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Cultural Diversity, Social Capital and Innovative capacity of Region-Industries

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Abstract

Many studies from innovation management and strategic management have put to light the positive role of social capital (SC) on innovative performance at firm level, firm's unit level, work team level, or even firm's individual members level. However, a review of these studies reveals that 2 different – and potentially antagonistic – aspects of SC are generally mentioned as playing a role in that process: the cohesive aspect (e.g. closure of the network, norms of reciprocity, density of network that eases knowledge diffusion, etc.) and the external range aspect (e.g. bridging positions, diversity of information exchanged, heterogeneity of links between the network's actors, etc.). While many authors have chosen to focus on one or the other aspect of SC in their studies, some have tried to put forth their complementarity (Reagans & Zuckerman, 2001; Tortoriello & Khrackhardt, 2010) and have shown that the effect of "Cultural diversity" on innovative performance is better accounted for through the combination of these two social capital variables. Adopting this bi-dimensional view of SC, we propose to study the impact of SC – and thus of cultural diversity – on innovative performance at a more aggregated level: the region-industry level.

In this paper, we develop a framework to test empirically the relation between SC and innovative performance at this level, in the context of the electric device industry, during the period 1997-2005, for 32 EU regions. We use the OECD REGPAT 2010 database of EPO patents to build each region-industry's network of co-invention relationships between relevant inventors, and to account for region-industry's innovative performance.

Keywords

Cultural diversity, social capital, regional innovation

JEL Classification

1. INTRODUCTION

Just like innovation and technical progress in societies have been shown to have a critical impact on countries' economic growth, regional innovation has been shown to have a critical impact on regional growth and employment (see Capello, 2009 for a review). Regions that are highly innovative tend to have more growth and better employment rates.
Moreover, many studies have shown that regional innovation itself is deeply influenced by knowledge production and diffusion (Arrow, 1962; Duranton & Puga, 2001). Hence, knowledge production and diffusion have become important matters of interest throughout the past decades.

While seminal papers of the geography of innovation literature have emphasized the importance of spatial proximity for knowledge diffusion (Jaffe, Trajtenberg, & Henderson, 1993), more recent studies have argued that proximity in social networks is actually the most important aspect of proximity that has to be taken in consideration. Since social networks are bounded in space to a wide extent, then knowledge diffusion also appears bounded in space (Breschi & Lissoni, 2009). But besides space, other types of mechanisms play a role in the formation of social networks patterns. Hence, the importance of such mechanisms in the diffusion of knowledge has also been underlined: Social or ethnic proximity (Agrawal, Kapur, & McHale, 2008), institutional proximity (Bell & Zaheer, 2007), friendship (Bell & Zaheer, 2007), inter-firm cooperation (Powell, Koput, & Smith-Doerr, 1996), or co-inventorship (Breschi & Lissoni, 2009) are some of the mechanisms that contribute to shaping social networks, and thus, that contribute to shaping knowledge diffusion.

More generally, these mechanisms reflect a fundamental property of social networks, put to light since the 50's by Merton & Lazerfeld : homophily. The concept of homophily expresses the idea that the actors of a social system are naturally more prone to form links with actors of the "same kind" as themselves. This property has been observed in many different settings and for many different definitions of the notion of "same kind" (McPherson, Smith-Lovin, & Cook, 2001) depending on the type of relationship studied. For example, in the case of knowledge exchange relationships, the fact of "living in the same area" (spatial proximity), "belonging to the same social or ethnic group" (social/ethnic proximity), "working in the same organization or on the same project" (organizational proximity, co-inventorship, inter-firm cooperation), specializing in the same industrial or technological sector (MAR conception of knowledge spillovers, for Marshall [1980] Arrow [1962] and Romer [1990]), can be considered as different aspects of the notion of "same kind".

These different types of proximities can also be defined in terms of Culture: national/regional/local culture, ethnic culture, organizational culture, professional culture. Hence, the sociological concept of homophily in social networks is closely linked to the idea that people are naturally more prone to form links with people of their own “culture”. The fact of sharing values, norms, and references associated with a common culture facilitates knowledge exchange. It provides a common cognitive basis. However it also reduces the scope of knowledge that can be reached through the interaction, since there is redundancy in the collective knowledge. Thus, one can assume that *cultural distance* between people that are in contact, (1) is not as frequent as *cultural proximity* between people that are in contact, (2) makes knowledge exchanges more difficult because of a lack of common cognitive basis, but (3) allows each people to reach a wider scope of knowledge. Starting from this statement, one can wonder about the overall impact that cultural diversity in a social system can have on its collective knowledge production.

And this question is relevant today more than ever, since throughout the past half-century, the globalization of the economy has yielded tremendous changes that have contributed to increase the level of cultural diversity in many places, and in many social systems. Hence, over this period of time, the issue of the impact of cultural diversity on different economic outcomes has become increasingly important for policy makers and managers, as well as for scholars. In particular, many authors have underlined the beneficial effect of cultural diversity on creativity and innovation in cities (Florida R., 2002), firms (Cox & Blake, 1991; Vedina, Fink, & Vadi, 2007), or firm’s units (Ely & Thomas, 2001). However, the beneficial effect of cultural diversity on innovation does not seem to be automatic. Indeed some authors have also shown that in certain contexts, no significant effect on innovative performance is associated with cultural diversity (Reagans & Zuckerman, 2001); several others have even highlighted the potential negative impact of cultural diversity on work group’s general performances if it is not accompanied by specific diversity management (Ely & Thomas, 2001; Cox & Blake, 1991). Hence, for firms and work groups, the positive effect of cultural diversity on innovation appears to be contingent on contextual factors, in particular on whether specific diversity management is implemented or not. At regional and national level, to our knowledge, no studies have directly addressed the issue of the impact of cultural diversity on innovation. Hence, even though one can extrapolate from the findings at firm level and work group level that the impact at regional level is probably also contingent on contextual factors, we know nothing so far about the nature of these contextual factors, nor about the way they influence the relationship between cultural diversity and innovation.

Following Reagans and Zuckerman (2001), we believe that an important step in assessing these contingent factors consists in studying directly the impact on innovation of two network variables on which Cultural Diversity has an impact, rather than studying the gross impact of cultural diversity. These two variables are *social capital* variables, and they correspond to two different aspects of the literature on social capital: *bonding social capital* and *bridging social capital*.

Initially centered on individuals (Bourdieu, 1980; Coleman, 1988), the concept of social capital has been extended to communities (Coleman, 1988), firm level (Nahapiet & Ghoshal, 1998), country level (Putnam, 2000) and more recently, region level (Akçomak & Weel, 2009). Social capital refers to the "collectively-owned capital" that an actor (individual, firm, community, region, country, etc.) can use individually to accomplish social and economic actions. Nahapiet & Ghoshal underline the fact that "much of this capital is embedded within networks of mutual acquaintance and recognition" (1998, p. 243). Thus, an actor's "position" in a social network, its "role" in this network, the cohesive subgroups to which it belongs, the types and amount of links that it has, the attributes of its partners, etc. are several aspects of social capital that witness for differences between actors in terms of capacity to use the collectively-owned capital. Thus, they provide potential explanations of the variance in behavior and outcomes between actors. In this paper we identify two broad aspects of social capital: cohesiveness and external range. While the earlier has been studied extensively in the social capital literature, the latter is derived from Burt's notion of structural holes and is also closely related to the "diversity" literature. Indeed, Reagans and Zuckerman (2001) show that the impact of diversity on R&D team's innovative performance is usually ambiguous when it is studied in a uni-dimensional way. Rather, one should consider the impact of diversity on 2 distinct social capital variables – cohesiveness and heterogeneity of links – since these impact are opposite. Following Reagans & Zuckerman's idea we aim at studying the impact of cultural diversity at region-industry level on innovative capacity, through a bi-dimensional approach of social capital.

At country and region level, because of the difficulty to collect social network data for large groups, social capital has been studied mostly through non-network approaches: analysts have used wide survey data on countries' general level of interpersonal trust (Knack & Keefer, 2001), or countries' and regions' general level of associative activity (Putnam, 2000), or on archive data like regions' date of emergence of institutions (Akçomak & Weel, 2009) to assess countries' and regions' level of social capital. To our knowledge, network approaches of social capital have been limited to groups, work teams, organizations, communities and inter-firm networks so far.

However, besides the technical limitation due to data collection, we believe that network approaches of regional social capital can be a very useful tool for explaining the heterogeneity between regions in terms of innovative capacity. Indeed, although structural aspects of social capital cannot be studied via survey or archive approaches, several researches suggest that such structural aspects are responsible for important differences between regional innovative capacities. A. Saxenian's compared analysis of two very important American regional industrial clusters specialized in high-tech (Silicon Valley on the one hand, and route 128, in the Boston region, on the other hand) between the 80's and the 90's, is probably one of the most striking illustration of this point (Saxenian, 1994). Indeed, the author shows that although these clusters presented similar profiles in the 80's and were both flourishing at this time, throughout the 90's, Silicon Valley became one of the most innovative district in the world, while route 128 slowly declined and disappeared. The author explains these different destinies by cultural and structural differences that existed from the beginning between the two regions in terms of average firm size, but also in terms of inter-firm cooperation, knowledge exchanges between people, and norms of cooperation. This original case study research gave rise to an extensive literature dealing with structural aspects of inter-firm networks and their consequences for firms (Ahuja, 2000), and also for industries (Powell, Koput, & Smith-Doerr, 1996) innovative capacity. However, no research to our knowledge has studied the impact of co-inventor network of a specific industry, in a specific region, on the innovative capacity of this region-industry. This is what we will aim at doing throughout this paper.

More precisely, the aim of this paper is to address this question: do structural aspects of a region-industry's social capital have an impact on its innovative capacity? And further, what aspects of such social capital have an impact on industry-region's innovative capacity?

Section 2 presents the aspects of social capital that have been shown to be beneficial for innovation or knowledge production in the literature. Section 3 describes the network framework we use to evaluate social capital. In section 4, we present and define the way we have addressed the question of individual's cultural attributes. In section 5 we present our empirical framework, including the data we have used, our variables, our model and the results of our empirical inquiry. Finally section 6 discusses the findings and concludes.

2. THEORETICAL FRAMEWORK

At regional level, like we mentioned earlier, it is very difficult at present time to collect sociometric data for each member of the regional population and to reconstitute the social network of a region. But structural approaches traditionally study the structural properties of social systems by reducing the network. This is done by focusing on a specific category of actors that is thought to have a particular role in the phenomenon studied, by focusing on a type of relationship specifically relevant for the phenomenon studied, and by specifying properly the frontiers of the system studied (Lazega, 2007).

Following the geography of innovation literature we consider that patent inventors constitute a category of actors that has a critical importance in regional knowledge production processes. Furthermore, following Breschi & Lissoni (2009), we believe that co-inventorship ties witness for a specifically important channel of knowledge diffusion, since in most cases, collaboration on a patent application implies a significant amount of time spent together and a significant amount of knowledge exchanged. As far as the frontiers of the system are concerned, we restrict regional networks of co-inventors solely to the inventors who live in the region studied (i.e. whose personal address is in the region), or who have lived in the region before.

Defined in these terms, we consider that the co-inventor network of a region is a satisfying reduction of this regions' social network of relationships between residents, as far as knowledge diffusion and innovative capacity are concerned. Hence, we propose to examine the impact on regional innovative capacity of several aspects of regional social capital, by using these reduced regional networks.

Cohesiveness

The first structural aspect of social capital that has been emphasized by the literature is closure (Coleman, 1988). Closure is the property of a network that features a significant amount of "closed triads" of actors, i.e. triads of actors in which a link exist between all 3 actors. The extreme form of closed network is the "clique", in which all triads are closed (i.e. all possible links exist).

The degree of closure of a network reflects a form of cohesiveness of the social system embedded in it. Coleman shows for example that in a community, the closure of a network of relationships that includes high school students and their parents has a significant positive impact on the formation of human capital (i.e. a negative impact on the rate of high school dropouts). The reasons of this impact are two-fold: first network closure helps to enforce the norms and values established by the system (if A has an obligation towards B, A will be more incented to fulfill this obligation if both A and B know a same third party C, than if A and B have no other common contact); and secondly, collective action is facilitated by such structure.

But as far as innovation is concerned, the impact of closure on innovative capacity is not simple. Indeed, by essence, innovating consists of going out of the "normal" way, leaving the track, and not necessarily respecting the norms. Thus, it is not surprising to observe that in innovation processes, pioneers are often marginal individuals, deviant people (Alter, 2000). Closure can then become a burden for innovation if it constrains the creativity of individuals, and individuals can have a better innovative capacity when they are peripheral to the network, or when they bridge separated parts of a network (Burt, 1992; 2004). This point of view regarding the link between closure and innovation has been dominant in the 90's.

However, more recently, researchers have started to highlight the importance of several cohesive aspects of social systems for innovation processes. For example, the positive role for firms' exploratory innovation of closure in their ego networks of alliance has been put forth (Phelps, 2010). Also, while a bridging position is traditionally associated with more creativity and innovativeness, Tortoriello & Krackhardt have underlined the fact the positive effect of trans-organizational bridging ties for scientists and engineers' capacity of innovation, is actually contingent on the fact that these bridging ties are part of a clique or not, i.e. if these ties are parts of a closed triad or not (Tortoriello & Krackhardt, 2010). The positive role of a system's cohesiveness on innovation has also been addressed through the concept of network density[1]: Reagans & Zuckerman note that the innovative productivity of R&D teams is enhanced by the density of their networks of communication relationships (Reagans & Zuckerman, 2001).

Based on these findings, we propose that the degree of cohesiveness of a region's co-inventor networks is positively associated with its innovative capacity. Let us note from now on, that we expect regional co-inventor networks to be sparse (weakly cohesive), because patents applications and publications represent only a very small portion of the actual knowledge exchanges between individuals and even between inventors. Also, we expect them to be clustered, in particular along organizational lines, since the patenting processes and the collaborating processes between inventors are not totally unconstrained. On the contrary, co-inventorship between individuals from different organizations is usually controlled and occurs most of the time in the frame of a contractual agreement between firms.

However, like illustrated by A. Saxenian (1994), in some regions, firms are more prone to create such agreements, inventors are more mobile between firms, firms collaborate more easily with individual inventors or public institutions (e.g. universities), or even, firms have more interest in

[1] Network density is simply calculated as the number of existing links in the network divided by the number of possible links. If the links are weighted, then density is calculated as ratio between the sum of actual weights and the sum of all possible maximum weights. Thus, density is a slightly different concept from closure, but both of them reflect a form of cohesion in a social system. For this reason, density is sometimes used as a proxy for closure since it is much easier to account for than closure itself.

the regional innovation and development, than in other regions. Our hypothesis is that all these differences result in social capital differences, and more specifically, in "cohesive" differences between regional co-inventor networks of an industry. This aspect of social capital is usually referred to as "bonding social capital".

"Closure" *per se* is difficult to measure in the regional networks we observe (because these networks are weakly connected, i.e. they are fragmented in numerous components). Thus, we retain the measure of "density" of these regional networks as a proxy for cohesiveness, like illustrated by Reagans & Zuckerman's study (2001) at work team level. Hence our first hypothesis is:

Hypothesis 1: the density of the co-inventors network of an industry-region is positively correlated with the capacity of innovation of this industry-region.

Heterogeneity of links / external range

Although *Cohesiveness* was the first social capital aspect to appear in the economic literature, the concept of *Brokerage* (or bridging) soon became prominent in this literature, and more specifically in the innovation literature. Ronald S. Burt was the instigator of this research trend. Indeed, in his book called *Structural Holes: the social structure of competition* (1992), he pointed to the fact that actors who occupy "broker" or "bridging" positions in networks (complete networks or ego networks) between sub-networks otherwise separated by *structural holes,* benefit from a specific advantage that they can exploit in different competitive games. This advantage comes from the fact that they have access to different pools of resources (information, knowledge, advices, etc.) that are not brought together usually.

Following this seminal work, numerous researches have focused on broker's advantage for different types of actors and in different settings. For instance, the advantage associated with a bridging position in terms of innovative capacity has been put forward for firms in alliance networks (Ahuja, 2000), for managers in knowledge sharing networks (Burt, 2004), as well as for inventors in knowledge sharing networks (Tortoriello & Krackhardt, 2010).

At this point, it is important to underline the fact that a broker position is beneficial for the actor that occupies this position in the network, but brokerage is not necessarily beneficial for the social system as a whole. It is an aspect of one actor's social capital, rather than an aspect of the group's social capital.

Of course, like illustrated by G. Ahuja's (2000), a group (e.g. a firm) can be studied as an entity embedded in a network of relationships with other entities of the same kind (e.g. alliance network between firms). In this case, the group's social capital can be assessed by its degree of bridging in the network. But, this type of analysis remains focused on the single actor's social capital, rather than on the "network's" social capital. The only thing that changes is the level of analysis. Despite the great interest of this type of analysis, the impact of brokerage inside the system, on the system's social capital is not evaluated. For example, determining whether a system characterized by a cohesive network without structural holes is more efficient than a system characterized by several subparts (clusters) bridged by brokers is a question that cannot be answered through the brokerage approach.

However several researches have tackled this issue indirectly, through different approaches. A first approach consists in studying the impact of the network's level of clustering, on the system's performance. The concept of clustering is linked to the concept of structural holes. The presence of clusters, or "cliques"[2] in a network, indicates the fact that subparts of the complete network are very cohesive, and rather disconnected from one another. This implies that there exist structural holes between these subparts. And since brokerage can be observed only in the presence of structural holes, the presence of brokers inside a network implies that the network is clustered.

However, although brokerage necessarily implies clustering, clustering doesn't necessarily imply brokerage. In fact, although these concepts are highly linked they are still different.

Another way of studying the impact of brokerage on the network's social capital is the concept of heterogeneity of links (or external range). This concept is an extension of the "diversity" studies. Indeed, a wide array of research has studied the impact of diversity on innovative performance or knowledge diffusion, in the fields of economics (Jacobs, 1969; Davis, 2009; Florida R. , 2002) as well as management (Ely & Thomas, 2001; Vedina, Fink, & Vadi, 2007).

In terms of network analysis, the idea behind these diversity studies can be translated as follows: bringing together diversified actors is assimilated to bringing together members of different social sub-networks that do not usually meet each other and do not usually exchange much knowledge

[2] Originally, a clique is defined as

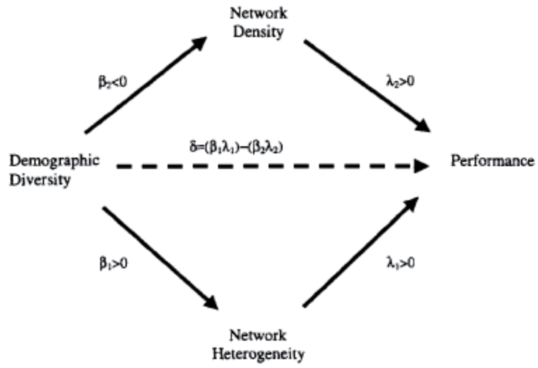
with one another. Hence diversifying actors implies creating bridges between these sub-networks, and further, implies a widening of the array of resource available to the system as well as a fostering of new ideas thanks to the confrontation of different views.

However, several criticisms have been formulated towards this type of study. The first criticism concerns the assumption that actors that have different individual attributes necessarily belong to different sub-networks. Despite the fact that homophily (i.e. the natural preference of actors to form links with individuals of the "same kind" as themselves) is one of the most regularly observed property of social networks (see *McPherson et al. [2001]* for a review of the concept of homophily in social networks, for different types of individual attributes and in different settings), this property is observed for different attributes depending on the settings and at different levels of intensity. Hence, ideally, this type of approach would request to use preliminary sociological investigations that identify the individual attributes that are the most subject to homophily in the socio-cultural context of the system studied. This is what Vedina, Vadi & Fink (2007) do for example, in their study of the impact of value diversity on innovativeness in the context of the Estonian society. Indeed, the first part of their paper is dedicated to a sociological and historical analysis of the Estonian society which explains how and why Estonian and Russian people living in Estonia share different sets of values and thus can be considered as different subgroups.

A second criticism of diversity studies assesses that bringing together diversified people doesn't necessarily imply creating bridges between them. Actually, in many cases, the global homophilic patterns of higher level socio-cultural settings tend to be reproduced in smaller scale systems. For example, diversity studies suggest that diversity policies in firms or work teams must be accompanied by specific actions of diversity management in order to create links between diversified workers rather than conflicts and fragmentation (Ely & Thomas, 2001).

In this perspective, some authors have proposed that evaluating the degree of bridging between diversified actors in a system rather than the gross diversity amongst actors of the system, is an interesting measure of the way individual actor's brokerage influences the group's social capital (Reagans & Zuckerman, 2001). This aspect of social capital is referred to as *bridging social capital,* and has been measured by the variable *"heterogeneity of links"* (or "*external range")* (Reagans & Zuckerman, 2001).

More generally, Reagans & Zuckerman show that the impact of "gross diversity" on innovative capacity is alternatively considered by scholars as positive ("optimistic view") or negative ("pessimistic view"). And they propose that the ambiguous effect associated with "gross diversity" actually results from the fact that "gross diversity" has two opposite impacts on the two social capital variables discussed above: on the one hand, a negative impact on the "cohesiveness" of R&D team's network (measured as network density), and on the other hand, a positive impact on the "external range" of these teams. Since both variables have a positive impact on innovation, the global effect of cultural diversity on innovation is unclear, and depends on the dominant social capital variable (figure 1 below, taken from *Reagans & Zuckerman [2001]*, illustrates the main point of their article).



We believe that similar assertions can be formulated at a region-industry level: The fact that inventors of a specific region-industry are diversified (i.e. culturally diversified population) doesn't necessarily imply that these actors will create bridging ties between one another[3]. Hence, measuring the extent to which diversified actors of a region-industry are able to form links between one another is an interesting way of measuring an aspect of a region-industry's social capital derived from individual actor's brokerage (Of course, like we mentioned, a preliminary analysis of the salient individual attributes that should be used to assess diversity is necessary). Thus, our second hypothesis is:

Hypothesis 2: the external range of the co-inventors network of a region-industry is positively correlated with the innovative capacity of this industry-region.

Note that this hypothesis is subject to controversy. In particular, two different views on the impact of knowledge spillovers oppose. On the one hand, following the seminal works of Jane Jacobs (1969), many scholars have shown that cross-sectoral diversified spillovers are beneficial to innovation and knowledge production. This view is totally coherent with the Hypothesis 2 of this paper presented above. However, on the other hand, other scholars assert that specialized knowledge spillovers are an important driver of knowledge production and innovation. This view

[3] Classical social mechanisms such as urban segregation, ethnic/cultural comunotarism, as well as classical industrial mechanisms such as technological/sectoral clustering, are good illustrations of this point.

is usually referred to as MAR spillovers, named this way after A. Marshall (1890), K. Arrow (1962) and P. Romer (1986) who have defended this view over time, for more than a century,. The evaluation of this hypothesis will thus be of particular interest.

Finally, following Reagans & Zuckerman's view of network based social capital's impact on R&D team's innovative capacity, let us add that the main effect expected from the 2 social capital variables presented above, is their combine effect. Indeed, these two variables are viewed as complementary resources rather than as substitutes for each other. In their paper, this point is confirmed by the significant positive effect associated with the product variable NETWORK DENSITY X NETWORK HETEROGENEITY[4] in the regression presented by the authors. Hence, our third hypothesis is the following:

Hypothesis 3: The co-invention network's External Range and Density of an industry-region are two complementary resources for this industry-region's innovative capacity.

3. NETWORK

We have seen that studying a region-industry's social capital through a network approach can be very interesting is terms of analysis, but that this type of approach presents several technical challenges that make it difficult to carry out. In particular:

- The size of the network studied
- The difficulty to collect sociometric data (links between actors)
- The difficulty to collect individual data for each actor

In this paper, we propose an experimental research strategy that aims at overcoming these challenges. Following Reagans & Zuckerman's (2001) view of social capital for innovation at work team level, we use Emmanuel Lazega's recommendation for the conception of structural analysis (Lazega, 2007) in order to precise how and why the analysis can be extended to regional level. In particular 3 main (interrelated) issues must be addressed: (a) the unit and level of analysis, (b) the choice of the relationships observed, and (c) the specification of the frontiers of the system studied. We will review these 3 issues successively.

4

3.1 Unit/level of analysis

About network analysis, Lazega reminds that "for groupings and reductions operated in the course of the analysis to have a sense, for the external validity of the results to be clearly established, the actors put in relation must belong to a same "category". Thus, a uniform base must be defined, social units of the same nature and same level of analysis (…)" (Lazega, 2007, p. 19)

At organizational or work team level, the units of analysis selected by authors are R&D teams, and the unit of analysis is the team member. The assumptions behind this choice are that all members of a team have the same status and nature, and that all of them can potentially play a comparable role in the innovation process of the team. These assumptions are fairly acceptable.

Extending the analysis to regional level is not straight forward. Indeed, at this level, different actors of different natures play a part in the invention process: firms, universities, other public organizations, individual inventors, etc.

Thus numerous extra factors of individual actor's fractionalization (e.g. part of active population or not, organization worked for, type of organization worked for, etc.) imply that the assumptions of status equality and equal potential participation to innovation are not acceptable anymore if each inhabitant of the region is included in the network studied.

However, selecting only a certain "category" of firm members and studying their network of relationships is an acceptable solution. This has been done in particular for inventors inside firms (Tortoriello & Krackhardt, 2010). Despite the variety of profiles, professional activities, and organizational belongings of these inventors, they all share several common attributes that make them a salient unit of analysis:

- Their contribution to technological innovation has been recognized by peers
- They all had the will to insert their innovation process in a common institutional frame which features peer evaluation, anteriority research, and standardization of claims and application.
- They all have the will to get retribution from their invention, by making it valuable for European Union markets.

3.2 Choice of the relationships observed

"In order to contribute to put to light and explain a system's regulation from the relationships between members, and the structuration of a social field from actor's strategies, the researcher must identify the resources whose circulation is vital for the system, as well as the productions, exchanges, controls and solidarity which characterize it." (Lazega, 2007, p. 19)

In the case of a system whose production is innovation or invention, one specific resource has been clearly identified by the literature as critical: knowledge. Thus, knowledge flows and exchanges have been studied extensively by this literature (…). A problem with this type of exchange is that it's mostly intangible and therefore, hardly accountable. Despite that, researchers have found different strategies to account for such transfers. The first one was to consider citation links as material tracks of knowledge flows (Jaffe, Trajtenberg, & Henderson, 1993; Agrawal, Kapur, & McHale, 2008).

More recently, some researchers have focused on co-inventorship links: the fact that two or more inventors are co-producers of an invention patent implies, in most cases, that they have spent time working together, that they have gathered their talents and knowledge to create something new, and that they must have significantly communicated with each other. In other words, it implies that they have exchanged a significant amount of knowledge.

For these reasons, we consider that co-inventorship ties between inventors constitute a significant social relationship for a structural analysis of the technological innovation system.

3.3 Specifying the frontiers of the system

Firstly, the frontiers of the system we want to study are geographic. For each region, we study the network of inventors whose address is in the region. But of course, these inventors can have co-inventorship ties with inventors who do not live in the region. This will allow us to evaluate each region's external range.

Secondly, the frontiers are also on technological field. Since all industrial sectors and technological fields do not have the same use of patents, we consider that it is difficult to include all inventors in a common system, because they do not operate on the same markets, nor with the same intensity. In order to unify the unit of analysis, we limit the scope of the analysis to a "single" technological field, corresponding to a "single" market.

In the case of our empirical part, we focus on the electric devices industry (NACE code: 27.1, 27.2, 27.3, 27.4 and 27.9), and the corresponding technological class of "basic electric elements" (IPC classes H01).

Also, temporal frontiers have to be discussed. When the priority year of a published patent is T, it means that the research and invention process that has been carried out by the inventors, resulted in an invention at T. But the process that gave birth to this invention is usually long. Following the literature, we will consider that this process is three years long on average. Hence, we will also consider that the co-invention network that is relevant to explain the innovative capacity in T, is the network of all ties formed between inventors from T-3 to T.

At the end of the line, in order to evaluate the social capital variables that are relevant for the innovative capacity of the electric device industry in region r at year t, we will use the co-inventor network that results from patents for which at least one inventor resides in region r, which features at least one H01 IPC sub-class, and whose priority date is between t-3 and t.

4. INDIVIDUAL CULTURAL ATTRIBUTES

The framework presented above suggests that individual's attributes must be determined, in order to measure the "distance in attributes" that separates connected individuals, and *in fine,* in order to measure the system's global external range. But like we mentioned earlier, the concept of "distance in attributes", as well as the underlying concept of "individual attribute", must be discussed and defined clearly.

Since we study innovative capacity and the knowledge diffusion that fosters it, we will focus on individual attributes that can have a significant impact on individual knowledge. Thus, the starting point of our demonstration will be "knowledge".

In order to conceptualize the mechanisms of innovation, Hatchuel *et al.* have built a general theory of conception (Halchuel & Weil, 2003) and based on it, they have explained how "innovative conception" is at the heart of modern intensive innovation mechanisms (Lemasson, Weil, & Hatchuel, 2006). Their main point is that these mechanisms are made of perpetual movements between the "knowledge space" (K) and the "concepts space" (C). "Knowledge space" is defined as "the space of propositions that have a logical status[5] for a designer D" (Halchuel & Weil, 2003, p. 5), while in contrast, a "Concept" is defined as "a proposition or a group of propositions that have no logical status in K". Hence, it is important to note that, with this definition of "knowledge", different people can give different logical status to a same proposition, but still share a common knowledge. For example, two people living in the same country, who do not have the same political opinion at all, still have a common knowledge of the political parties of their

[5] Further "We call "logical status of a proposition", an attribute that defines the degree of confidence that D assigns to a proposition. In standard logic, propositions are "true" or "false". In non standard logic, propositions may be "true, false or undecidable" or have a fuzzy value. (…) In the following, we will assume for simplicity that in K, we have a classic "true or false" logic. But the theory holds independently of the logic retained." (Halchuel & Weil, 2003, p. 5)

country, of their representatives, of the political History of their country, etc. Their common culture provides them with common pieces of knowledge.

Further let us also note that in this "Knowledge space / Concept space" view,

The innovative conception dynamic is then made of movements between K and C. The "designers" or inventors start from K and build "concepts" by recombining existing pieces of "knowledge". This movement is called a "disjunction" (knowledge => concept). And for some "concepts", they manage to assign them a logical status through experiments, discoveries, creation a prototypes, demonstrations, etc. By doing this, they transform these concepts into "knowledge". This movement is called "conjunction". The new knowledge created can then be used to create new "concepts", and so on. This dynamic is illustrated by figure 2, taken from *Hatchuel & Weil, 2003* [p. 10]. We will retain *Hatchuel et al.'s* definition of "knowledge" and "concepts" for the remainder of the paper.

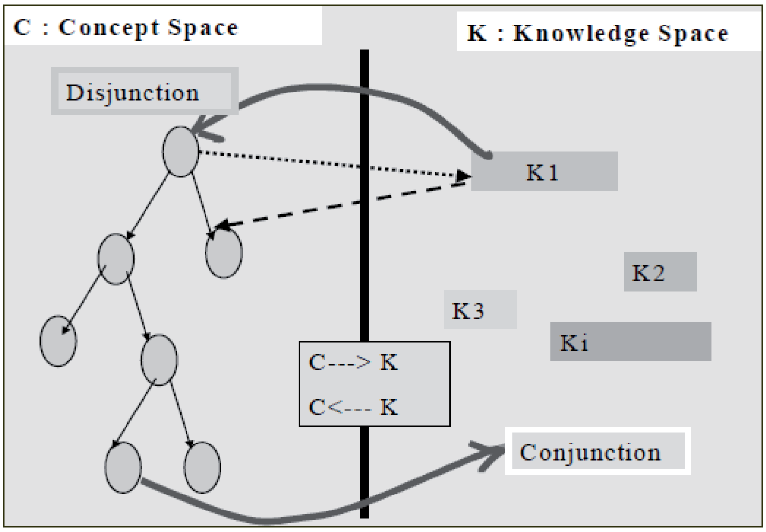


Figure 2. C-K dynamics

This framework illustrates formally how and why cultural diversity – and the diversity of knowledge associated to it – amongst inventors engaged in the same innovative process can have a positive impact on the results of this process: "concepts" are built by recombining existing pieces of knowledge. Hence when the pool of existing knowledge is too redundant, recombination is difficult. In contrast, when designers are able to give logical status to a pool of propositions that are different from one designer to another, the possibilities of recombination are augmented.

It also illustrates how new knowledge builds over time resulting from previous knowledge. During this process, the inventors share a part of their knowledge with the other designers engaged in the same process, and thus their knowledge tend to converge over time. This knowledge distance decrease must be taken into account in the evaluation of individual attributes.

The homophily property of networks suggests that individuals sharing certain personal attributes tend to form links with people of the same kind (homophily of choice). But this property can be viewed the other way around. People who happen to spend time together for different reasons (living in the same place, working for the same company, belonging to a same promotion in college, etc) tend to form and preserve links over time (homophily of opportunity), which leads them to develop common knowledge, that can be embodied by a new common attribute (the attribute can be explicit or tacit).

This conception of Knowledge has led us to formulate 2 hypotheses concerning the relevant way of defining individual attributes in order to measure a group's "external range" in the context of innovation and knowledge diffusion.

Hypothesis 4a : Individual Attributes are not exclusive. Individuals' identities are made of several attributes.

Hypothesis 4b: individuals who happen to spend time together acquire explicit or tacit common individual attribute.

Considering these hypotheses, we have identified 2 categories of such attributes that we will be able to account for in our empirical analysis:

- *Geographical attributes* => attributes resulting from geographical positions of an individual throughout his life (country of birth, country of residence, nationality, region of residence, etc.)

- *Activity attributes* => attributes resulting from the activities that an individual does (professional activity, technological specialization, leisure activity, etc.)

For each inventor, the geographic attribute is represented by a vector of proportions indicating the different countries in which the inventor has lived, and the proportion of his patents for which her address is in this country. For example, if *John Martins* is an inventor who has invented 4 patents in his life at date T, 2 when he was living in Tokyo and 2 while in his present place in London, his geographical attribute vector is composed of 0 for each country, except UK and Japan, where the share is 0,5 for both. This is illustrated by the table below:

Inventor Name	Inventor Id	AT	BE	…	SE	UK	US	JP
John Martins	MAMZ1678	0	0	…	0	0,5	…	0,5

For each inventor, the activity attribute or "technological attribute" (the type of activity of the inventor is determined by his technological specialization) is represented by a vector of proportions indicating the different IPC classes that appeared in the inventor's patents, and the proportion of each IPC class amongst the total number of IPC classes. For example if the IPC codes of John Martins's 4 patents are the following:

Patent Publication Nb	IPC codes	Nb A21 class	Nb H01 class	Nb H02 class	Total number codes
EP0004567	H01H1/023 ; H01H1/027 ; H01H3/00 ; H01B1/02	0	4	0	4
EP0234897	H01B3/00 ; H01H1/023 ; A21B1/52	1	2	0	3
EP1236754	H01B1/02 ; H02J1/08	0	1	1	2
EP1256090	H02J11/00 ; H01J13/00 ; H01K1/26	0	2	1	3
TOTAL		1	9	2	12
SHARE		0,08	0,75	0,17	1

Then John Martins' technological profile is represented by the following vector:

Inventor Name	Inventor Id	A01	A21	…	H01	H02	…	H05
John Martins	MAMZ1678	0	0,08	…	0,75	0,17	…	0

In this setting, we can see that individual's cultural attributes evolve over time and that they relate to two different dimensions of individual culture. This traduces our evolving and multidimensional conception of a person's cultural profile. It also enables us to account for the fact that people who collaborate repeatedly tend to converge in knowledge, as they obtain common patents with the same IPC codes, which make their technological profiles get closer to each other.

5. EMPIRICAL FRAMEWORK

5.1 Database

We use data from 4 databases:

- The PATSTAT 2009 database edited by PATSTAT, a sample of which was kindly made available for our research by the *Observatoire des Sciences et Technologies* (OST) in Paris. This database provided for each EPO patent:
    - Received citations
    - Applicant's Person_Id in PATSTAT 2009
    - Patent's Application_Id in PATSTAT 2009
    - Patent's Publication number at OEB

- The EPO REGPAT 2010 database edited by OECD, derived from PATSTAT 2009 by adding to the geolocalization (region code and country code) of inventor's and applicant's addresses. This database provided for each EPO patent:
    - Inventor's names
    - Inventor's addresses
    - Inventor's region code
    - Applicant's names
    - Applicant's addresses
    - Applicant's region code
    - Patent's IPC code
    - Patent's Priority year
    - Patent's application year
    - Patent's Publication number at OEB
    - Patent's Application Id in REGPAT 2010 (different from Application ID in PATSTAT 2009)

- The EEE PAT 2011 database, co-edited by EPO, EUROSTAT and the ECOOM lab from Louvain Catholic University, also derived from PATSTAT 2009 by harmonizing applicant's names and classifying them by broad sector of activity (public sector, private sector or individual). This database provided for each EPO patent:

- Harmonized Applicant's names
- Applicant's sector of activity
- Patent's Application Id in PATSTAT 2009

- The EUROSTAT database, edited by EUROSTAT, which allowed us to gather the control variables at regional level.
  - Regional GDP/inhabitant
  - Regional share of High-tech and Mid-tech manufacturing employees
  - Regional investment in R&D for private sector, public sector and universities
  - Regional Human Ressource in Science & Technology (education)

The first step in creating our database was to isolate the patents which concern the industrial sector of electric equipment. In the IPC classification, the section H, "Electricity", is divided into 6 classes: H01 ("basic electric elements"), H02 ("generation, conversion or distribution of electric power"), H03 ("Basic Electronic Circuitry"), H04 ("Electric Communication Technique"), H05 ("Electric techniques not otherwise provided for"), H99 ("Subject Matter not otherwise provided for in this section").

We could have selected both H01 and H02 for our study, because these are the most relevant classes for electric equipment sector. But due to the large number of patents that this represents, and to the technical limitations that we face, we decided to focus only on the H01 class: "basic electric elements", which is the most represented class of the section.

Once this choice was made, we selected in EPO REGPAT 2010, all patents that featured at least one[6] IPC code belonging to the H01 IPC class. We found 185,898 distinct OEB patents corresponding to these criteria (from hereafter "H01 patents"). From this list, we listed all the inventors of these patents. After going through a disambiguation process of inventor's names, the number of inventors was 180,215[7]. And from these inventors, we made a third list of all the OEB patents invented by these inventors, whether they feature a H01 IPC code or not (from hereafter "H01 inventors' patents"). This represents 262,153 distinct patents. So doing, we created a database in which each OEB patent of each H01 inventor is listed. Hence this procedure enabled

[6] Patents can be assigned as many IPC codes as necessary, depending on the claims.

[7] The identification of distinct inventors represents a significant part of the work, since there is a lot of misattributions and duplications of "Inventor's Id" in any patent database. Indeed, the inventor's names features spelling mistakes, letters omissions or substitutions, different words order, etc. Thus a process of name dizambiguisation is necessary in order to identify inventors properly. Following, Raffo & Luhillery, 2009 we accomplished a 3-step disambiguization process (cleaning, parsing and filtering) using EUROLIO's disambiguating program "Detect Doublon" (created by J. from EUROLIO).

us to get a complete view of each inventor's patenting activity, of each inventor's patenting profile.

List N°	List short name	Description	Number of observations
List 1	*H01 patents*	All distinct patents that feature at least one IPC code belonging to the H01 IPC class	185,898
List 2	*H01 inventors*	All distinct inventors who have participated in at least one H01 patent	180,215
List 3	*H01 inventors' patents*	All distinct patents in which at least one H01 inventor has participated	262,153

We used these patenting profiles to determine inventor's individual attributes. We proposed in section II that individual's attributes that are relevant for knowledge production and diffusion can be split into 4 categories: geographic attributes (GA), activity attributes (AA), and organizational attributes (OA) and status attributes (ST). Although not all of these categories of attributes can be addressed thanks to the information contained in patents, several attributes can still be evaluated. In particular, we focus on two attributes belonging to 2 different categories:

- ***"Inventor's region" (GA):*** *the OECD REGPAT database provides a coding of inventor's addresses which allows knowing in which NUTS 2 region her address is located.*

- ***"Inventor's technological field of specialization" (AA):*** *we assume that when an inventor obtains a patent in a technological field, it means that this inventor has a certain expertise in this technological field.*

And like we explained in section II, the types of individual attributes that we focus on are not exclusive, and they evolve throughout a lifetime. Individuals accumulate different attributes during their lives by living in different places, by doing different activities, by being part of different organizations, and by being granted different statuses in the course of their lives.

In our study, we express this dynamic non-exclusive conception of individual attributes by describing an inventor N at date T, by 2 vectors of attributes proportions:

- ***G: vector of "country of residence" proportions**. Inventor's addresses can change from one patent to another. G represents the share of each country amongst an inventor's list of addresses.*

- ***T: vector of "IPC classes" proportions**. Each patent feature several IPC codes (9-digits) that can belong to different IPC classes (3-digits). Additionally, inventors can obtain several patents throughout their lives. Thus T indicates the share of each IPC class amongst the total number of IPC codes of an inventor's patent.*

Of course, G and T evolve over time. Hence we measure them at each date of the period, in order to take into account individual evolutions. This formal description of inventor's individual attributes enables us to measure, at each date, the Geographic Attributes Distance (DGeo) and the Technological Attribute Distance (DTech) that separates any pair of inventors at each date. These distances are calculated as:

$$DGeo_{ijt} = \frac{\sum_{k=1}^{K} |PG_{itk} - PG_{jtk}|}{2}$$

$$DTech_{ijt} = \frac{\sum_{s=1}^{S} |PT_{its} - PT_{jts}|}{2}$$

Where,

$PG_{itk} = the\ proportion\ of\ country\ k\ in\ inventor\ i's\ geographic\ profile\ at\ time\ t$

$PT_{its} = the\ proportion\ of\ IPC\ class\ s\ \ in\ inventor\ i's\ technological\ profile\ at\ time\ t$

Let us note several interesting features of this measure: first, DGeo and DTech take values between 0 (identical profiles) and 1 (totally different profiles). Secondly, if two inventors co-invent a patent, then the same IPC classes are added to their pool of individual attributes, so that the individual profiles of the two inventors converge. This is very salient with our conceptual framework since we mentioned in section II that common attributes are built by people who interact with one another over time.

As we will see, being able to measure geographic and technological distance between any pair of inventors will enable us to measure at each date *t*, each region's *r* geographical external range $DGeo_{rt}$ and technological external range $DTech_{rt}$.

For the creation of our region sample, we focused on UE regions. And since many regions displayed very low levels of patenting, we also decided to focus only on the most active regions in terms of H01 patenting. In the end, our sample is composed of the EU regions in which at least 500 OEB H01 patents have been granted. This results in a 32 regions sample (Table 1 gives the list of these regions).

Pays	Code region	Nom région
DE	DE11	Stuttgart
	DE12	Karlsruhe
	DE13	Freiburg
	DE14	Tübingen
	DE21	Oberbayern
	DE23	Oberpfalz
	DE25	Mittelfranken
	DE26	Unterfranken
	DE27	Schwaben
	DE30	Berlin
	DE71	Darmstadt
	DE92	Hannover
	DEA1	Düsseldorf
	DEA2	Köln
	DEA5	Arnsberg
	DEB3	Rheinhessen-Pfalz
	DED2	Dresden
	DEG0	Thüringen
FI	FI18	South Finland
FR	FR10	Île de France
	FR62	Midi-Pyrénées
	FR71	Rhône-Alpes
	FR82	Provence-Alpes-Côte d'Azur
IT	ITC1	Piemonte
	ITC4	Lombardia
NL	NL41	Noord-Brabant
SE	SE11	Stockholm
	SE12	Östra Mellansverige
UK	UKH1	East Anglia
	UKJ1	Berkshire, Buckinghamshire and Oxfordshire
	UKJ2	Surrey, East and West Sussex
	UKJ3	Hampshire and Isle of Wight

Table 1: the 32 regions of our sample

5.2 Variables

Dependant variable

Ln PAT (Logarithm of the Number of H01 patents):

Following the Griliches-Jaffe framework, we use a classical Knowledge production function with substitutable factors. Hence, we use the log of our knowledge production variable (*number of H01 patents granted,* whose priority date is T and for which at least one inventor's address is located in R) for our estimation.

Independent variables

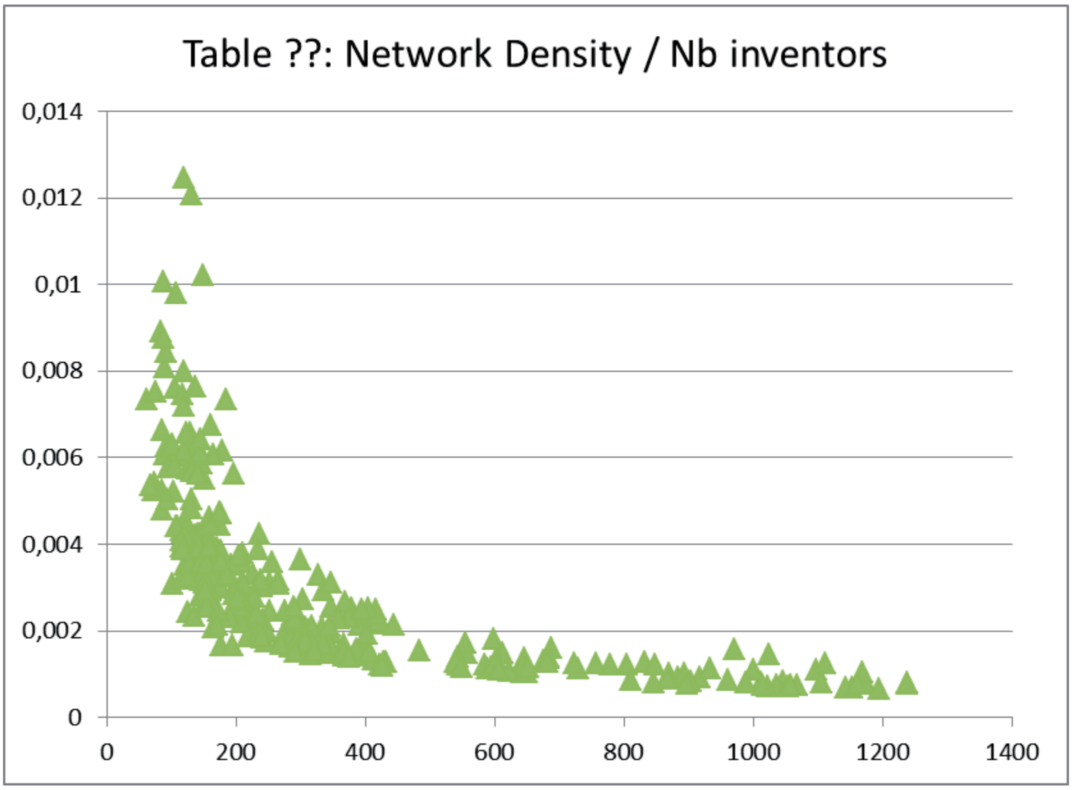
Network Density (DENS): Reagans & Zuckerman (2001) use this variable as a proxy for cohesiveness. It is expected to have a positive impact on the industry-region's innovative capacity. Network Density is calculated as the number of existing links in the network divided by the number of possible links (i.e. [number of actors in the network] X [number of actors in the network – 1]). Just like all the network variables, it is calculated for the network composed of the co-inventors links formed between T-3 and T-1.

$$DENS_{R(T-3,T-1)} = \frac{L_{(T-3,T-1)}}{N(N-1)}$$

Where N represents the number of inventors in the network, and $L_{(T-3,T-1)}$ represents the number of links formed between these inventors between T-3 and T-1.

Like we mentioned earlier, it is also expected to be low on average, since competition between firms as well as innovation appropriation issues naturally push firms not to share knowledge with other firms. Even though it is more and more recognized as an important driver of innovation, inter-firm collaborations remain a minority of the cases.

Additionally, an important empirical property of social networks is that their density decreases with the size of the network (number of agents) more than proportionally. Indeed, while the theoretical amount of links that an agent can form can increase infinitely with the size of the network, the physical and cognitive properties of human beings imply that the amount of links they can form cannot grow infinitely. Hence, the comparison of networks' densities between large and small networks reveals difficult. This empirical bias of network density has been highlighted by several authors (Friedkin, 1981, Faust, 2006). (Table ?? below displays the cloud of the observations plotting network density on number of inventors).



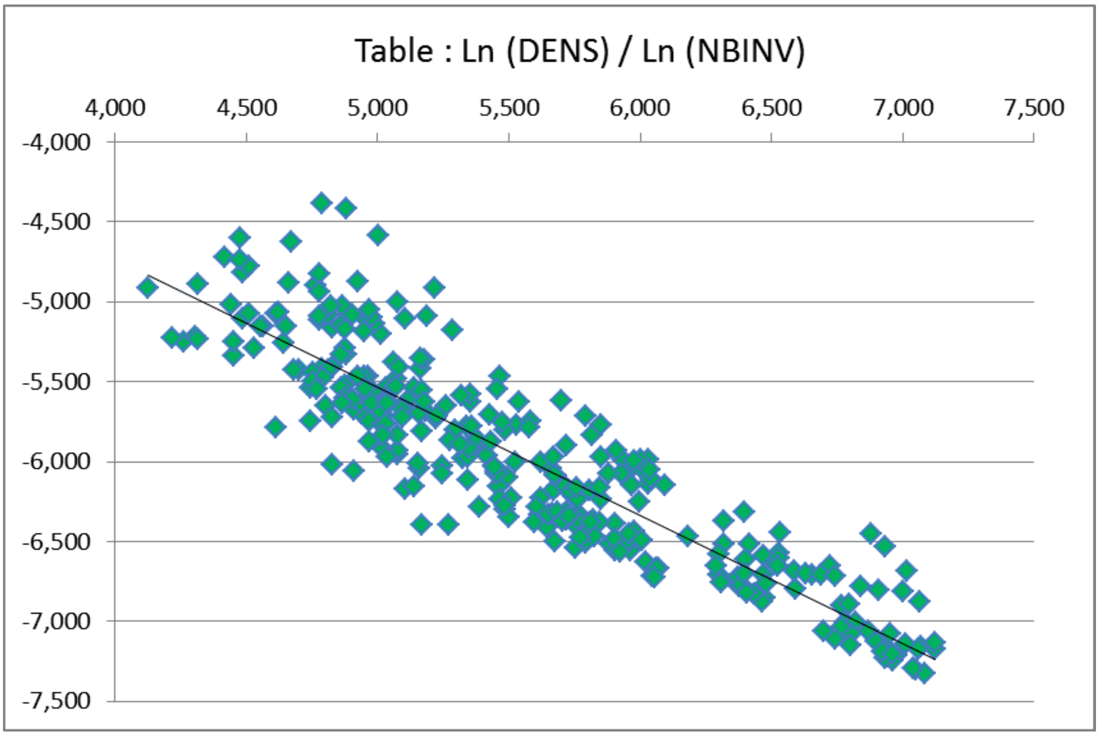
For this reason, we have chosen not to use the gross network density as an indicator of cohesiveness, but rather, a normalized value of the density. This normalized value was obtained through a log-linear regression of the variable DENS (network density), explained by the variable NBINV (number of inventors). Indeed, the distribution of the observations seems to follow an empirical relation of the form:

$$DENS = \frac{1}{a.NBINV^b}$$

So that, the distribution of the Ln follows a linear relation:

$$Ln\,(DENS) = \; a - b\;Ln(NBINV)$$

This relation is illustrated by table ?? below.



Finally, after having determined the estimated a and b coefficients of this regression (resp. -1,528 and -0,801) and checked their significance (both p-values <0.0001) as well as the quality of the regression (adj. R^2 = 0,816), we have used the residuals as our explanatory variable (RES_LNDENS).

Thus, this explanatory variable displays positive values when the observed network density is superior to the predicted value, with regard to the number of inventors, and is negative when the predicted value is inferior to the predicted value.

<u>DTECH and DGEO:</u>

The next 2 explanatory variables are the mean "technological" distance and mean "geographical" distance between inventors that have co-invented patents in the region. These variables are comprised between 0 and 1. 0 means that all inventors linked to each other have the exact same characteristics. 1 means that they all have totally different characteristics.

<u>RES_LNDENS X DTECH and RES_LNDENS X DGEO</u>:

Finally, the last 2 explanatory variables are the cross products of the cohesiveness and technological external range on the one hand, and of the cohesiveness and geographical external range on the other hand.

CONTROL VARIABLES

Ln (EMP TOT) Market Size:

we need to control for the agglomeration effect that results from the size of the region, and more specifically, from the size of the job market. The measure is obtained from the EUROSTAT database which gives us each region's total employment. Our control variable is the average total employment between T-3 and T-1.

Share of Mid-Tech Employment (EMP MT):

this variable controls for the sectoral distribution of the region. In particular, since electric devices industry is part of the Mid-Tech category of industrial sector (see EUROSTAT), one must control for this category's share of employment in the region. Unfortunately, we did not have more precise data on the sectoral specialization in electric device industry. This control variable would obviously improve the quality of the adjustement.

Ln (GDPPC) GDP par capita:

Research is a long, costly and risky process (in particular the patenting process) for firms and individuals. This implies that in poor regions (where GDP par inhabitant is low) firms and individuals can be more reluctant to invest and involve in such processes. Including the GDP per inhabitant as a control variable controls for this effect.

Human Resources in Science and Technology – education (HRST EDU):

this variable accounts for the human capital effect. Human capital is considered as a driver for technological progress, like illustrated by Romer's (1990) and Lucas' (1988) endogenous growth model. An important part of Human Capital holds in the average education level of the population. In order to measure such capital, countries account for inhabitants' education level. Human Resources in Science and Technology is composed of the people who have whether "successfully completed education at the third level in an S&T field of study" or who are "not formally qualified as above but employed in a S&T occupation where the above qualifications are normally required" (EUROSTAT website). We use the former part HRST EDU to account for human capital.

5.3 Descriptive statistics

The following tables show the descriptive values of our variables and displays the correlation between all explanatory and control variables.

Simple statistics						
Variable	N	Mean	Standard error	Sum	Minimum	Maximum
LN_EMPT-3	315	7.12092	0.50024	2243	6.19267	8.52323
SHAREMHT-	316	0.08459	0.03755	26.73153	0	0.18353
SHAREHRST	315	0.31758	0.08440	100.03823	0.10479	0.53208
LN_GDPPCT	320	10.14846	0.21329	3248	9.59560	10.69799
RES_LNDEN	320	1.25E-7	0.27604	0.0000400	-0.72099	1.02590
DTECHT-3	320	0.18377	0.04575	58.80504	0.06415	0.28867
DGEOT-3	320	0.10932	0.06685	34.98196	0.01035	0.37841
RESLNDENS	320	-0.00501	0.05235	-1.60234	-0.17247	0.17387
RESLNDENS	320	-0.00180	0.03101	-0.57464	-0.12618	0.13871

Coefficients de corrélation de Pearson Proba > |r| sous H0: Rho=0 Nombre d'observations									
	LN_EMPT-3	SHAREMHT-3	SHAREHRSTT-3	LN_GDPPCT-3	RES_LNDENS	DTECHT-3	DGEOT-3	RESLNDENS X DTECH	RESLNDENS X DGEO
LN_EMPT-3	1.00000	-0.10775	0.03917	0.31581	-0.01634	-0.25721	-0.04059	0.01081	0.00474
		0.0561	0.4885	<.0001	0.7727	<.0001	0.4729	0.8485	0.9332
	315	315	315	315	315	315	315	315	315
SHAREMHT-3	-0.10775	1.00000	-0.51330	0.13959	-0.33884	0.58926	-0.31885	-0.33687	-0.22443
	0.0561		<.0001	0.0130	<.0001	<.0001	<.0001	<.0001	<.0001
	315	316	315	316	316	316	316	316	316
SHAREHRSTT-3	0.03917	-0.51330	1.00000	0.14514	0.03470	-0.18107	0.09696	0.01207	0.00684
	0.4885	<.0001		0.0099	0.5395	0.0012	0.0858	0.8311	0.9037
	315	315	315	315	315	315	315	315	315
LN_GDPPCT-3	0.31581	0.13959	0.14514	1.00000	-0.18597	0.21807	0.04800	-0.16594	-0.11741
	<.0001	0.0130	0.0099		0.0008	<.0001	0.3921	0.0029	0.0358
	315	316	315	320	320	320	320	320	320
RES_LNDENS	-0.01634	-0.33884	0.03470	-0.18597	1.00000	-0.39772	-0.09761	0.96845	0.83926
	0.7727	<.0001	0.5395	0.0008		<.0001	0.0812	<.0001	<.0001
	315	316	315	320	320	320	320	320	320
DTECHT-3	-0.25721	0.58926	-0.18107	0.21807	-0.39772	1.00000	0.03391	-0.32411	-0.29365
	<.0001	<.0001	0.0012	<.0001	<.0001		0.5456	<.0001	<.0001
	315	316	315	320	320	320	320	320	320
DGEOT-3	-0.04059	-0.31885	0.09696	0.04800	-0.09761	0.03391	1.00000	-0.05674	-0.07812
	0.4729	<.0001	0.0858	0.3921	0.0812	0.5456		0.3116	0.1633
	315	316	315	320	320	320	320	320	320
RESLNDENS X DTECH	0.01081	-0.33687	0.01207	-0.16594	0.96845	-0.32411	-0.05674	1.00000	0.83482
	0.8485	<.0001	0.8311	0.0029	<.0001	<.0001	0.3116		<.0001
	315	316	315	320	320	320	320	320	320
RESLNDENS X DGEO	0.00474	-0.22443	0.00684	-0.11741	0.83926	-0.29365	-0.07812	0.83482	1.00000
	0.9332	<.0001	0.9037	0.0358	<.0001	<.0001	0.1633	<.0001	
	315	316	315	320	320	320	320	320	320

We observe that there is no correlation between the explanatory variables (besides of course, the cross products variables).

5.4 Model specification

We use a panel regression model with random effects. The specification of our model is the following:

$$\begin{aligned} Ln\, P_{rt} = \ & \alpha + \beta 1.RES\_LNDENS_{(t-3,t-1)} + \beta 2.\, DTECH_{(t-3,t-1)} \\ & + \beta 3.\, (RES\_LNDENS \times DTECH)_{(t-3,t-1)} + \beta 4.DGEO_{(t-3,t-1)} \\ & + \beta 5.\, (RES\_LNDENS \times DGEO)_{(t-3,t-1)} + \beta 6.Ln\, EMP\, TOT_{(t-3,t-1)} \\ & + \beta 7.\, SHAREMT_{(t-3,t-1)} + \beta 8.SHAREHRST_{(t-3,t-1)} + \beta 7.\, Ln\, GDPPC_{(t-3,t-1)} \\ & + \varepsilon_{rt} \end{aligned}$$

5.5 Results

The table below displays the results for different combinations of the explanatory variables

DEP: Ln PAT	Model 1	Model 3	Model 2	Model 4
Intercept	5,253***	3,781*	5,203**	4,201*
LN_EMPT-3	0,0469	0,122	0,026	0,066
SHAREMHT-3	4,415**	3,757**	4,491**	3,884**
SHAREHRSTT-3	0,887	0,771	0,772	0,738
LN_GDPPCT-3	-0,194	-0,085	-0,173	-0,087
RES_LNDENS	-0,179*	0,525*	-0,046	0,555*
DGEOT-3			0,135	0,302
DTECHT-3		-0,541		-0,663
RESLNDENS X DGEO			-1,275	-0,603
RESLNDENS X DTECH		-3,654		-3,353**
R-squ	0,042	0,048	0,051	0,068
Hausman Test for random effect	0,111	0,243	0,287	0,431
Nb of cross section	32	32	32	32
Time series length	10	10	10	10

The results show that in the full model (model 4) as well as in the model with the DTECH and RES_LNDENS X DTECH variables (model 2), RES_LNDENS has a significant positive effect on knowledge production. This confirms hypothesis 1.

Concerning hypothesis 2, neither DTECH nor DGEO have any positive effect in any of the tested models.

Finally the product variable of RES_LNDENS and DTECH has a significant negative impact on knowledge production in model 4. This is a counter-intuitive result with regards to our hypothesis 3.

Besides the quality of the regression is rather poor since the R^2 does not reach 0,1 in any of the models.

6. CONCLUSION

Even though the effects and the significance of the results are limited, the influence of a network's cohesiveness on the knowledge production it yields is confirmed by our estimation: The denser a network (relatively) the more productive it is in terms of knowledge production.

In contrast, the results do not enable us to confirm the hypothesis about the role of technological and geographical external range in the innovation processes of a region-industry. However, the absence of significant correlation between DTECH / DGEO and Ln PAT does not discard this hypothesis. Additionally, given the rather exploratory aspect of these explanatory variables, more effort can be done in trying to make them better proxies for technological and geographical external range.
Further, the inclusion of *organizational external range* is another important improvement to carry out, in order to better proxy the theoretical concept of external range. Indeed, in patenting processes, the influence of organizational strategies in deciding which collaboration are achieved and which are not, should not be neglected. Organizational distance between collaborating inventors is an important element in allowing a widening of the scope of reachable knowledge.

Concerning the cross product variables, the results are not very clear and significant and cannot be interpreted at this point.

Another important improvement of the model to carry out concerns the control variables: in particular, a better account of the sectoral specialization of regions, could yield a greater stability in the results across specifications.

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