1.972993	.5389898	.6931472	3.676301
8.	Absolute difference in experience	4069	3.144651	2.090464	0	5.966147
9.	Average experience	4069	3.920225	1.33827	1.098612	5.971262
10.	Common (= 1)	4069	.028754	.1671349	0	1
11.	Common (=2)	4069	.0103219	.1010837	0	1
12.	Common (= 3)	4069	.0044237	.0663717	0	1
13.	Common (= 4)	4069	.0014746	.0383764	0	1
14.	Social proximity (= 2)	4069	.04522	.2078118	0	1
15.	Social proximity (=3)	4069	.0292455	.1685147	0	1

Note : all continues variables are in logs except Technological proximity and are taken for the period prior to attachment

A.3. Correlations

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1.	1.0000														
2.	0.1659*	1.0000													
3.	-0.2816*	-0.1311*	1.0000												
4.	0.3147*	0.1359*	-0.0143	1.0000											
5.	-0.2231*	-0.0715*	-0.0093	-0.3545*	1.0000										
6.	0.0299	0.0886*	-0.0675*	0.0340*	-0.0202	1.0000									
7.	0.0564*	0.2208*	-0.0686*	0.0495*	-0.0027	0.6941*	1.0000								
8.	-0.1423*	-0.0319*	-0.0552*	-0.2762*	0.0741*	0.1806*	0.1407*	1.0000							
9.	0.1335*	0.1391*	-0.1487*	0.1256*	0.0413*	0.3164*	0.4814*	0.2991*	1.0000						
10.	0.1902*	0.0858*	-0.0486*	0.2725*	-0.0858*	0.0247	0.0502*	-0.2589*	0.0832*	1.0000					
11.	0.0893*	0.1020*	0.0540*	0.2057*	-0.0755*	-0.0124	0.0512*	-0.1536*	0.0881*	-0.0176	1.0000				
12.	0.0678*	0.0287	0.0105	0.1376*	-0.0503*	0.0395*	0.0509*	-0.1003*	0.0510*	-0.0115	-0.0068	1.0000			
13.	0.0561*	0.0370*	-0.0139	0.1060*	-0.0376*	0.0057	0.0393*	-0.0578*	0.0329*	-0.0066	-0.0039	-0.0026	1.0000		
14.	0.2293*	0.1363*	-0.0125	0.3860*	-0.1299*	0.0301	0.0925*	-0.3274*	0.1336*	0.7906*	0.4693*	0.3063*	0.1766*	1.0000	
15.	0.1559*	0.0897*	-0.0447*	0.2556*	-0.0909*	0.0204	0.0855*	-0.2611*	0.1677*	-0.0299	-0.0177	-0.0116	-0.0067	-0.0378*	1.0000

Note : * $p<0.05$

A. 4. Test of the independence of irrelevant alternatives (IIA).

The IIA assumption is assessed using the Hausman and Small and Hsiao test.

Test of the independence of irrelevant alternatives (IIA)

	Hausman tests of IIA assumption				Small-Hsiao tests of IIA assumption			
Omitted	chi2	df	P>chi2	evidence	chi2	df	P>chi2	evidence
Closure	2.701	7	0.911	for Ho	7.374	7	0.391	for Ho
Notie	-24.221	7	---	---	5.330	7	0.620	for Ho
Bridge	0.730	7	0.998	for Ho	3.353	7	0.851	for Ho

Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.

Note: If chi2<0, the estimated model does not meet asymptotic assumptions of the test.

(Number of observations =4069)

According to Freese and Long (2006), "The negative test statistics are very common; Hausman and McFadden (1984:1226) note this possibility and conclude that a negative result is evidence that IIA has not been violated. "

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Tab. 7 – Rare events logit of the likelihood of a network tie								
	Closure	Closure	Closure	Closure	Closure	Bridge	Bridge	Bridge
Geographical proximity	1.060***	1.850***	1.372***	0.789***	0.507*	1.118***	1.106***	1.087***
	(0.218)	(0.243)	(0.246)	(0.240)	(0.214)	(0.117)	(0.134)	(0.136)
Technological proximity	1.531*	1.457*	0.569	1.455*	0.554	0.947*	0.942*	0.955*
	(0.692)	(0.648)	(0.626)	(0.670)	(0.659)	(0.379)	(0.380)	(0.382)
Same applicant	2.121***	1.490***	1.013**	2.211***	1.695***	1.261***	1.291***	1.269***
	(0.256)	(0.256)	(0.323)	(0.273)	(0.304)	(0.182)	(0.231)	(0.184)
Geographical proximity x same applicant		-1.686***	-1.517***				0.049	
		(0.322)	(0.335)				(0.280)	
Same type	-0.563*	-0.385	-0.567+	0.065	-0.247	-0.521**	-0.522**	-0.442+
	(0.279)	(0.281)	(0.318)	(0.358)	(0.402)	(0.169)	(0.169)	(0.264)
Geographical proximity x Same type				0.909**	0.597+			0.093
				(0.326)	(0.332)			(0.249)
Border	1.243***	0.379	-0.751	1.052**	-0.036	0.652***	0.654***	0.644***
	(0.352)	(0.430)	(0.490)	(0.381)	(0.434)	(0.177)	(0.174)	(0.176)
Degrees - Abs.diff.	-0.172	-0.192+	-0.086	-0.167	-0.062	0.241*	0.242*	0.240*
	(0.117)	(0.115)	(0.170)	(0.115)	(0.169)	(0.112)	(0.112)	(0.112)
Degrees - Avrg	0.214	0.175	-0.136	0.205	-0.104	-0.517**	-0.517**	-0.515**
	(0.189)	(0.191)	(0.278)	(0.188)	(0.271)	(0.161)	(0.162)	(0.161)
Experience - Abs.diff	0.476**	0.560**	0.764***	0.497**	0.701***	0.060	0.063	0.059
	(0.184)	(0.182)	(0.206)	(0.182)	(0.200)	(0.116)	(0.117)	(0.116)
Experience - Avrg	-0.381*	-0.404*	-0.466*	-0.390*	-0.444*	-0.221*	-0.220*	-0.222*
	(0.159)	(0.157)	(0.181)	(0.160)	(0.181)	(0.107)	(0.107)	(0.107)
# common partners (= 1)			2.702***		2.783***			
			(0.317)		(0.328)			
# common partners (= 2)			3.599***		3.732***			
			(0.596)		(0.618)			
# common partners (= 3)			2.079**		2.144**			
			(0.742)		(0.790)			
# common partners (= 4)			1.357		1.215			
			(1.003)		(0.994)			
Constant	-11.609***	-11.180***	-10.964***	-11.730***	-11.480***	-8.799***	-8.810***	-8.823***
	(0.644)	(0.610)	(0.706)	(0.649)	(0.750)	(0.360)	(0.365)	(0.369)
Observations	1604.000	1604.000	1604.000	1604.000	1604.000	2421.000	2421.000	2421.000

72,801 dyads (Intra-component ties: 11% realized ties vs. 0.00429% in population;
Bridging ties 11% realized ties vs. 0.005424% in population) * $p < 0.05$; ** $p < 0.01$; ***$p < 0.001$.