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How proximity matters in innovation networks dynamics along the cluster evolution. A study of the high technology applied to cultural goods

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ABSTRACT

The role of proximity in innovation and inter-organisational networks has recently received increasing attention in management, organisational, economic geography and regional studies. Despite the rich literature devoted to these themes, most contributions on networks are mainly static, as they focus more on the network's structure than its dynamics. Our aim is to investigate the role of various forms of proximity in innovation network dynamics along the cluster evolution. The article focuses on two specific research questions: (i) How do the different forms of proximity influence the formation of innovation networks? and (ii) Does the impact of different forms of proximity change during the cluster's evolution?

The analysis investigates the cluster of High Technology applied to Cultural Goods in Tuscany and adopts an advanced econometric method such as the Stochastic Actor-Oriented Models to investigate the evolution of the networks over a time period of more than ten years.

1. Introduction

The role of proximity in innovation and network dynamics has recently received increasing attention in management studies (Knoben & Oerlemans, 2006; Molina-Morales, Belso-Martinez, Mas-Verdù, & Martinez-Chàfer, 2015; Presutti, Boari, & Majocchi, 2011; Ritter & Gemunden, 2003), organisational studies (Oerlemans & Meeus, 2005), economic geography (Boschma, 2005; Boschma & Frenken, 2010), etc. However, several theoretical frameworks are used and different forms of proximity are investigated.

The most investigated form of proximity is geographical proximity. Spatial proximity and co-location of economic activities have traditionally been considered as important factors for competitiveness and innovation starting from Marshall and the concepts of agglomeration economies, industrial district and cluster. The clustering effect facilitates knowledge spillovers (Audretsch & Feldman, 1996) and promotes interactive learning among local networks (Belussi, Sedita, & Sammarra, 2010). Geographical proximity also facilitates the transmission of information and knowledge among firms and employees (Bell & Zaheer, 2007).

Nevertheless, geographical proximity has recently been criticised (Knoben & Oerlemans, 2006) as it does not consider the relevance of global and not-localised knowledge networks (Rallet & Torre, 1999). In particular, this stream of research has been particularly prolific in management and organisational studies, where an increasing number of contributions have started to investigate the important role of several forms of proximity in knowledge sharing and inter-organisational collaboration (Knoben & Oerlemans, 2006; Molina-Morales et al., 2015), innovation success (Ritter & Gemunden, 2003), and firms' performances (Oerlemans & Meeus, 2005).

Some authors even investigate how geographical proximity could impede entrepreneurship and innovation (Ben Letaifa & Rabeau, 2013). Others show that the benefits of geographical proximity in a cluster are not equally distributed to all firms, but depend on the position of a firm in the local network (Bell & Zaheer, 2007; Morrison & Rabellotti, 2009).

Despite the rich literature devoted to these themes, most contributions on networks are mainly static, as they focus more on the network structure than network dynamics according to an evolutionary approach. Only recently few contributions adopt an evolutionary perspective on network dynamics (Balland, De Vaan, & Boschma, 2013; Castro, Casanueva, & Galán, 2014; Giuliani, 2013; Ter Wal, 2013). This stream of research investigates several forms of proximity underlining that the various forms of proximity have different impacts on firms' innovativeness, and that they change during the cluster evolution (Menzel & Fornahl, 2010).

This study contributes to the debate on the importance of different forms of proximity. The aim is to investigate the role of various forms of proximity in innovation network dynamics along the cluster evolution. The article focuses on two specific research questions: (i) How do the different forms of proximity influence the formation of innovation networks? and (ii) Does the impact of different forms of proximity change during the cluster's evolution?

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The article focuses on the cluster of High Technology applied to Cultural Goods (HTCG) localised in Tuscany, where several innovations for cultural goods and policy-supported innovation networks have been developed in the last decades (Lazzeretti and Capone, 2016). It is important to investigate this business as the context is multidisciplinary and involves many high technologies (chemistry, physics, opto-electronics, ITC, etc.), which are usually applied to a totally new sector (cultural goods) (Casprini, Pucci, & Zanni, 2014). This could enrich the research agenda on how and which forms of proximity facilitate transversal innovations applied to new sectors and industries.

A new generation of Stochastic Actor-Oriented Models for social networks is now available, which may help advance the study of network dynamics. For the purpose of this study, five forms of proximity are investigated: geographical, social, institutional, cognitive, and organisational proximity. This paper applies a stochastic actor-based simulation approach with the SIENA package (Snijders, Van De Bunt, & Steglich, 2010) to 42 policy-supported innovation networks developed over 15 years (1995–2012) in order to investigate the network evolution over time. It focuses on network dynamics and analyses how these change during the cluster evolution, from a phase of emergence to growth (Menzel & Fornahl, 2010).

2. Innovation networks, proximity and network dynamics

In fields where scientific or technological progress is developing rapidly and the sources of knowledge are widely distributed, networks can become the locus of innovation (Powell, Koput, & Smith-Doerr, 1996). There is in fact a mature literature on networks of innovators and on their role in knowledge creation (Phelps, Heidl, & Wadhwa, 2012; Powell & Grodal, 2005). The growth of knowledge-intensive industries has increased the importance of networks in R&D, strategic alliances and so forth.

Among the literature on innovation networks, several authors investigate formal contractual networks such as those created via subcontracting relationships, alliances or research consortia, and there are also several studies on informal ties based on common membership in professional or trade associations. (Powell & Grodal, 2005).

Corsaro, Cantù, and Tunisini (2012) distinguish between three main perspectives on innovation networks – macro, meso and micro – but the boundaries between these levels are quite blurred. Studies within the macro perspective investigate the impact of innovation networks on macro systems, where the single actor has a secondary role. The meso perspective focuses mainly on the processes at dyadic and network levels, while the micro level perspective is concentrated on the single firm.

Within the meso and micro levels, important contributions derive from the influence of sociological issues, the application of social network analysis and the theory of embeddedness (Granovetter, 1973; Burt, 1992, and others). This research branch has mainly focused on the analysis of the network structure and the position occupied therein by organisations.[1]

This latter contribution has motivated the study of dyadic relationships, which provides relevant clues at the meso level. In recent years, this kind of research, powered by advanced techniques (SIENA, ERGM, etc.), has undergone an evolutionary breakthrough into the study of network dynamics over time.

A related line of research started to focus on *proximity*, exemplified by Boschma and Frenken's work (2010), began with static investigations, but has recently explored how the proximity between two actors can influence innovation networks in a dynamic setting.

Among those adopting an evolutionary approach, Balland (2012) investigated proximity and the evolution of collaboration networks in Global Satellite Navigation Systems in the VI Framework Programme during the period 2004–2007. He shows that geographical, organisational and institutional proximities favour collaborations, while cognitive and social proximities do not play a significant role. The author also underlines that geographical proximity maintains its relevance over time. Balland et al. (2013) study the evolution dynamics of the video game industry and the formation of network ties between firms along the life cycle of a creative industry from 1987 to 2007. They indicate that innovation relationships take form through a mechanism that is stable over time, whereas their weight is subject to change. Cognitive and geographical proximities are increasing determinants as the industry evolves over time.

Ter Wal (2013) explores the interplay between geographic distance and triadic closure, seen as the two main driving forces in the evolution of collaboration within inventor networks in German biotechnology. As the industry changes over time, the direct impact of geographic distance on network formation decreases and that of transitivity increases. Molina-Morales et al. (2015) analyse a foodstuffs cluster in Spain with Exponential Random Graph Models, aiming to clarify the detrimental effects and complementarities that may arise among proximity dimensions. They found a negative effect of cognitive and institutional proximity dimensions on the creation of linkages in advanced stages of the cluster life cycle.

Heringa, Horlings, van der Zouwen, van den Besselaar, and van Vierssen (2014) analyse *ego-alter* relationships among professionals in the Dutch water sector. They find that social and cognitive proximities have a positive effect, while geographical and organisational proximities have a negative effect. Morrison, Balland, and Belso-Martínez (2016) investigate informal relationships in business and technical networks in a Toy cluster in Spain. Their results underscore the positive impact that geographical, cognitive and institutional proximities can have, but also suggest that the dynamics of the two networks differ. Proximity is more crucial for technical knowledge networks, while embeddedness plays an equally important role in the dynamics of both networks. Table 4 summarises the main results of this literature, highlighting in particular research that developed evolutionary analyses.

However, proximity in itself is not a positive supporting factor for innovation. Too little proximity between firms could be detrimental to interactive learning and network formation, whereas too much of it could create 'lock-in' problems (Geldes, Felzensztein, Turkina, & Durand, 2015) or impede innovation (Ben Letaifa & Rabeau, 2013). This is called the *paradox* of proximity (Broekel and Boschma, 2012). In the literature there is evidence that too much cognitive proximity can reduce inter-firm knowledge exchange and too much proximity between agents in any of the dimensions might harm their innovative performance.

As already seen, the core studies on proximity have focused on innovation networks, but not all the relevant literature has confined itself to them. For example, Geldes et al. (2015) analyse inter-firm marketing cooperation by exploring all the different forms of proximity. The authors point up that marketing relationships are mainly influenced by social proximity, while the geographical has no relevance. In particular, this study investigates how geographical proximity moderates the relationship between inter-firm marketing cooperation and non-spatial dimensions of proximity.

Cantù (2010) argues that the convergence of cognitive and technological proximities can generate innovation. She focuses on how proximity supports innovation, demonstrating that different proximity dimensions influence firm boundaries, in accordance with the approach of the Industrial Marketing and Purchase (IMP) group to business-to-business relationships (Hakansson & Snehota, 1995, 2006). She uses a qualitative approach of semi-structured interviews to investigate the network relationships in a spin-off of the ceramics business. Finally,

[1] Granovetter (1973) stresses the importance of the links built up with distant actors from usual network of contacts, which shares redundant knowledge. Creating links with cognitively distant actors is crucial for innovation and acquisition of new knowledge. Burt (1992) states that the discontinuities or *structural holes* occurring in the socio-relational fabric are the main determinants of actors' behaviour.

Nicholson, Tsagdis, and Brennan (2013) try to integrate the approach of industrial marketing and that of evolutionary economic geography on proximity and spatial embeddedness in business relationships.

2.1. Hypothesis of the research

Boschma (2005) stressed the fact that innovation is fostered by various dimensions of proximity. He proposed five dimensions of proximity, in which cognitive, organisational, institutional, social and geographical proximities increase the probability of forming relationships with others. In other words, organisations establish collaborations more easily with counterparts that are of the same typology, co-located in the same area, belonging to the same group, etcetera.

We follow this contribution notwithstanding that the various forms of proximity are not unanimously interpreted in the literature. For instance, Knoben and Oerlemans (2006) present an ISI web literature analysis of several studies on proximity proposing a classification into seven dimensions. Nonetheless, in this stream of research, most contributions focus on the above recalled five dimensions. For these reasons, we elaborate five hypotheses for our investigation.

2.1.1. Geographical proximity

The literature on externalities usually takes for granted that agglomeration economies derive from three distinct sources; namely, a qualified labour force, specialised suppliers and knowledge spillovers. In this respect, some authors stressed that innovative clusters of small and medium enterprises are characterised by higher levels of inter-firm imitation, sharing of common knowledge, and mutual learning among organisations (Tallman, Jenkins, Henry, & Pinch, 2004). Geographical proximity also facilitates the transmission of knowledge among firms and employees (Bell & Zaheer, 2007).

Several researches consider geographical proximity as a prerequisite for positive externalities in clusters, especially in innovation (Geldes et al., 2015). Proximity provides opportunities for repeated interaction and thus the creation of social capital. Co-location provides opportunities for interaction and social and professional contacts. It creates an environment that facilitates trust as well as the rapid diffusion of ideas and knowledge spill-overs (Audretsch & Feldman, 1996).

H1. Organisations are more likely to form ties with other organisations co-located in the same cluster or geographically close to each other.

2.1.2. Cognitive proximity

The other four dimensions appear to be disconnected from physical proximity, as they express a relational proximity that is related to the interaction between actors (Boschma, 2005). The concept of cognitive proximity has been developed by Nooteboom (1999). Cognitive proximity is commonly defined as a similarity in the way actors perceive, interpret, understand and evaluate the world (Knoben & Oerlemans, 2006).

Cognitive proximity is particularly important for promoting innovation, starting from the concept of absorptive capacity (Cohen & Levinthal, 1990), knowledge bases (Nooteboom, 1999), and *proximité* (Rallet & Torre, 1999). Firms with a similar knowledge base exchange and acquire external knowledge more easily and efficiently. This could be done by investing in innovation internally or acquiring external employees in order to develop a shift in the level of internal absorptive capacity.

Furthermore, the related-variety approach (Frenken, Van Oort, & Verburg, 2007), which has received growing attention in the literature, investigates the key factors of economic development and innovation by pointing out the need for a local system to have a certain degree of cognitive proximity.

H2. Organisations are more likely to form ties with actors with whom they share a common interpretative scheme or the same knowledge base.

2.1.3. Organisational proximity

Organisational proximity refers to rules and procedures that link organisations within the same framework. It concerns the intensity of relations and the degree of autonomy within these organisational frameworks. The literature provides two major definitions of organisational proximity (Balland, 2012). The first definition refers to the specific form of proximity existing among firms of the same group, that is, within parent companies, etc. (Balland, 2012; Heringa et al., 2014; Capaldo & Petruzzelli, 2014). For example, the pooling of in-house functions can reduce costs by facilitating the exchange of engineers, technicians, etc.

Broekel and Boschma (2012) propose an alternative way to define organisational proximity. In their view, it is the degree to which organisations have similar routines and incentive mechanisms. Knoben and Oerlemans (2006) define it as a routine in the sense of an executable capability for repeated performances in a specific field. In this context, other measures are also used: for instance, D'Este et al. (2013) take prior experience with a partner as a measure of organisational proximity, while Oerlemans and Meeus (2005) measure this through the number of research collaborations a firm establishes with a variety of external actors.

Prior collaborative experience indicates the development of organisational routines and thus an enhanced capacity to work together and participate in innovation networks. This is particularly true for temporary project organisations in policy-supported networks.

H3. Organisations are more likely to form ties with the same corporate group or actors with prior collaboration experiences.

2.1.4. Institutional proximity

In most studies, institutional proximity is defined as the similarity of informal constraints and formal rules shared by actors (Boschma, 2005). Usually, this aspect is related to belonging to the same institutional form (such as firms, research centres and universities) (Heringa et al., 2014; Molina-Morales et al., 2015). Institutional proximity measures whether two firms are exposed to the same institutional context (Balland et al., 2013). In other words, the sharing of formal or informal rules and codes increases the likelihood that actors will start a partnership.

Etzkowitz and Leydesdorff (2000) argued that innovation is strongly promoted by inter-organisational networks formed by organisations of different typology—in particular, firms, institutions and universities. The Triple Helix approach is based on the insight that the innovative potential in economies lies in a more prominent role of universities, industry and government in the production, transfer and application of knowledge. Thus, institutional forms figure as critical determinants of innovation in this approach.[2]

In other studies, the concept of institutional proximity is also based on similarities between the institutional frameworks of countries and regions, such as their legislative conditions, labour relations, business practises, accounting rules and training systems (Knoben & Oerlemans, 2006). Geldes et al. (2015) define institutional proximity as the set of practices, laws, rules and routines that facilitate collective

[2] The Triple Helix model represents a policy vision that underlines how the creation of a 'university–industry–government' triad is relevant for developing innovations. It is not clear whether organisations (at actor level) are more likely to develop partnerships with organisations having a similar vs different institutional form. This approach however underlines a special opportunity for organisations to also benefit from the development of partnership with different actors. For reference, see for instance Corsaro et al. (2012), who focus on innovation networks, in which they investigate the role of actors' heterogeneity.

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action; and they point out that organisations tend to form more partnerships with other actors when they share these principles.

H4. Organisations are more likely to interact when they have the same institutional form.

2.1.5. Social proximity

The concept of social proximity is built upon the observation that economic relationships may reflect social ties (Granovetter, 1973) in terms of friendship, kinship and experience at the micro level (Boschma, 2005). Broekel and Boschma (2012) emphasize the role of the 'old boys network', highlighting the importance of previous individual relationships and trust-building for innovation networks. Heringa et al. (2014) focus on the social embeddedness of ego and alter, pointing out that several studies on formal relationships use the collaboration history of actors, such as an earlier co-invention or the geodesic distance in a social network, as a proxy for social proximity (Balland, 2012). The fact that an ego repeatedly collaborates with the same alter indicates the formation of mutual trust diffused across their network of relationships. Boschma and Frenken (2010) point out that the role of social proximity implies that partners of partners are more likely to interact due to the reputation and trust effects created by repeated contacts between them (Balland, 2012).[3]

This idea of proximity is based on the way specific agents are more or less deliberately positioned in (production, R&D, etc.) relationships with other agents, and the way the agents shape and maintain relations.

H5. Partners of partners are more likely than others to interact, i.e. social proximity favours collaboration.

3. Data and methodology

3.1. Data sources

The present study represents the last stage of a long-term research project focusing on the HTCG cluster in Tuscany.

In the course of previous investigations, we had analysed some innovation networks in the HTCG business, particularly as regards innovative developments applied to cultural goods in policy-supported inter-organisational networks of Tuscany (Lazzeretti & Capone, 2016).

Subsequently, we turned to the analysis of policy-supported innovation networks developed by the subjects operating in the local cluster, given that such networks have clearly played a relevant role in promoting innovation in this business (IRPET, 2012; Lazzeretti, Capone, & Cinti, 2011).

The analysis involved the collection of qualitative and quantitative data providing the fullest possible information about the phenomenon under study. The quantitative data mainly concerned the policy-supported innovation networks established in the Tuscan cluster.[4]

This information was collected through a questionnaire that was submitted by email to the main regional research organisations specialised in this business. The organisations that were sent the survey had been selected on the basis of their involvement in the proposal, sent to the Tuscany Region in 2011, for the constitution of a Technological District in Cultural Goods (TDCG), and of their actual participation in the district.[5] They represent the most important promoters of innovation in the HTCG business at the regional level. We surveyed all the (public) research centres and universities operating in the region of Tuscany. The group consisted of 15 actors, including six research centres affiliated to national research institutes and nine university departments and faculties.

We checked the data and identified some key actors for the cluster in 2012, then held some in-depth interviews so as to look into the dynamics of innovation. Finally, we verified the information by checking regional, national and international project databases. The selection criterion was to include projects with at least one participant from the Tuscan cluster.

In total, data was gathered from 42 networks, related to projects funded through regional, national and international donors, covering a time-span of over 15 years (1995–2012) and involving small, medium and large firms, research centres and universities. To the best of our knowledge, this information is representative of all the policy-supported innovation networks in the HTCG business in Tuscany.

For each actor, in addition to the number of networks in which he had participated, other useful features for the elaboration of descriptive statistics were investigated: received financial contributions, location, typology, competencies, etc.

In order to analyse network dynamics, the database was pre-arranged for the application of social network analysis (Wasserman & Faust, 1994) with the aim of highlighting the inter-organisational relationships activated by co-participation in innovation networks. The link between two organisations (firms, universities, research centres, etc.) indicates co-participation in the same network.

In order to examine network dynamics along the cluster life cycle, we built three matrices for the years 2000, 2005 and 2010, representing the networks at the three different periods of time.[6]

The choice of the period of analysis was motivated by several factors. The year 2011 marks a turning point, since the local cluster was acknowledged in that year by the Tuscany Region with the establishment of the TDCG. For this reason, we decided to focus on the previous period and investigate the cluster's development before its formal recognition.

We chose 2000 as the start of the study period because the relevant business activities only became significant after 1999 (Fig. 1). In order to explore two time periods of equal length, we have built three matrices for the time evolution of the networks for the cluster's emergence and growth stages. The 2000–2005 period is considered the emergence phase and the 2005–2010 period is considered the growth phase (IRPET, 2012).

3.2. Methodology

In order to investigate the dynamics of network evolution, this work has been based on Stochastic Actor-Oriented Models (SAOM) (Snijders et al., 2010). The module SIENA of R (Simulation Investigation for Empirical Network Analysis) carries out the statistical estimation of models for the evolution of social networks.

SAOMs are used to model longitudinal network data. The dependent variable is the evolving relation network, represented by repeated measurements of a directed graph. The network evolution is modelled as the consequence of actors initiating new relations or withdrawing existing relations such that a more rewarding configuration for the actor in the network emerges, to which a random influence is added. This goal is modelled on a so-called *objective function* the actors try to maximise. The models are continuous-time Markov chain models that are implemented as simulation models.

SIENA is recognised as a very promising tool to study the dynamics of networks (Balland, 2012; Castro et al., 2014; Giuliani, 2013; Ter Wal, 2013). As the model estimates and tests parameters from empirical data, it considers networks' changes as an evolutionary process. It

[3] This is usually the case of two actors who, being at a 'social distance of two', have a higher probability of getting connected.

[4] Morrison et al. (2016) underline that an alternative approach to investigate networks is to collect primary data with prospective o retrospective method. In the latter, the researcher collects information on past relationships, a main limitation is potential cognitive distortion such as faulty attributions or lapses of memory. Besides, the main limitation of prospective data collection is that subjects might drop out of the study (Morrison et al., 2016).

[5] Regional law 539/2011 on the Technological District in Cultural Goods, Tuscany Region.

[6] The bipartite (two-mode) network has then been transformed into a uni-partite (one-mode) network, i.e. with 'organisation to organisation' links.

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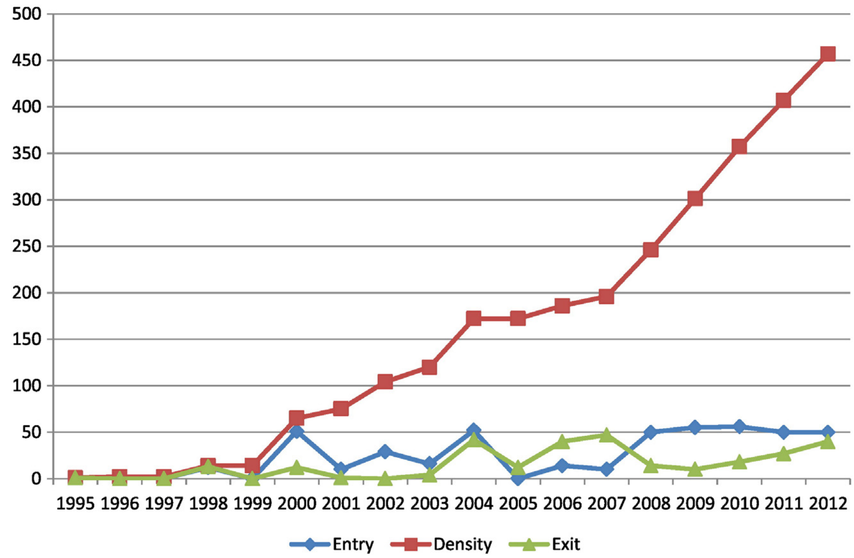

Fig. 1. Actors' entry, exit and density in HTCG.
Source: authors' elaborations.

considers micro dynamics to form the overall network evolution and considers change as an iterative process, between two or more observed moments.

SIENA uses an iterative Markov chain Monte Carlo algorithm to estimate parameters from observed data based on the methods of moments. The first observed network is used as the starting point for the simulations. The stochastic approximation algorithm simulates the evolution of the network and estimates the parameters that minimise the deviation between the observed and simulated network.

The estimation is modelled through two functions (Snijders et al., 2010). The first is called 'rate function', which is a function of distribution along time and specifies the frequency in which actors change a relation within the network (form or remove a tie). It can be equally applied to all the actors or depend on a single actor's attribute or position in the network.

The action taken by each actor is stochastically determined by the second function, called the 'objective function'. This objective function could be divided into three parts. The first function is an 'evaluation function' that models the satisfaction of actors in the different possible configurations of the network. To allow asymmetry in the creation and termination of ties, two other functions could be estimated: a 'creation function' expressing aspects of network structure playing a role only for creating new ties and an 'endowment function' only for maintaining existing ties.

In a simple specification, the model can be estimated only with the evaluation function, considering the rate function constant and the creation and endowment functions equal.

In the simple specification, the probabilities of an actor forming or withdrawing a tie depend on the *objective function*, which expresses how likely it is that an actor will change its network, and is a weighted sum of a set of effects:

$$f_i(\beta, x) = \sum_{k=1}^{L} \beta_k s_{ik}(x)$$

where $f_i(\beta, x)$ is the value of the objective function for actor i and β_k are the statistical parameters indicating the strength of the effect $s_{ik}(x)$. The $s_{ik}(x)$ are the selected effects from a range of structural, individual covariate, and dyadic covariate effects. If β_k equals 0, the corresponding effect plays no role in the network dynamics. If β_k is positive, then there will be a higher probability of moving in a direction where the corresponding effect will be higher. If β_k is negative, the contrary applies.

Estimates of the parameters in the objective function are approximately normally distributed, which means that the parameters can be tested by referring the t-ratio to a standard normal distribution (Snijders et al., 2010).

The probability that an actor i makes a change and chooses between some set C of possible new states of the network is given by:

$$p_{ij}(x) = \frac{\exp(f_i(x(i \rightsquigarrow j)))}{\sum_{h=1, h \neq i}^{g} \exp(f_i(x(i \rightsquigarrow h)))} (j \neq i)$$

where $p_{ij}(x)$ is the probability of changing anything. Higher values of the objective function indicate the preferred direction of changes.

Table 1
Operationalization of the variables.
Source: authors' elaborations.

Variables	Operationalization
Proximity	
H1 Geographical proximity	Co-location in municipality (same region/country)
H2 Institutional proximity	Same typology (firms, cultural organisation, research centres/universities)
H3 Cognitive proximity	Same scientific domains
H4 Organisational Proximity	Prior collaboration experiences (Years of experience between *ego* and *alter*)
H5 Social (network) proximity	Opposite of 'number of actor pairs at distance 2'
Status effect	
Density	Degree
Preferential attachment	Degree of alter
Attributes (actor)	
Funds	Total collected funds
Experience	Numbers of years since entry in HTCG network
Number of funded networks	Number of funded networks
Leadership	Network leader

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This formula is used in multinomial logistic regressions and means that the probability of an actor making a change is proportional to the exponential transformation of the objective function of the new network resulting from this change (Snijders et al., 2010). The next paragraph describes the $s_{ki}(x)$ effect applied in our study.

3.3. Operationalisation of the variables

The various dimensions of proximity as a driver in the formation of innovation networks have been turned into variables (Table 1).

Geographical proximity is determined according to a co-location of actors. This effect has also been divided into four classes depending on their location in: the municipality of Florence, the region of Tuscany, Italy and Europe.

Cognitive proximity occurs when organisations share the same kind of knowledge base. This permits them to exchange knowledge and communicate faster and more easily. Each actor has been classified on the basis of its role in the innovation networks and with respect to the following classes: Environmental, Chemistry, Conservation, Diagnostic, Physics, ICT, Optoelectronics, Restoration, Visual 3d. In other words, these are the scientific domains of the actors related to HTCG.

Institutional proximity is usually defined when organisations have the same institutional form. Therefore, we classified actors on the basis of the following classes: research centres, public institutions, small and large firms, and universities.

Organisational proximity is usually measured by analysing formal inter-organisational relationships, for example considering firms in the same group (Balland et al., 2013). In our case, this is not relevant as groups are not involved. We opt to measure it using temporary project organisation as a proxy. Organisational proximity is therefore measured by the year of collaborations of a pair, which means that two actors that work together for some years have developed some organisational routines that help them work together. D'Este, Guy, and Iammarino (2013) also adopt this approach.

Social proximity is usually measured as a triangle or dyadic closure in a directed network, as cliques are not considered coherent measures in bipartite data. Balland (2012) points out that accounting transitive triplets to measure transitivity is inadequate for affiliation networks constructed from bipartite data, and leads to an artificially high transitivity parameter. Social proximity is thus measured with the 'opposite[7] of the number of actor pairs at distance 2', which is a measure of network closure already used in other research studies (Balland, 2012). Snijders et al. (2010) point out that stronger network closure will lead to fewer geodesic distances equal to 2. The number of actors at distance 2 takes into account indirect connections between actors. The fewer the indirect connections between actors, the stronger the tendency toward network closure.

We include also a variable to measure the preferential attachment calculated as the 'degree of alter'. As control variables, actors' attributes are also considered: *experience in HTCG networks* (no. of years) and *Size* as the number of involved innovation networks, and eventually, the role as *network leader*.

4. The evolution of innovation networks in high technology applied to cultural goods

4.1. The cluster of high technology applied to cultural goods

HTCG is a newly emerging business for firms in various industries, such as ICT, geology, chemistry, biology, engineering and physics-optoelectronics. This is particularly true for Florence and Tuscany where a technological cluster has formed over time, specialising in the restoration and enhancement of their rich and internationally-renowned cultural heritage (IRPET, 2012).

Recent research has also been devoted to the study of innovation in HTCG. Casprini et al. (2014) analysed business modules in HTCG, surveying 30 firms in Tuscany. The public research report of IRPET (2012) was among the firsts to analyse this business, pointing out its relevance in Tuscany from an innovation perspective.

The local cluster started to develop in the early 2000s, thanks to policies supporting inter-organisational networks in HTCG. The cluster developed rapidly and, after about ten years, reached a total of more than 400 associated actors: firms, research centres and universities. In 2011, the Tuscany Region recognised the relevance of this sector and founded the TDCG in order to support local R&D activities and improve local governance.

4.2. The evolution of the innovation networks

Fig. 1 presents the evolution of the networks from 1995 to 2012, showing the number of involved actors, its density, and the entry–exit dynamics. The networks developed in the early 2000s, recorded a significant growth in the last decade, reaching 450 actors with about 50 entries per year. This confirms the importance of this business, which has attracted more and more companies, research centres and universities.

Fig. 2 presents the different configurations of the network: the period 2000–2005 is the phase of emergence of the cluster, and the second period (2005–2010) is the period of development. The network passes from the first stage of emergence to the first development stage, and it is still growing at the moment.

In 2000, the network showed a weak structure focused on institutional and research centres, which are the major players. The network is cohesive, but focused on few actors. In 2005, a substantial change started to emerge. The network became steadily more structured, the number of actors grew exponentially. Among the actors, economic actors also started to appear such as small and large firms. The overall network, however, is composed of sub-networks from different disciplines. The smaller sub-networks are still composed of institutional actors and research organisations, while the larger sub-networks also involve many local small and medium enterprises.

In 2010, the network was fully connected around the previously identified sub-networks, all players in the Triple Helix emerged and its connectivity was very thick. This configuration shows a phase of development of the global network that achieves a high level of complexity.

Table 2 presents the descriptive indexes of the network in the three snapshots. The average degree increased in the period, pointing out a network that gradually became more and more complex. The density of the network decreased from 0.6 to 0.1 underlining a gradual decrease of cohesiveness. The average distance gradually increased in the period with the growth of the network. The number of actors increased from 26 in 2000 to 357 in 2010.

5. The analysis of the network dynamics

The results of parameters estimation, elaborated with R-SIENA, are presented in Table 3. All estimations are based on 1000 simulation runs and four phases. The Conditional Method of Moments was used. The convergence of the models is good in all cases and no problems of multicollinearity were encountered.[8]

[7] For an easier interpretation of results, we decided to use the opposite of this effect, as it is positively correlated with social proximity. If it produces a positive parameter, the estimation shows a positive effect of social proximity on network formation.

[8] The rate parameter indicates the number of opportunities for an actor to make a change in its network between the two periods. This effect is estimated by comparing the network in the two periods of time and determining the average number of changes necessary for the actors to produce the observed shift (Snijders et al., 2010).

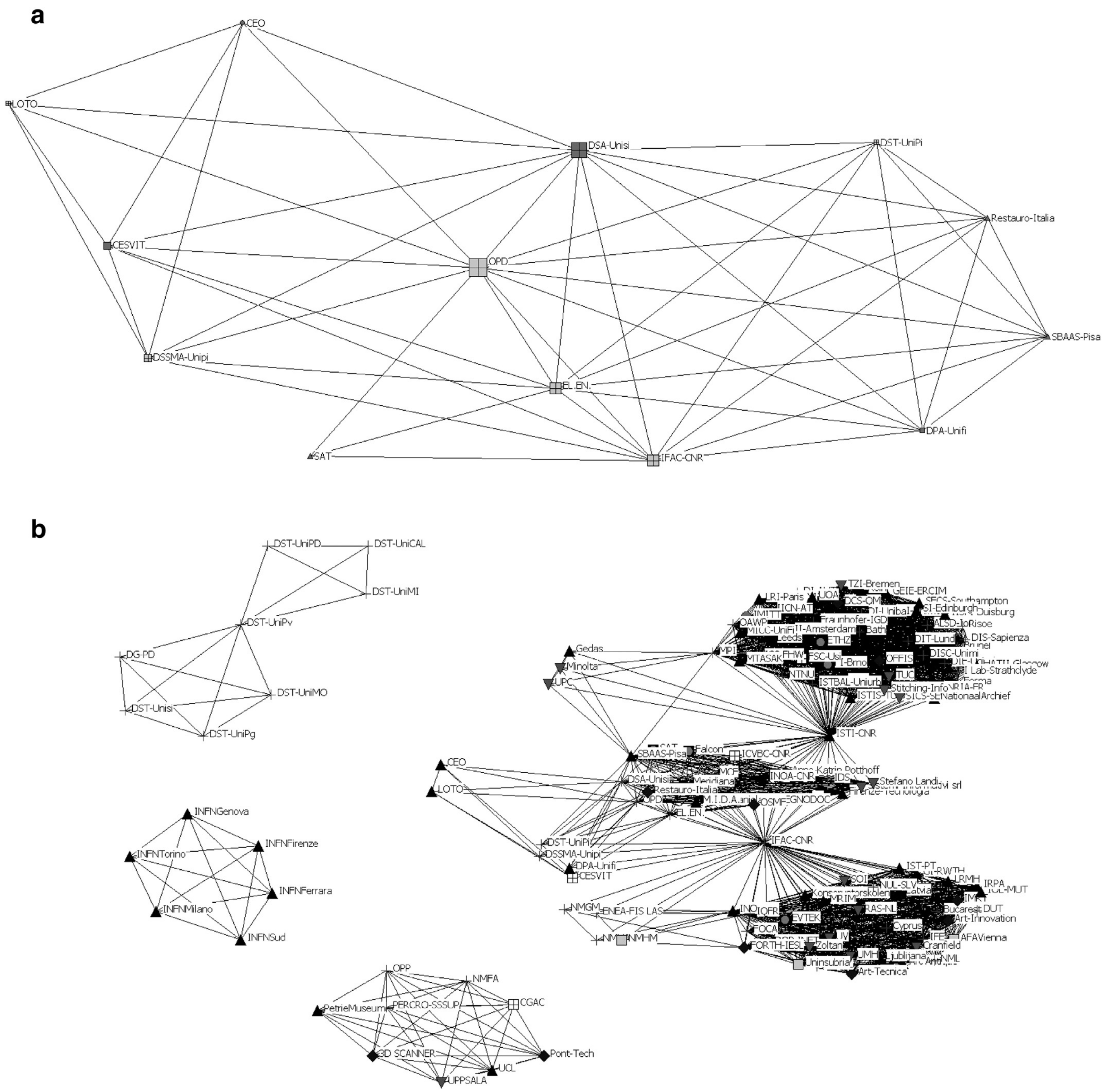

Fig. 2. The evolution of the networks on HTCG: 2000, 2005 and 2010. 2a: 2000 2b: 2005 2c: 2010
Source: authors' elaborations.

The rate parameter shows the probability of the actor forming new ties during the period as a measure of network change.[9]

Model 1 estimates the actors' attributes, Model 2 estimates the proximity variable in the emergence phase (period 2000–2005), while Model 3 estimates the development phase (period 2005–2010). If a parameter is positive and significant, it indicates that it is a determinant of network formation.

[9] Estimates of the parameters in the objective function are approximately normally distributed, which means that the parameters can be tested by referring the t-ratio (parameter estimate divided by standard error) to a standard normal distribution (Snijders et al., 2010). Snijders proposes to approximate them to a standard normal distribution, and considers absolute values greater than 2 as significant at the 5% level, and absolute values greater than 2.5 as significant at the 1% level.

The value of the rate parameter is positive and significant. It indicates that on average every actor established more relationships in the emergence phase than in the development phase. The parameter of the degree is negative and significant in Model 1, showing a similar value to other studies on the dynamics of the network, while it is not significant in the other models. The parameter of the *preferential attachment* is not significant.

We now analyse the parameters of the various dimensions of proximity. As expected, geographical proximity is an important factor as firms tend to develop relationships with other actors of the same cluster. Geographical proximity is more important in the emergence phase than in the development phase. Its impact is double in the first phase.

Cognitive proximity is positive and shows that the analysed actors are more likely to create new relationships with other subjects of the

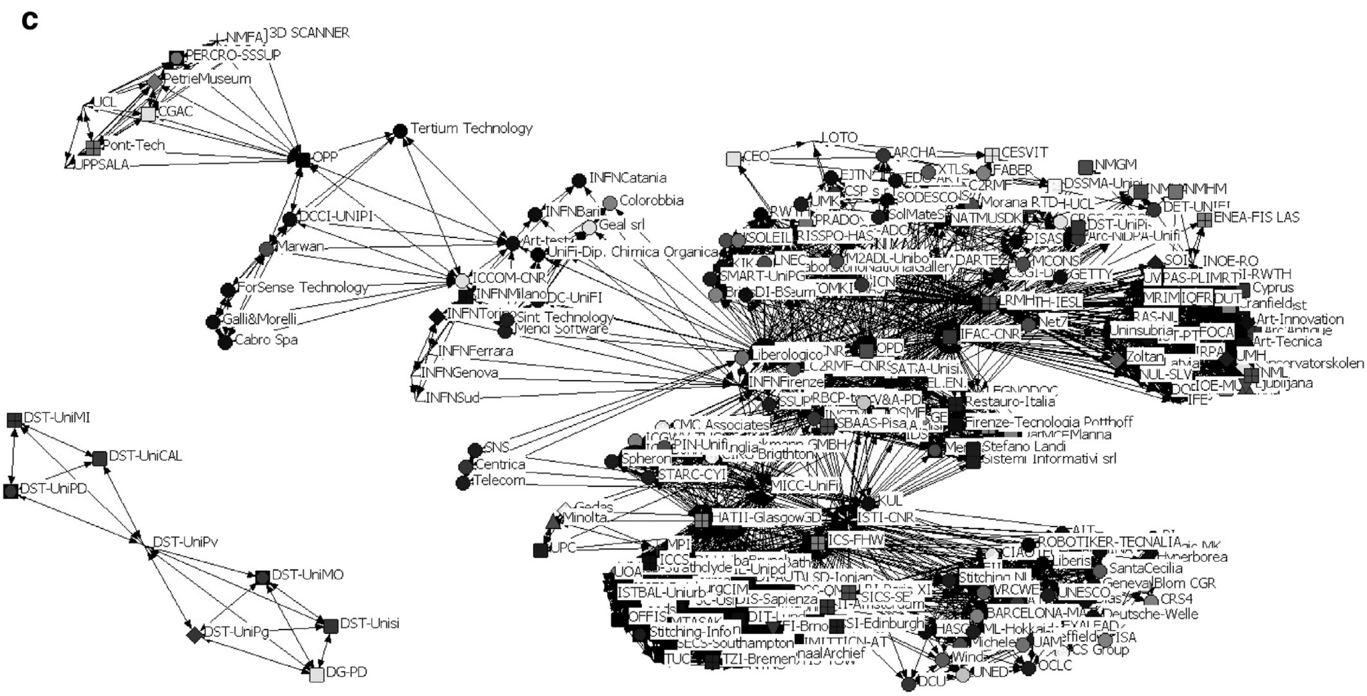

Fig. 2 (*continued*).

same scientific domain. This is contrary to what could be expected in the field of HTCG, rich of transversal innovations and cross-fertilisation dynamics. Both these values are positive in the two phases, but in the development phase, they decrease and their importance is reduced. This could indicate the increasing importance of cross-fertilisation linkages among actors of different scientific domains as the cluster develops.

Institutional proximity is positive and significant in the first phase, while it is not significant in the second period. In the emergence phase, it is extremely important and it indicates that at the beginning of the cluster life cycle, actors are more likely to form ties with actors of the same typology.

Organisational proximity is positive and significant. In the emergence phase, it is more important that in the development phase when it is close to zero, thus indicating that the experience developed between two actors is a smaller factor for the creation of new ties during the second period.

Social proximity is significant and positive in both periods. In the first period, the significant positive effect confirms the tendency toward network closure. Therefore, indirect connections are reduced and there is a tendency to develop relationships with partners of partners. In the development phase, the parameter is still positive but close to zero, which seems to suggest a transition toward a different kind of behaviour. In the development phase, this parameter tends to decrease, indicating that relationships do not develop according to those factors anymore. Presumably, this is because peripheral partners that were included in the innovation network at its inception are gradually forced out by growing competition in favour of relationships built among more central actors.

The estimations of the different forms of proximity in the two phases of cluster emergence and growth are graphically represented in Fig. 3.

Table 2
The evolution of the network. SNA index and composition.
Source: authors' elaborations.

	2000	2005	2010
Network indexes			
Networks	7	17	38
Average degree	7.538	29.554	24.569
Density	0.628	0.214	0.097
Connectedness	1	0.704	0.939
Fragmentation	0	0.296	0.061
Average distance	1.372	2.025	2.519
No. actors	26	172	357

6. Discussion and comparisons with other studies

By way of conclusion, it is worth comparing the results of the present analysis with those of other recent studies on different forms of proximity, with a special emphasis on those studies that carried out an evolutionary analysis over time (Table 4).

Let us look first at the results of static analyses. Most of the works agree on the relevance of geographical proximity, whereas analyses of other kinds of proximity yield more conflicting results. The only contrarian contributions are those of Molina-Morales et al. (2015) and Heiringa et al. (2015), which both register a negative effect of geographical proximity on innovation. In Molina-Morales et al. (2015) an adverse effect is also recorded for cognitive and institutional proximities. The results of all the other studies are in line with ours.

Let us now look at the evolutionary studies. Here, given the limited number of contributions, the results are more heterogeneous. All forms of proximity, except for geographical proximity, become less significant as networks develop. Our results are in line with these studies.

More specifically, in our analysis, the influence of geographical proximity diminishes over time, yet remains one of most relevant parameters. This may be because this form of proximity has a fundamental influence over the early stages of cluster development.

Even the influence of social proximity, according to our analysis, diminishes over time, a result which is in line with the findings of Balland et al. (2013). This form of proximity is initially important, but as the cluster develops and competition grows, its influence wanes. The only contrarian study in this regard is that of Ter Wal (2013), but this may be because Ter Wal focuses on a specific issue within cluster development (co-inventions).

Table 3
Estimation results.
Source: authors' elaborations. Standard error in brackets.

	Model 1		Model 2: Introduction (2000–2005)		Model 3: Development (2005–2010)	
Variables	Estimations	T-ratio	Estimations	T-ratio	Estimations	T-ratio
Rate parameter	4.4566*** (0.0098)		15.3180*** (0.2011)	26.82	4.6739*** (0.1835)	25.47
Degree (density)	−0.3041*** (0.0970)	3.1350	−0.1540 (0.2011)		−0.609 (0.4332)	1.41
Preferential attachment (degree of alter)					2.6685 (1.9125)	1.40
Geographical proximity			2.334** (1.824)	3.98	1.4646*** (0.3512)	4.17
Cognitive proximity			2.1037** (0.9499)	−1.717	0.9663*** (0.3009)	3.21
Institutional proximity			3.9251** (1.9145)	−0.223	−0.0339 (0.2612)	0.13
Organisational proximity			1.3668** (0.9772)	−0.657	0.0220*** (0.0069)	3.19
Social proximity			5.7882*** (2.4532)	0.301	0.4531*** (0.0971)	4.67
Funds similarity	−1.2023*** (0.2986)	4.0264			−5.8114*** (1.0325)	7.57
Leadership similarity	3.3067*** (0.3986)	8.2957				
Experience	3.5518*** (0.1854)	19.1575				
No. networks	−6.6663*** (0.3061)	21.7781 4.0264				
Iterations	1220		1737		1606	

** 0.05.
*** Significance at 0.01 level.

All of these works document the way in which different networks develop from emergence up through later development phases. They demonstrate that physical nearness and social relations among actors are critically important determining factors at the cluster's inception, but that their formative influence diminishes as the cluster evolves and matures (see, for example, the implementation of projects in the European Community's Framework Programme). Overall, the literature suggests that, in the future, social proximity will be even less important, but that geographical proximity will continue to play a significant role.

7. Conclusions

Innovation networks are today among the most analysed topics in innovation studies. Several contributions have focused on the role of inter-organisational collaboration in promoting innovation. Such interest has

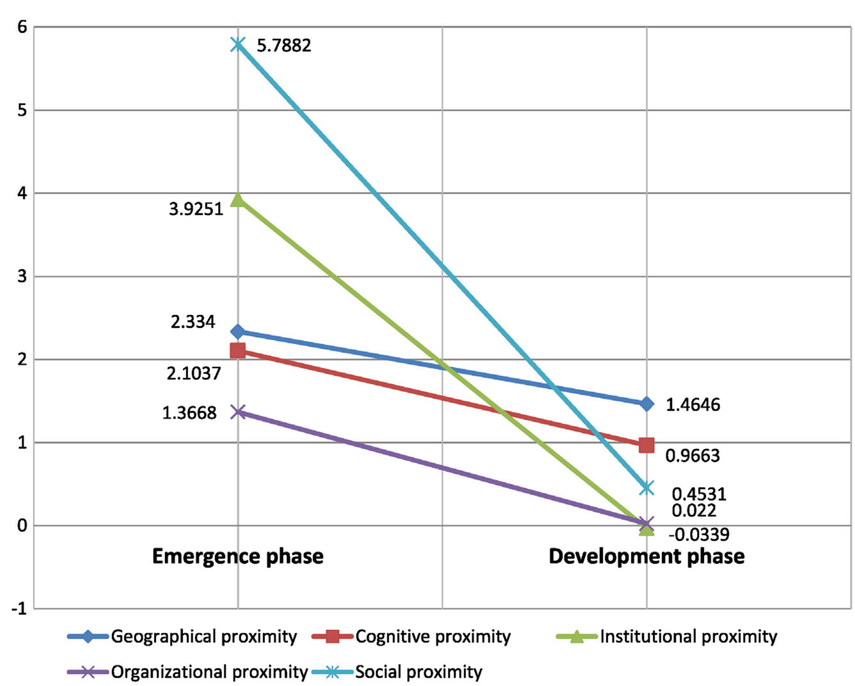

Fig. 3. Evolution of the impact of the various forms of proximity in the period.
Source: authors' elaborations.

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Table 4
Overview of the most relevant literature findings on the impact of the different dimensions of proximity on innovation networks: focus on evolutionary analysis.
Source: authors' elaboration from Heringa et al. (2014).

Contributions	Outcome	Approach	Proximities					Evolution along time				
			Geo	Cogn.	Inst.	Org.	Soc.	Geo.	Cogn	Inst.	Org	Soc
Autant-Bernard, Billand, Frachisse, and Massard (2007)	Nanotech projects in FP6 in EU	Static	0/+	+								
Balland (2012)	Satellite navigation systems projects in FP6 in EU	Dynamic	+	0	+	+	0	=		=	↓	
Balland et al. (2013)	Video game industry	Dynamic	+	+	+	+	+	↑	=	↓	↓	↓
Broekel and Boschma (2012)	Dutch aviation industry	Static	+	−		0	+					
Heringa et al. (2014)	Dutch water sector	Static	−	−		−	+					
Molina-Morales et al. (2015)	Foodstuffs cluster in Spain	Static	−	−	−	+	+					
Morrison et al. (2016)	Toy cluster in Spain in technical and business networks	Dynamic (technical)						+	+	+	0	
		(Business)						0	0	0	0	
Ter Wal (2013)	Patents in German biotech	Dynamic	+				+	↑				↑
Our study	Innovation networks in HTCG	Dynamic	+	+	+	+	+	↓	↓	0	↓	↓

Legend: the up (down) arrow means an increasing (decreasing) effect of the analysed proximity along the period.

increased also thanks to the growing attention paid to the dynamics of open-innovation and the current difficulties faced when implementing innovations within the confines of a single firm.

The present contribution is related to this discussion, and suggests that the literature has much to gain by coupling the qualitative approach with quantitative surveys of network dynamics, with special emphasis on their formation and evolution over time.

This article has focused on two specific research questions: (i) How do the different forms of proximity influence the formation of innovation networks? and (ii) Does the impact of different forms of proximity change during the cluster's evolution?

With respect to the first research question, we have quantitatively measured the different kinds of proximity and shown their different impact on the formation of innovation networks, obtaining results that are in line with the most recent studies. As to the second question, we have proven that the different kinds of proximity change with the passage from emergence to development in cluster evolution.

It is worth noting that these studies may have interesting managerial implications for private initiatives aimed at developing inter-organisational collaborative activities for innovation. The present analysis suggests that social and institutional proximities represent the most relevant determinants in the early, formative phases of clusters, while cognitive and geographical proximities become influential at the later, developmental phases. At any rate, all forms of proximity tend to have less of an impact on the formation of innovation networks as time goes on, but the influence of cognitive and geographical proximities exhibits a slower decrease.

This finding suggests that innovation networks are often initially incubated within a network of stable relationships among enterprises, often among (institutionally) homogeneous partners, but that the networks outgrow this “incubator” as the cluster develops, competition increases and partners become more heterogeneous. Nonetheless, even in this more competitive setting, the interaction with localised actors in the cluster continues. Also, these features are still likely to change in the future.

The managers of enterprises that are at a mature stage of development should start looking for technological leaders outside of the immediate geographical vicinity. Public policies stimulate the participation of subjects outside the cluster and the country. On this issue, it might be interesting, for example, to further investigate the significance not just of local social networks, but also of the long networks that compose the global value chain.

An additional valuable feature is that of the role of social proximity. Our study demonstrates that the most important firms in the local network always play a significant role, while those playing a marginal role find themselves increasingly excluded from the network's central nodes as competitive pressure intensifies. It is therefore essential for managers to position themselves strategically within the local network and to participate in collaborative R&D activities that will have a determinant value over the long run.

It is necessary, however, to mention some limitations in the analysis. This work is focused on the study of formal innovation networks through the analysis of policy-supported ones. As discussed in literature, however, these only represent the tip of the iceberg of innovation-based relationships, and informal innovation relations are just as important as formal ones. Few studies have analysed informal relationships in network evolution from a quantitative perspective (Casanueva, Castro, & Galán, 2013; Morrison et al., 2016). We believe that this line of research holds great promise for the future.

In addition, it is our opinion that the advanced techniques being elaborated in network analysis will accelerate the development of quantitative research on network evolution, which is currently still in its infancy.

Finally, the definition of different forms of proximity should be more extensively investigated in the future as there is still little clarity or unanimity within the existing multidisciplinary literature on the precise nature of the various dimensions of proximity. However, this study is part of an interesting and growing stream of research on innovation network dynamics in which the evolutionary approach, infused with robust quantitative methods, is generating significant results.

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References

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review*, *86*, 630–640.
Autant-Bernard, C., Billand, P., Frachisse, D., & Massard, N. (2007). Social distance versus spatial distance in R&D cooperation. *Papers in Regional Science*, *86*, 495–519.
Balland, P. A. (2012). Proximity and the evolution of collaboration networks. *Regional Studies*, *46*(6), 741–756.
Balland, P. A., De Vaan, M., & Boschma, R. (2013). The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987–2007. *Journal of Economic Geography*, *13*, 741–765.
Bell, G. G., & Zaheer, A. (2007). Geography, networks, and knowledge flow. *Organization Science*, *18*(6), 955–972.
Belussi, F., Sedita, S., & Sammarra, A. (2010). Learning at the boundaries in an “Open Regional Innovation System”: A focus on firms' innovation strategies in the Emilia Romagna life science industry. *Research Policy*, *39*, 710–721.
Ben Letaifa, S., & Rabeau, Y. (2013). Too close to collaborate? How geographic proximity could impede entrepreneurship and innovation. *Journal of Business Research*, *66*, 2071–2078.
Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, *39*, 61–74.
Boschma, R., & Frenken, K. (2010). The spatial evolution of innovation networks: A proximity perspective. In R. Boschma, & R. Martin (Eds.), *The handbook of evolutionary economic geography* (pp. 120–135). Cheltenham UK: Edward Elgar.

Broekel, T., & Boschma, R. (2012). Knowledge networks in the Dutch aviation industry: The proximity paradox. *Journal of Economic Geography*, *12*, 409–433.

Burt, R. (1992). *Structural holes: The social structure of competition.* Cambridge: Harvard University Press.

Cantù, C. (2010). Exploring the role of spatial relationships to transform knowledge in a business idea—Beyond a geographic proximity. *Industrial Marketing Management*, *39*, 887–897.

Capaldo, A., & Petruzzelli, A. M. (2014). Partner geographic and organizational proximity and the innovative performance of knowledge-creating alliances. *European Management Review*, *11*, 63–84.

Casanueva, C., Castro, I., & Galán, J. L. (2013). Informational networks and innovation in mature industrial clusters. *Journal of Business Research*, *66*, 603–613.

Casprini, E., Pucci, T., & Zanni, L. (2014). Business model shifts: a case study on firms that apply high technology to cultural goods. *Technology Analysis & Strategic Management*, *26*, 171–187.

Castro, I., Casanueva, C., & Galán, J. L. (2014). Dynamic evolution of alliance portfolios. *European Management Journal*, *32*, 423–433.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*, 128–153.

Corsaro, D., Cantù, C., & Tunisini, A. (2012). Actors' heterogeneity in innovation networks. *Industrial Marketing Management*, *41*, 780–789.

D'Este, P., Guy, F., & Iammarino, S. (2013). Shaping the formation of university–industry research collaborations: What type of proximity does really matter? *Journal of Economic Geography*, *13*, 537–558.

Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From national systems and 'Mode 2' to a triple helix of university–industry–government relations. *Research Policy*, *29*, 109–123.

Frenken, K., Van Oort, F. G., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies*, *41*, 685–697.

Geldes, C., Felzensztein, C., Turkina, E., & Durand, A. (2015). How does proximity affect interfirm marketing cooperation? A study of an agribusiness cluster. *Journal of Business Research*, *68*, 263–272.

Giuliani, E. (2013). Network dynamics in regional clusters: Evidence from Chile. *Research Policy*, *42*, 1406–1419.

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology*, *78*, 1360–1380.

Hakansson, H., & Snehota, I. (1995). *Developing relationships in business networks.* London: Routledge Edition.

Hakansson, H., & Snehota, I. (2006). No business is an island: The network concept of business strategy. *Scandinavian Journal of Management*, *22*, 256–270.

Heringa, P. W., Horlings, E., van der Zouwen, M., van den Besselaar, P., & van Vierssen, W. (2014). How do dimensions of proximity relate to the outcomes of collaboration? *Economics of Innovation and New Technology*, *23*, 689–716.

IRPET (2012). *Il settore dell'Alta Tecnologia applicata ai beni culturali in Toscana.* Firenze: IRPET.

Knoben, J., & Oerlemans, L. A. G. (2006). Proximity and inter-organizational collaboration: A literature review. *International Journal of Management Reviews*, *8*, 71–89.

Lazzeretti, L., Capone, F., & Cinti, T. (2011). Open innovation in city of art: The case of laser in conservation of artworks in Florence. *City, Culture and Society*, *2*, 159–168.

Lazzeretti, L., & Capone, F. (2016). R&D networks in high technology applied to cultural goods. A social network analysis. *Sinergie Italian Journal of Management*, *34*, 75–99.

Menzel, M. P., & Fornahl, D. (2010). Cluster life cycles: Dimensions *and* rationales of cluster evolution. *Industrial and Corporate Change*, *19*, 205–238.

Molina-Morales, F. X., Belso-Martinez, J. A., Mas-Verdù, F., & Martinez-Chàfer, L. (2015). Formation and dissolution on inter-firm linkages in lengthy and stable networks in clusters. *Journal of Business Research*, *68*, 1557–1562.

Morrison, A., & Rabellotti, R. (2009). Knowledge and information networks in an Italian wine cluster. *European Planning Studies*, *17*, 983–1006.

Morrison, A., Balland, P. A., & Belso-Martínez, J. A. (2016). The dynamics of technical and business knowledge networks in industrial clusters: Embeddedness, status, or proximity? *Economic Geography*, *92*, 35–60.

Nicholson, J., Tsagdis, D., & Brennan, R. (2013). The structuration of relational space: Implications for firm and regional competitiveness. *Industrial Marketing Management*, *42*, 372–381.

Nooteboom, B. (1999). Innovation and inter-firm linkages: new implications for policy. *Research Policy*, *28*, 793–805.

Oerlemans, L. A. G., & Meeus, M. T. H. (2005). Do organisational and spatial proximity impact on firm performance? *Regional Studies*, *39*, 89–104.

Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of Management*, *38*, 1115–1166.

Powell, W. W., & Grodal, S. (2005). Networks of innovators. *The Oxford handbook of innovation (2005)* (pp. 56–85).

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Inter-organizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly*, 116–145.

Presutti, M., Boari, C., & Majocchi, A. (2011). The importance of proximity for the start-ups' knowledge acquisition and exploitation. *Journal of Small Business Management*, *49*(3), 361–389.

Rallet, A., & Torre, A. (1999). Is geographical proximity necessary in the innovation networks in the era of global economy? *GeoJournal*, *49*, 373–380.

Ritter, T., & Gemunden, H. G. (2003). Network competence: Its impact on innovation success and its antecedents. *Journal of Business Research*, *56*, 745–755.

Snijders, T. A. B., Van De Bunt, G. G., & Steglich, C. (2010). Introduction to actor-based models for network dynamics. *Social Networks*, *32*, 44–60.

Tallman, S., Jenkins, M., Henry, N., & Pinch, S. (2004). Knowledge, clusters, and competitive advantage. *Academy of Management Review*, *29*, 258.

Ter Wal, A. L. (2013). The dynamics of the inventor network in German biotechnology: Geographical proximity versus triadic closure. *Journal of Economic Geography*, *13*(6).

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications.* New York: Cambridge University Press.

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