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Knowledge Networks and Strong Tie Creation: the Role of Relative Network Position

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Abstract

The proximity literature usually treats proximity in terms of common attributes shared by agents, disregarding the relative position of an actor inside the network. This paper discusses the importance of such dimension of proximity, labelled as in-network proximity, and proposes an empirical measurement for it, assessing its impact (jointly with other dimensions of proximity) on the creation of strong knowledge network ties in ICT in the region of Trentino. The findings show that actors with higher in-network proximity are more attractive for both other central actors and peripheral ones, which is further strengthening their position within the network.

Keywords: knowledge networks, in-network proximity, strong ties, proximity dimensions.

1. Introduction

The significant role of knowledge and knowledge networks in the innovation process is central in the literature on regional development. Regions create and use knowledge to build competitive advantage (Asheim et al, 2007). Knowledge networks operate as channels for knowledge creation and transfer (Owen-Smith & Powell, 2004; Boschma & ter Wal, 2007), through social and business links (Granovetter, 1973). These relationships can be more or less intense (Granovetter, 1973).

A key issue in the literature of knowledge networks is how agents choose other agents for the creation and transfer of knowledge. The literature acknowledges that this happens because of similarities in the attributes of the actors which are referred to as homophily in the sociology literature (Borgatti & Foster, 2003), or proximity in the economic geography literature (Boschma, 2005). The proximity literature has produced several classifications of proximity (Torre & Rallet, 2005, Boschma, 2005; Broekel & Boschma, 2012; Caragliu & Nijkamp, 2016). The common feature of these taxonomies is that they consider the similarities in the attributes of the actors, but they disregard their relative position within the network.

The relative position of an actor within the network, however, seems to be important for the creation of strong ties between actors that are beneficial for the actors in order to face uncertain situations (Rost, 2011). Actors are likely to seek to create strong collaborative ties with other more central actors in the knowledge network, than with more peripheral ones. This is because the relatively more central actors are associated with a higher number of connections and, consequently, an easier reach to knowledge resources.

The aim of this paper is to define a new measure of proximity, the in-network proximity, able to cover this gap in the literature. Apart from the conceptual justification and definition of this kind of proximity, the paper will also propose an empirical measurement, examining how it affects the probability of repeated collaborations (strong ties) between actors.

This study places itself within the literature on core-periphery network structure (Morrison & Rabellotti, 2009) and on the effect of proximity on knowledge networks that take into consideration the centrality of actors inside the network (Autant-Bernard et al, 2007; Cassi & Plunket, 2015). However, compared with the existing empirical studies that use the absolute difference of centralities of actors inside the network, this paper contributes with an analytical method of assessing whether two actors can be considered central or peripheral, and simultaneously distant or proximate between them.

For doing so, we use the quantiles of the absolute differences and the sums of all pairs of actors inside the knowledge network. Empirically, we assess the impact of in-network proximity, alongside other kinds of proximity on the occurrence of repeated research collaborations based on a unique set of data on collaborative projects in Information and Communication Technologies (ICT) in the Italian region of Trentino.

The paper is structured as follows. Section 2 presents a critical review of the literature on the different dimensions of proximity, pointing out the relevance of the relative distance between actors within a network. Section 3 provides a definition and a measurement for in-network proximity. Section 4 presents the data of the case study analysis, in which the role of in-network proximity on networks' development is tested. Section 5 presents the results of the analysis, and Section 6 discusses the conclusions and the implications out of the findings of the study.

2. Knowledge networks and the importance of actors' proximity

The literature confirms that the similarity in the characteristics of actors (proximity) is important for the development and reinforcement of collaboration between them (Boschma 2005; Boschma & Frenken, 2010; Balland et al, 2015). However, proximity means more than just geographical closeness: two actors in a knowledge network can demonstrate proximity although they are not geographically close. Several works provided different classifications of proximity (Torre & Rallet, 2005; Boschma, 2005; Broekel & Boschma, 2012; Caragliu & Nijkamp, 2016). The most used classification is the one by Boschma (2005) who proposed five dimensions of proximity that affect the propensity of actors to exchange knowledge and innovate. These dimensions are geographical, cognitive, organizational, social, and institutional proximities.

Geographical proximity is represented by the physical distance of two actors and is regarded beneficial for knowledge transfer. In the empirical studies, the geographical proximity is measured by the absolute geographical distance between two actors (Broekel & Boschma, 2012), travel time (Ejermo & Karlsson, 2006), or by categories of geographical proximate actors, like inside the country, neighbouring countries and the rest of the world (Ponds et al, 2007; Hansen, 2015), or just local and non-local (Boschma & ter Wal, 2007).

Cognitive proximity expresses the overlapping in knowledge bases of actors. To measure cognitive proximity, empirical studies use proxies such as technological profiles derived from patent data (Nooteboom et al, 2007), statistical classifications of economic activities, like NACE codes (Broekel & Boschma, 2012; Broekel, 2015), or industrial classification with digits (Boschma et al, 2009; Boschma et al, 2012).

Organizational proximity concerns the degree of similarity of actors in organizational terms. Organizational proximity is assumed to help the knowledge exchange and reduce the transaction costs. Empirically, there is a distinction between profit and non-profit organizations, or private and public (Cantner & Graf, 2006; Broekel & Boschma, 2012). Alternatively, the organizational proximity can be measured in terms of subsidiaries of the same parent organization (Balland, 2012; Balland et al, 2015; Broekel, 2015).

Social proximity refers to the embeddedness of actors in the micro-level, in terms of friendship, kinship, and experience (Boschma, 2005). The majority of the empirical literature tends to consider the idea of social proximity equivalent to the concept of strong ties (Broekel, 2015). Alternatively, in the empirical literature, social proximity is treated as the possibility of two actors to be close socially after sharing a common situation back in time (Broekel & Boschma, 2012) or the degree that individuals affiliated to the organizations under research are socially interacting between them out of the organizational context (Huber, 2012).

Finally, institutional proximity is an aspect of proximity where the actors share common institutional and cultural attributes (Gertler, 2003; Capello et al, 2009). Institutional proximity provides to the actors stable conditions for knowledge transfer (Boschma & Frenken, 2010). It can be expressed by either formal institutions, such as laws, or informal institutions, such as cultural norms, which affect the way in which actors coordinate their actions.

The common characteristic of all the aforementioned dimensions of proximity is that they take into consideration the attributes (characteristics, values) that individual actors may share. They disregard the relative position of an actor inside the network, and in this case inside the knowledge network. This element, however, can be assumed to be extremely relevant for the occurrence of strong ties. This idea stems from the theory of preferential attachment, which supports that the most connected (central) nodes are more probable to receive new links (Barabasi & Albert, 1999).

Since the actors become part of the network, they increase their connectivity according to how much they are suitable to compete for connections (Bianconi & Barabasi, 2001). In this way, the fitter nodes outcompete the less fit ones. So, when a new actor enters into the social network, it seeks to be connected with centrally positioned, well-established actors (Newman, 2001; Wagner & Leydesdorff, 2005). Hence, there is a cumulative advantage for the better positioned actors (Gluckler, 2007). Future ties tend to form around strong ties by processes of trust and indirect referrals. In this way, persistent and resilient network structures emerge within tightly connected groups of actors. Simultaneously, the networks tend to expand through a process in which the actors seek for diversity of relations (Glucker, 2007; Morrison & Rabellotti, 2009).

Based on preferential attachment (Barabasi & Albert, 1999), literature has considered the position of the actors in terms of actor's and tie's attributes and in structural way (brokerage and bridging ties, triadic closure).

The idea of brokerage and bridging ties is connected to the Granovetter's (1973) strength of weak ties. Bridging is the activity in which a tie connects separate sub-networks inside the main network (Everett & Valente, 2016). Bridging ties enable actors to tap on resources that otherwise they would not be able to have access to, and the control of such ties may empower actors inside the network (Cassi & Plunket, 2015; Everett & Valente, 2016). This control of an actor over a bridging tie is defined as brokerage (Burt, 2005; Everett & Valente, 2016). Hence, brokerage is treated as a node attribute, and highlights the importance of the position of an actor inside the network.

Again, originating to Granovetter (1973) and closely connected to the notion of brokerage (Burt, 2005), another measure that underlines the importance of an actor's position inside the network is the triadic closure. Triadic closure is the case when a node acts as an intermediary, connecting two other actors, translated in a social context as 'a person introducing two of its personal acquaintances to each other' (Opsahl, 2013; ter Wal, 2013). Therefore, in case that two actors are not connected with each other, the actor that is a common connection holds, in one hand, a favourable position, which though requires effort in preserving two separate relationships, and these two separate actors are more probably to connect with each other (ter Wal, 2013). Triadic closure is frequently used by the literature as a structural measurement of the 'status' or 'reputation' of an actor inside the network (Balland et al, 2016).

In line with strong and weak ties (Grannovetter, 1973), we assume that actors which have 'privileged' positions (in terms of bridging, triadic closure, or in our case centrality) inside the network, to know and trust each other, so they are preferred for collaboration. However, their knowledge may overlap; therefore, bearers of new knowledge may be more peripheral or new actors in the network.

3. In-Network Proximity: a definition and a measurement

3.1 In-network proximity: a definition

Taking into consideration this core-periphery function of social networks, this paper introduces the concept of in-network proximity, defined in terms of the position of the actor inside the network in respect with the rest of the actors. In other words, in-network proximity measures how central the actor is in the network, compared with the centrality of other actors. In case that two actors are in-network proximate, this means that they have similar central or peripheral positions in the network, while if they are in-network distant, the one is more central and the other more peripheral.

Thus, central actors that are better in-network positioned are expected to be more preferred for repeating collaboration, either by peripheral or by other central actors. This leads us to distinguish three cases: two actors can be either central and proximate, or peripheral and proximate, or in-network distant, and this is assumed to have a different impact on the occurrence of repeated collaborations. More precisely, the in-network proximity is expected to be relevant in two specific circumstances, leading to two different research hypotheses:

H1a: The fact that two actors are central and in-network proximate is important for the reinforcement of repeated collaborations (strong ties) between them.

H1b: In-network distance is important for the reinforcement of repeated collaborations (strong ties) between central and peripheral actors.

A necessary premise to the definition of in-network distance concerns the interpretation of proximity. In fact, actors can be in-network proximate or distant in more than one way. An actor can be considered more central in relation with the rest of the agents of the network in terms of the number of connections that it has (*degree centrality*) (Freeman, 1978). *Closeness centrality* (Freeman, 1978) constitutes another way to measure the importance of an actor inside the network. It indicates how close this actor is to all the other actors of the network. Finally, eigenvector centrality constitutes a measure for the influence of the actor to the rest of the network (Newman, 2008), taking into account the importance of the agents connected to this actor.

As the centrality of the actors can be assessed by different points of view, the relative position of an actor considering its centrality inside the knowledge network may have differentiated meaning (Broekel & Boschma, 2012; Cassi & Plunket, 2015). Therefore, we disentangle the aforementioned hypotheses on the effect of in-network proximity and distance, taking into consideration three different types of centrality, namely degree, closeness, and eigenvector centralities. The hypotheses form as follows:

H2a: The position of a pair of actors in terms of their degree centrality affects positively the reinforcement of repeated collaborations (strong ties) between them.

H2b: The position of a pair of actors in terms of their closeness centrality affects positively the reinforcement of repeated collaborations (strong ties) between them.

H2c: The position of a pair of actors in terms of their eigenvector centrality affects positively the reinforcement of repeated collaborations (strong ties) between them.

3.2 In-network proximity: the measurement

For measuring in-network proximity, it is necessary to assess two elements: the position of the single actor inside the knowledge network, and the distance of its position from the position of the rest of the actors inside the network (proximity). In terms of proximity we identify the case that two actors are distant, which implies simultaneously that one is relatively positioned more centrally than the second, and the case that two actors are proximate. In terms of position in the network, these two actors can be either both relatively central (proximate), or both relatively peripheral (proximate). Therefore, we can distinguish the following three cases:

$$A\ pair\ of\ actors\ can\ be \begin{cases} in-network\ distant \\ in-network\ proximate \begin{cases} both\ central \\ both\ peripheral \end{cases} \end{cases}$$

For every pair, two actors for being proximate, they need to have a relatively low absolute difference of their centrality scores, while for being central they need to have a relatively high sum of their centrality scores, which means that they have to be below or above certain thresholds. In order to set the lower (L) and upper (U) threshold for this study, we use the quartiles (Q [25] and Q [75]) of the distributions of absolute differences, and centrality scores respectively[1].

Estimating the distribution of the absolute differences of all the pairs of actors the lower threshold is L= Q[25] and the lower adjacent value is defined as x_i, such that $x_i \geq L$, and $x_{(i-1)} < L$. Therefore, an absolute difference between two actors can be characterized relatively low, if $absdif_{ij} < L$. On the other hand, centrality score constitutes an actor attribute that has to be expressed in a dyadic way. For an actor to be characterized relatively central or not, we estimate the distribution of the centrality scores of all the actors in the knowledge network. The upper threshold, in this case, is U = Q[75] and the upper adjacent value is defined as x_i, such that $x_i \leq U$, and $x_{(i+1)} > U$. The centrality score of an actor should be $x_i > U$, for the actor to be considered relatively central. For every pair of actors in the knowledge network, both of them are considered central if the sum of their centrality scores is higher than 2U. Thus, a pair of actors is characterized central, if $sum_{ij} > 2U$.

Summing up, two actors are in-network proximate and both centrally when they have relatively low absolute difference and relatively high sum of their centralities. They are in-network proximate and both peripherally positioned, when they have relatively low absolute difference and relatively low sum in their centralities. They are in-network distant in any other case.

4. The Empirical Case

4.1 The region of Trentino (Italy)

[1] The quartiles of the distribution are selected as moderate thresholds. Alternatively, different percentiles could (2%, 9%, 91% and 98%), or even the outliers could be used for defining stricter conditions of proximity and centrality. In this latter case the lower threshold is $L = x[25] - \frac{3}{2}(x[75] - x[25])$ and the upper threshold is $U = x[75] + \frac{3}{2}(x[75] - x[25])$.

The present research analyses the network of actors participating in collaborative projects in the ICT regional innovation system of Trentino in Italy. The region of Trentino has some unique characteristics regarding its geography, history and funding policy. Geographically, Trentino is located in the passage that connects Italy with Austria and further with Germany. Due to its location, it is linked to both German and Mediterranean markets. Historically, Trentino has been an agricultural region with “soft” industrialization during the 1960's and 1970's. Although agriculture has still strategic importance for the provincial economy, the last twenty years Trentino had an impressive growth in the number of businesses in the ICT sector. Finally, the region is an Autonomous Province, enjoying considerable autonomy from the Italian central government and has its own elected government and legislative assembly. The province is in control of 9/10 of the taxes collected in its territory. During the last two decades, the province of Trento has invested heavily in the ICT sector, with the purpose of making Trentino a key technology hub in Central Europe.

4.2 Data from R&D projects

The data source most used in the literature to trace knowledge transfer depicted in knowledge network form is the patent data (Cantner & Graf, 2006). However, in the ICT field, there is not a lot of patenting activity, while when it exists the quality of these patent is difficult to be assessed, making the use of patent data in several cases quite problematic.

In this paper, we use data on R&D collaborative projects on ICT sector that include at least one actor located in Trentino. It is a complete primary dataset, that includes the entire population of projects, and consequently of the actors that participated in such project for a period of fifteen years (2000-2014). There are two R&D projects before 2000, however, they are not taken into consideration, as the Autonomous Province of Trento started investing heavily on ICT research and development since 2000. We collected the entire population of projects (regionally, nationally, internationally, publicly or privately funded) using the following procedure. The complete list of public and private organizations with activity on the ICT sector was retrieved by the official website of the regional authority. For every organization in this list, we visited their official websites, where they publish their R&D activity. We crosschecked the projects collected with this method, as well as, the list of organizations, in the web catalogues of research projects of European Commission (CORDIS), the Autonomous Province of Trento, and smaller public and private funders.

Data on R&D projects include information at the level of organizations, like the title, acronym and abstract of the project, start and concluding dates, funding source, list of participants and coordinating actor. For every participant and coordinator, all projects include location and type of organization. In Trentino, for the period from 2000 until 2014, a total number of 2,394 actors were identified, participating in 543 ICT R&D projects. The average duration of the projects is 3.6 years.

From these actors, 6.55 per cent (157 actors) is located in Trentino, 15.29 per cent (366 actors) is located in other regions of Italy, and the rest 78.15 per cent (1,871 actors, the biggest part of the actors) is located in other countries. Additionally, there is a detailed distinction of actors in terms of incentives and orientation of organization. The actors are distinguished in universities, research centres, large firms, SMEs, public agencies, and other kinds of organizations. So, 20.12 per cent (481 actors) of the actors is universities, 23.16 per cent (555 actors) concerns research centres, 19.57 per cent (468 actors) is large firms, 25.08 per cent (601 actors) is SMEs, 7.26 per cent (174 actors) is public agencies, and the rest 4.8 per cent (115 actors) concerns other kinds of organizations.

4.3 Multiplexity of networks and regression

Networks are multiplex entities, with a variety of agents connected between them in a variety of relationships (Lazega & Pattison, 1999; Skvoretz & Agneessens, 2007). This happens as the actors interact in different social contexts that overlap in an extent. Therefore, the constellation of the actors participating in ICT R&D projects in Trentino can be connected between them with different relationships indicating knowledge transfer. The collected data provides this type of information on collaboration, coordination and funding of projects, indicating interaction with an actor that plays a specific role inside the knowledge network.

The aforementioned kinds of relationships (collaboration, coordination, and funding) can be traced for all the R&D ICT projects in Trentino and indicate knowledge transfer between actors. The main relationship is the collaboration between two actors. It is implied by the common partnership of two actors in the same R&D project. The assumption here is that knowledge flows without restrictions among the partners of every project, and consequently partnership in the same projects implies information sharing (Inkpen & Tsang, 2005; Assimakopoulos et al, 2016; Tsouri, 2019).

Other two kinds of relationships indicating knowledge transfer were extracted by the data, being significant for the existence and management of the knowledge creation and transfer in every project. The first is the relationship of coordination. It comes from the interaction of a project participant directly with the coordinating agent of the project. The role of a coordinator is to distribute and collect the knowledge produced by the project. Therefore, the coordination relationship appears important for the diffusion and the management of knowledge inside the network (Fritsch & Kauffeld-Monz, 2010; Phelps et al, 2012). The second relationship identified is the funding relationship, which is important for the existence of the project itself and, as a result, for the transfer of the knowledge among the participants (Landry et al, 2007). Simultaneously with the flows of funds from the funding entities to the participants, these funding entities act like knowledge pools and requiring knowledge back in the form or reports.

Data on these three kinds of relationships, namely collaboration, coordination and funding, collected for the Trentino ICT sector, in combination with the agent characteristics (e.g. location, organizational kind), can be depicted in three different networks (collaboration, coordination, and funding), used to empirically verify the hypotheses H1 and H2. Descriptive evidence for the cumulative knowledge transfer by the three different types of relationships in the period 2000 up to 2014 is presented in Table 1. The collaboration network demonstrates small world properties. These properties allow fast access to the most peripheral actors of the network. The coordination network appears to be less centralized than the other two networks. This implies the existence of few high degree actors inside the network that are connected with a high number of low-degree actors, reflecting the accumulation and management of knowledge by certain actors in the knowledge network. In contrast, the funding network is highly centralized, implying the existence of a dominant big funding agency and a range of other much smaller funders.

Table 1: Descriptive knowledge network measurements of Trentino ICT Collaboration, Coordination, and Funding Networks (2000-2014)

	Collaboration Network (2000-2014)	Coordination Network (2000-2014)	Funding Network (2000-2014)
Nodes	2394	2394	2394
Edges	46148	4090	2717
Average Degree	43.277	3.831	2.101
Network Diameter	4	7	7
Graph Density	0.016	0.001	0.001
Network Centralization	0.380	0.083	0.895
Average Clustering Coefficient	0.872	0.274	0.024
Average Shortest Path Length	2.536	3.917	2.385

The statistical analysis was performed with Gephi (Bastian et al, 2009) and UCInet (Borgatti et al, 2002)

The data of the Trentino ICT R&D projects can be summarized in three one-mode sociomatrices (actor x actor), portraying the three different networks resulting from the collaboration, coordination and funding relationships. The result is three square matrices with rows and columns the number of actors, depicting actor-to-actor interactions. In addition, the characteristics of the agents are expressed in the same, dyadic, way, resulting to square matrices of the same size with the rest of the variables.

The linear model that represents the interactions between the matrices/variables cannot be estimated by the standard OLS, due to the presence of structural autocorrelation in this type of relational data. The observations are not independent, since they are interactions between the same actors in the network. This causes problems in the estimation of the model with the standard statistical and econometric methods. To avoid this problem, we use Quadratic Assignment Procedure (QAP), a permutation method that makes no assumptions about the distribution of the parameters (Cantner and Graf 2006; Maggioni et al, 2011; Graf & Kruger, 2011; Broekel & Boschma 2012; Cantner & Rake 2014, Tsouri, 2019). It creates a permutation distribution that could have been produced by random datasets, with the same structure but different node assignments as the initial dataset, permuting the rows and columns of the dependent variable. Therefore, the p-value produced is the frequency of the coefficients of the permuted dataset compared with those of the original dataset. For example, if the coefficient of the original dataset is greater than 95% of the coefficients of the random datasets, then it is significant at the 0.05 level, as it was the same large or larger to five of 100 permutations. Thus, QAP is considered suitable method for this study, due to the dyadic structure of the data and the amount of interactions treated.

5. Explaining the knowledge network by the relative position of the actors

5.1 Model and variables

In this paper we depicted the collaboration network as an $n \times n$ adjacency matrix, Y, where for every case, y_{ij} is equal to zero, if the actors at i and j positions have no common participation in a project, or y_{ij} is equal to a positive integer that represents the existence and the strength of the tie between these two actors. According to Granovetter (1973) the strength of a tie equals to many times the actors i and j have cooperated between them. The generalized formula that estimates the strength of the undirected ties of the collaboration network is the following:

$y_{ij} = \alpha + \beta' x_{ij} + \varepsilon_{ij}$ *for all* $i<j$,

where y_{ij} is the value estimated for the relationship between i and j that this model explains. The matrix x_{ij} includes all the explanatory and dummy variables that relate i and j.

The dependent network (Collaboration) is the existence and strength of ties in the simplest relationship that implies knowledge transfer, the collaboration network, as it was formed in the end of 2014. It takes the value zero when two actors have not collaborated at all, and a positive integer value if they did, according to the number of projects the two actors have co-participated in. In order to explain the existence and the strength of these relationships we use three sets of variables: the first one is the coordination and funding networks, representing different types of collaborations that indicate knowledge transfer, the second group is the dummies that represent the different dimensions of proximity, and the third set is the representation of the relative position of an actor inside the network (in-network proximity).

The coordination network (Coordination) is the representation of the relationship between a coordinating actor and the rest of the participants of the project. We take it in consideration as the specific status of certain actors as coordinators of projects, and the interaction of project participants with them may be of importance for stronger collaborations. The funding network (Funding) is the depiction of the funding relationship between funding entities and participants of projects. Interactions of participants with these specific actors also may affect the strengthening of collaboration between agents.

In the second set of variables we use three of the aforementioned dimensions of proximity, namely the geographical (GEOPROX), the institutional (INSTPROX), and the organizational (ORGPROX) proximities[2]. Assuming that two actors are geographically proximate when they

[2] In this paper, we do not control for the effects of cognitive and social dimensions of proximity. There are not sufficient data for the national and regional projects to control for cognitive proximity in the actor level. The omission of these projects would result to the loss of important information on the knowledge creation and transfer network inside the region. On the other hand, this paper does not

are both located inside Trentino, we employ a dummy variable that equals to one in this case and zero otherwise. Institutional proximity relates to the cases when one actor is located inside Trentino and the other in any other region of Italy[3]. Consequently, these two actors belong to the same institutional context at the national scale, as they act under the same laws, norms, and culture. The dummy variable we employ to express institutional proximity equals to one if the interaction is national and zero otherwise. The third dummy variable controls for organizational proximity and expresses the case when two actors belong to the same organizational context (they are both universities, research centres, SMEs, large firms, or public agencies).

In the third set of variables employed belong the variables that describe the in-network proximity of actors in different centrality terms. In other words, they express how proximate or distant are two actors according to their relative position inside the knowledge network. We control for the effect of the relative position of the actors in terms of three different kinds of centrality, namely degree, closeness, and eigenvector centralities. For each one of them we employ a dummy matrix that includes the cases that two actors are either both central and proximate or distant, while we consider as reference case when they are both peripheral and proximate. Therefore, we employ the following in-network proximity variables: central and proximate actors according to degree centrality (DEGCENT_central_proximate), distant actors

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control for social proximity, as the repeated interactions are treated as an attribute of a relationship of a pair of agents, and not as an attribute of a specific organization.

[3] The institutional proximity has been assessed at the national scale. When we split the Italian regions in north and south, assuming that Trentino has more institutional similarities with other Italian regions in the north, the result remained insignificant. Hence, actors in Trentino consider actors located in the rest of the Italian territory as equal, without differentiating between north and south. This probably happens because the institutional setting of Trentino differs considerably from the rest of Italian regions in terms of autonomy.

according to degree centrality (DEGCENT_distant), central and proximate actors according to closeness centrality (CLOSCENT_central_proximate), distant actors according to closeness centrality (CLOSCENT_distant), central and proximate according to eigenvector centrality (EIGCENT_central_proximate), and distant according to eigenvector centrality (EIGCENT_distant).

As the purpose of the paper is to examine the effect that has the similarity or difference in the relative position of two actors on their strong tie connectivity, we test both the overall effect of two similarly or differently positioned actors (H1), and the effect of each type of centrality (H2). For this purpose we employ the following model.

(1) $Collaboration = Coordination + Funding + GEOPROX + INSTPROX + ORGPROX + DEGcentralproximate + DEGdistant + CLOScentralproximate + CLOSdistant + EIGcentralproximate + EIGdistant$

The correlation between the networks and the proximity dimensions, displayed in Table 2, suggests that there is significant interaction between the depended and independent variables. In some cases, the independent variables are not significantly interacting between them, but still the correlation is not so high for implying autocorrelation between them. This first evidence from the variable correlations are empirically verified in the interpretative analysis discussed in the following session.

Table 2: QAP correlations between the variables of the model

	Collaboration	Coordination	Funding	GEOPROX	INSTPROX	ORGPROX	DEGCENT Central proximate	DEGCENT distant	CLOSCENT Central proximate	CLOSCENT distant	EIGCENT Central proximate	EIGCENT distant
Collaboration	1.000 (0.000)											
Coordination	0.476 (0.001)	1.000 (0.000)										
Funding	0.084 (0.001)	0.182 (0.001)	1.000 (0.000)									
GEOPROX	0.002 (0.059)	0.000 (0.583)	0.007 (0.052)	1.000 (0.000)								
INSTPROX	0.000 (0.413)	0.001 (0.210)	0.001 (0.203)	0.389 (0.001)	1.000 (0.000)							
ORGPROX	0.002 (0.047)	0.001 (0.228)	0.001 (0.107)	0.011 (0.001)	0.009 (0.001)	1.000 (0.000)						
DEGCENT Central proximate	0.038 (0.001)	0.005 (0.006)	-0.001 (0.543)	-0.002 (0.268)	0.003 (0.024)	0.001 (0.350)	1.000 (0.000)					
DEGCENT distant	0.021 (0.001)	0.007 (0.001)	0.002 (0.263)	-0.000 (0.461)	0.003 (0.053)	0.006 (0.108)	-0.184 (0.001)	1.000 (0.000)				
CLOSCENT Central proximate	-0.002 (0.095)	-0.002 (0.018)	-0.002 (0.167)	-0.003 (0.161)	-0.000 (0.421)	-0.004 (0.079)	-0.003 (0.123)	-0.034 (0.001)	1.000 (0.000)			
CLOSCENT distant	0.002 (0.108)	0.002 (0.035)	0.002 (0.155)	0.003 (0.140)	0.000 (0.462)	0.004 (0.084)	0.003 (0.117)	0.034 (0.001)	-1.000 (0.001)	1.000 (0.000)		
EIGCENT Central proximate	0.014 (0.001)	0.000 (0.308)	-0.000 (0.232)	-0.001 (0.120)	-0.000 (0.473)	0.000 (0.333)	0.001 (0.167)	0.004 (0.001)	0.007 (0.001)	-0.007 (0.001)	1.000 (0.000)	
EIGCENT distant	0.020 (0.001)	0.006 (0.001)	0.004 (0.090)	0.003 (0.185)	0.001 (0.338)	0.010 (0.021)	0.025 (0.001)	0.100 (0.001)	-0.382 (0.001)	0.382 (0.001)	-0.025 (0.001)	1.000 (0.000)

The statistical analysis was performed with UCInet (Borgatti et al, 2002)

5.2 The role of in-network proximity in the strategic choices of organizations

Table 3 presents the estimates of Equation (1), examining the effect of the three groups of factors on the collaboration ties for the period 2000 up to 2014.

Table 3: The effect of the different types of in-Network proximity on the strong collaborative ties (2000-2014)

Dependent variable: Collaboration ties (2000-2014)				
	Model without in-network proximity aspects		**Model with in-network proximity aspects**	
	Coefficients (P-values)	**Standard Errors**	**Coefficients (P-values)**	**Standard Errors**
Coordination	1.330*** (0.001)	0.002	1.329*** (0.001)	0.003
Funding	0.006*** (0.001)	0.003	0.006*** (0.001)	0.002
Geographical Proximity	0.007* (0.062)	0.005	0.007* (0.075)	0.005
Institutional Proximity	0.001 (0.288)	0.002	0.001 (0.350)	0.002
Organizational Proximity	0.001* (0.052)	0.000	0.001* (0.071)	0.000
Degree Central and Proximate			0.057*** (0.001)	0.001
Degree Distant			0.008*** (0.001)	0.000
Closeness Central and Proximate			0.003 (0.580)	0.001
Closeness Distant			-0.001 (0.143)	0.001
Eigenvector Central and Proximate			0.159*** (0.001)	0.007
Eigenvector Distant			0.006*** (0.001)	0.001
R-sq	0.226		0.229	
Observations	5,728,842		5,728,842	
The statistical analysis was performed with UCInet (Borgatti et al, 2002)				

The strong coordination and funding ties (other types of knowledge) during the entire period are affecting positively and significantly the overall strong collaboration ties. The effect of the coordination ties appears to be much more intense than the funding ones. This means that the relationship of two actors when one of them is coordinator of a project, affects extensively the strong collaboration between these two actors. Therefore, the management of knowledge by an actor is evaluated more for strong collaborations. The effect is much smaller when the one of the two actors is a funding entity, although still significant.

The second set of variables are three of the traditional dimensions of proximity. The overall effect of the proximity dimensions is positive. However, only the geographical and organizational proximities seem to have a significant effect on the strong collaboration between actors. Therefore, if two actors are located in the same region, they create a stronger collaboration, while the fact that two actors are located in the same country does not appear to have an effect on the strong collaboration creation. Yet, two actors that they operate under the same organizational context (they are both SMEs, large firms, universities, research centres, or public bodies), create a strong collaboration between them.

The in-network proximity in general appears to be significant for the formation of strong collaborations in the Trentino ICT knowledge network (partially verifying H1a). This underlines that when two nodes are both relatively central in the knowledge network, they collaborate more with each other. Similarly, when two nodes are distant inside the knowledge network, one is relatively central and the other relatively peripheral, this affects positively the strong collaboration between them in the ICT field in Trentino (partially verifying H1b). Without assessing the directionality of this relationship, we can say that two in-network distant actors are creating stronger collaborative ties. In all the three dimensions of in-network proximity or distance assessed in the paper (referring to degree, closeness, and eigenvector centrality measures), when two actors are central and proximate the effect is higher, in significance and intensity, than when they are in-network distant.

Taking into consideration the kind of centrality measurement of the in-network proximity, we observe that degree and eigenvector centralities have a significant effect to the ability of strong tie creation by a pair of actors (verifying H2a and H2c). The closeness centrality has no significant effect to the strong collaborative ties, when it is considered for the measurement of in-network proximity (rejecting H2b). Moreover, the eigenvector centrality has a larger positive effect on the strong collaboration than the degree centrality, in terms of in-network proximity. Two in-network proximate and central actors in terms of eigenvector create stronger ties, than two in-network proximate and central actors in terms of degree centrality. This does not hold in the case of in-network distant actors.

6. Conclusions

Until today, there are several classifications of proximity (Torre & Rallet, 2005; Boschma, 2005; Broekel & Boschma, 2012; Caragliu & Nijkamp, 2016) with more frequently used the one of Boschma (2005), which also the present paper follows. Also, several dimensions were added, either differentiating from the most commonly used five dimensions, for example, 'relational proximity' (Coenen et al, 2004), and 'cultural proximity' (Knoben & Oerlemans, 2006), or by exploring different non-spatial or network attributes of the actors, like the 'regional network proximity' (Wanzenboeck, 2018). However, there was little attention to the relative position of the actors inside the network, and the effect that their position has into their collaboration.

The theoretical contribution of this paper is the introduction of a new type of proximity, taking into consideration the relative position of actors inside the network in terms of centrality. To this direction there were several attempts characterized by the absolute differences in centrality (Autant-Bernard et al, 2007; Cassi & Plunket, 2015), however they explore the relative position of the actors partially, as they can express only how much distant are two actors in terms of centrality inside the network.

The in-network proximity, described in this paper, is defined in terms of different centrality measures (degree, closeness, eigenvector). Two actors may be central and proximate, central and peripheral, or distant inside the network. This affects their ability to create strong collaborative ties. More specifically, central and proximate actors create stronger ties, which is in line with the theory of preferential attachment (Barabasi & Albert, 1999). The centrally positioned actors repeat collaboration with other central actors in the network, as central actors gather more 'reputation', signalling that they will possess the needed knowledge resources. Relatively peripheral actors, either not so active or new, inside the network, behave in a similar way. They seek for cooperation with relatively central actors in order to tap on knowledge resources they do not acquire. The effect on the creation of strong ties when a pair of actors is in-network distant is less strong than the effect between two central actors. Although, we cannot control for the directionality of the phenomenon, we speculate that the peripheral actors try to create strong ties with central actors for strengthening their position and reach to resources and expertise they may not have. On the other hand, central actors repeat collaborations with more peripheral actors, in order to avoid the 'lock-in', and get access to new, external knowledge and skills (Bathelt et al, 2004; Malerba, 2009; Crespo et al, 2013).

The empirical research on data of collaborative ICT projects from Trentino region in Italy showed that not all kinds of centrality have the same effect on the creation of collaboration strong ties. The in-network proximity that uses centrality measures calculated by number of collaborations (degree and eigenvector centralities) have a significant effect opposed to the measure of centrality calculated through shortest path length (closeness centrality). This means that for strong ties creation the number of collaborations an actor has may signal its 'reputation', resulting to stronger collaborative ties. The eigenvector centrality effect appears to be larger than the one of degree centrality. This happens as eigenvector centrality takes into consideration the centrality of the collaborators (in terms of degree) of an actor. Therefore, firms in Trentino network seek to create strong collaborations with actors connected to other important actors.

The above findings convey relevant policy implications, as well. When designing innovation policies, local policy makers have to take into consideration the strategic behaviour of actors in the knowledge transfer process inside the network. Since, more central actors are the most preferred for the strong tie creation, non-directed policies are likely to reinforce their dominance in the network, slowing down the emergence of peripheral actors and new entrants. This strategy may be sub-optimal when dynamic peripheral actors miss opportunities to be chosen for repeated collaboration. In fact, innovation policy might be more effective if it is targeting balanced sub-networks of projects, in order to strengthen the position of the peripheral actors in the system. This would constitute these peripheral actors more attractive for future collaborations with new entrants, strengthening the entire knowledge network, and consequently facilitating knowledge transfer.

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