The Impact of Similarity on the Networking Behaviors of Organizations

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The impact of similarity on the networking behaviors of organizations: a mixed-methods study in healthcare

ABSTRACT

This paper illustrates the dynamics of inter-organizational collaboration by exploring the effects of similarity on the networking behaviors of organizations operating in a place-based service sector. We collected data over a six-year period, on a network of hospital organizations, and employ a mixed methods approach consisting of longitudinal models for network analysis and multiple case studies. We find that organization similarity, measured in terms of similar organizational logics and practices, has a positive effect; organizational similarity, measured as similar size, has a negative effect. Finally, we found that cognitive similarity has a negative effect on their networking behavior. Implications for researchers, policy makers and practitioners are discussed.

Keywords

Inter-organizational collaboration, similarity, mixed-methods approach, R-Siena , organizational theory

INTRODUCTION

Previous research highlights the importance of inter-organizational collaboration for organization performance (Powell, Koput & Smith-Doerr, 1996). Notwithstanding the broad consensus on the importance of collaborations (Steensma 1996, Huxham, 1996), this well-established and large literature is lacking in studies that analyze how collaboration evolves overtime. Interest in understanding how and why inter-organizational collaboration change overtime is a relatively recent and is related to a new strand of research that investigates these phenomena using concepts and methods from organizational sociology and network theory (Borgatti & Foster, 2003; Lee et al., 2011).

In the present study we look at the dynamics of inter-organizational collaboration in a geographically bounded network. The literature explains the networking behavior of organizations focusing on different levels of analysis (Ebers, 1999). At the actor level, most research concentrates on discerning the motivations of actors in forging networking relationships. Cooperation can allow organizations to increase their revenue, mitigate competition, obtain cost-efficient access to crucial know-how, skills, complementary resources and capabilities, and coordinate their use of existing resources more efficiently (Gulati & Gargiulo, 1999; Ingram & Yue, 2008; Kilduff, Tsai & Hanke, 2006; Powell, Koput & Smith-Doerr, 1996). At the relational level, the literature shows how existing and past relations among organizations may act endogenously to induce networking (Gulati & Gargiulo, 1999; Soda, Usai & Zaheer, 2004), and how the position that an organization occupies in the web of industry relations affects the formation of networking relationships (Burt, 1992; Gulati, 1995). At the institutional levels, scholars identify cultural, industry, and regional environmental conditions that facilitate and constrain engagement in inter-organizational relationships. The literatures on economic geography, industrial districts, and spatial regional clustering of specialized resources and know-how are examples (Becattini, 1991; Giuliani, 2013).

Despite this large and heterogeneous literature, knowledge about the dynamic process of creating, maintaining, or growing linkages within a network is still emergent and there is need for more research (Ahuja, Soda & Zaheer, 2012; Lee, 2009). Specifically, we explain how inter-organizational collaboration is affected by similarity distinguishing between cognitive and organizational similarity. Despite the recent empirical advances and theoretical extensions of the similarity framework, several studies have adopted a static approach, or have analyzed a short period of time. In this paper we attempt to propose a shift from static to dynamic perspective in order to better understand the relationships between proximity and networking behavior of organizations.

Following Monge and Contractor (2003) we conceive organizational similarity as similar inter-organizational traits in terms of organizational logics and practices and organizational size, and cognitive similarity as the extent to which actors working in different organizations share and use common knowledge, capacities, and expertise. To empirically investigate the role of similarity in defining and shaping the dynamics of organizational collaboration, we rely on original fieldwork and longitudinal data (six consecutive years) on patient transfer relations within a regional community of hospital organizations in Italy.

Patient transfer flows reflect collaboration and the existence of underlying relationships between the hospitals involved (Iwashyna, Christie, Moody, Kahn & Asch, 2009; Lee et al., 2011; Lomi & Pallotti, 2012; Mascia, Di Vincenzo & Cichetti, 2012). Patient transfers between hospitals are directly observable and require high levels of coordination and communication. The transfer of a patient requires the exchange of detailed clinical information which by definition, is complex due to the growth and specialization of clinical knowledge and the multiple combinations of conditions that patients can be subject to, and involves the co-construction of an understanding of the patient that needs also to consider the cognitive aspects of the actors involved in the exchange (Cohen, Hilligoss & Amaral, 2012). To our knowledge, there are no studies that provide a longitudinal investigation of the determinants of patient transfer and the many dimensions that can affect the evolution of inter-organizational collaboration in this empirical context.

We employ a mixed methods approach. In a first step, we employed a quantitative stochastic actor-based model for network dynamics (Snijders, Steglich & Van de Bunt, 2010) in order to identify the endogenous and exogenous determinants underlying the propensity of organizations to collaborate. Subsequently, we employed a qualitative case study analysis (Creswell, 2003) in order to verify and understand more deeply the results obtained in the first step of analysis. This model choice allows simultaneous attention to the inter-subjective systems of meanings and localized network structural mechanisms that play important roles in the development of social ties (Kilduff & Tsai, 2003; Kilduff et al., 2006). Measures of social ties are often aggregated to patterns in a larger sample or path-dependent algorithms of network action, while entirely qualitative studies and analyses of social capital can be ambiguous and often overly descriptive (Lounsbury & Ventresca, 2003). Mixed data sources and methods provide a more comprehensive understanding of why the underlying links or generative mechanisms between network structural forms and human agents performing relational and cognitive actions occur in a particular way (Kilduff & Tsai, 2003; Lee, 2009).

We begin by developing some hypotheses related to the effect of organizational and cognitive proximity on the evolution of the social ties that shape a geographically bounded network. Then we present the research setting and methodology. Finally we conclude discussing the implications of this work for researchers and practitioners.

THEORETICAL BACKGROUND AND HYPOTHESES

The literature underlines the strategic importance to organizations of their networks of relationships (Gulati, Nohria & Zaheer, 2000; Hughes, Morgan, Ireland & Hughes, 2014). These relationships can improve organizational performance by promoting the sharing of crucial information, resources, and knowledge (Carmeli & Azeroual, 2009) and supporting the generation of new ideas and innovations (Laursen, Reichstein & Salter 2012; Yli-Renko, Autio & Sapienza, 2001). To obtain these benefits, organizations need to create social capital through strategic networking to shape fruitful relationships (Hughes et al., 2014). In this study we understand social capital as “the sum of the actual and potential resources embedded within, available through, and defined from the network of relationships possessed by an individual or social unit” (Nahapiet & Ghoshal, 1998, p. 243). The process of creating social capital allows organizations to signal their value as partners and to create value (Adler & Kwon, 2002; Inkpen & Tsang, 2005; Wu, 2008). In the absence of social capital, lack of trust, obligations, and reciprocity can render organizations unwilling to share knowledge and resources with a partner (Adler & Kwon, 2002). Therefore, it is crucial to understand the dynamics of social capital to capture how it develops over time.

Social capital development refers to the networking behaviors of organizations aimed at developing relationships with partners that have the potential to support them (Ng & Feldman, 2010). Hughes et al. (2014) discuss these networking behaviors using the structural dimension of social capital identified by Nahapiet and Ghoshal (1998). The structural aspect of networking activities reflects the structure of the relationships an actor develops (Nahapiet & Ghoshal, 1998) and captures the extent to which social ties among actors emerge (Hughes et al., 2014).

We know precious little about how organizations develop their structure of relationships over time. In this paper, we explore the role of similarity, and investigate its impact on the choice of external partners. We focus and formulate specific research hypotheses on two fundamental dimensions of similarity – organizational and cognitive similarity. In line with previous studies (e.g. Gilly & Torre, 2000; Knoben & Oerlemans, 2012; Ahuja et al., 2012), we assume these different dimensions of similarity are important determinants of inter-organizational relations.

Organizational similarity and the dynamics of organizational collaboration

In this paper we assume that organizational similarity can be conceived both as adherence to the same institutional space and as similar organizational dimension. More specifically, the location of two organizations in the "same space of relations" and a shared "reference space" increase their organizational similarity, which in turn, increases the development of patterns of inter-organizational coordination and collaboration (Gilly & Torre, 2000).

We operationalized these two aspects of organization similarity in terms of Local Health Authority (LHA) membership and organizational dimension similarity. Belonging to the same LHA (i.e. organizational context) leads to a common understanding of the hospitals' working practices: the presence of similar routines allows the actors to understand the activities they need to accomplish (Feldman, 2000) and how these activities should be sequenced (Nelson & Winter, 1982; Torre, 2008). Furthermore, as the organizations interact in the same organizational context they tend to develop more similar structure, behavioral focus, and strategic position, and therefore can find it easier to coordinate their activities (Powell, White, Koput & Owen-Smith, 2005).

On the contrary, we posit that organizational similarity understood as organizational dimension similarity is likely to have negative effect on the propensity of the organizations to collaborate (Mulford & Mulford, 1977). Usually, larger organizations are often more attractive partners than small organizations based on their greater availability of resources and infrastructures (Foster & Meinhord, 2002). However, the service overlaps among organizations may have a negative effect on the propensity to collaborate (Arya & Lin, 2007). Several studies of patient transfer among hospitals (Iwashyna et al., 2009; Lee et al., 2011) show that the direction of relationships goes from smaller to larger hospitals, and this takes place by virtue of factors such as the greater availability of beds, competencies, and different medical specialties, and generally more advanced diagnostic technologies.

We therefore formulate two hypotheses about the impact of organizational similarity on hospitals' propensity to collaborate. Firstly, we hypothesize that the belonging to the same organizational context, over time, enhances the formation of inter-organizational collaborative ties. Secondly, we hypothesize that similarity in the organizational dimension is not conducive to inter-organizational collaborative ties. More formally:

Hypothesis 1a: *Organizational similarity in terms of similar institutional context will increase the likelihood of patient transfer between hospitals overtime.*

Hypothesis 1b: *Organizational similarity in terms of similar organization dimension will decrease the likelihood of patient transfer between hospitals overtime.*

Cognitive similarity and the dynamics of organizational collaboration

According to Wuyts, Colombo, Dutta S. & Nooteboom B. (2005), cognitive similarity is the extent to which actors similarly perceive, interpret, understand, and evaluate the world. Thus, cognitive similarity represents a measure of cultural homogeneity (Molina-Morales, Garcia-Villaverde & Parra-Requena, 2014).

The literature provides contradictory findings for cognitive similarity. Some findings show that it favors knowledge exchange between organizations (Knoben & Oerlemans, 2006) enhances innovation (Dakhli & De Clerq, 2004) and organizational performance (Krause, Handfield & Tyler, 2007), and diminishes conflicts and misunderstandings in communication (Inkpen & Tsang, 2005). This similarity increases the likelihood of inter-organizational collaborations because it reduces the cognitive distance between the partnering organizations searching for mutual benefits, and provides identity for organizations in search of exchange partners (Lazega, 2009). On the other hand, the literature on alliance formation argues that organizations will tend to create collaborative ties in order to access specialized complementary assets (Colombo, Grilli & Piva, 2006), and what really matters are technological competencies, absorptive capacity, and the cognitive distance between the organizations (Inkpen & Tsang, 2005; Nooteboom, 2000; Wuyts et al., 2005). Based on the latter line of research, we assume that in the healthcare sector greater cognitive similarity reduces the tendency for hospitals to exchange patients.

Our assumption is supported also by Cohen and colleagues (2012), which demonstrates how the presence of some cognitive distance between actors involved in the exchange of patients among hospitals enhances handoff (i.e. patient transfer) safety and efficiency. More specifically they state that: "…it can be seen that different mental models are not necessarily good or bad but that the way they are handled during a handoff is what actually matters. […] Especially when a diagnosis is unclear, a discussion between two participants with similar mental models may be less safe, as both may be agreeing on an incorrect diagnosis" (Cohen et al., 2012, p. 5).

In similar vein, as the behavior of hospitals is aimed at maximizing and identifying the most appropriate care for each specific clinical case of patient transfer, we assume that high levels of cognitive similarity determines, in a negative way, the networking behavior between the two organizations, and therefore inhibits over time the creation of a tie. More formally:

Hypothesis 2: *Cognitive similarity will increase the likelihood of patient transfer between hospitals overtime.*

METHOD

Empirical context

We examine the dynamics of patient-sharing relations within the entire network of hospitals providing services to patients in Abruzzo, a region in central Italy with a population of approximately 1,300,000 residents.

The Italian National Health Service (I-NHS) is a publicly funded health system that provides universal coverage. The government, at the central level, allocates resources to 20 Italian regions and is responsible for defining the core benefit packages and ensuring that basic coverage is provided to the entire population. However, responsibility for the organization and delivery of health services is totally devolved to the regions. Regional governments have wide autonomy in planning, allocating resources, and organizing regional level services, and are solely responsible for delivering health care services to their resident populations.

The Abruzzo regional health system is entrusted to six LHAs, and health care services are provided by 35 hospital organizations (22 public and 13 private). Of the 22 public hospitals, two are teaching hospitals. Public hospitals provide highly specialized hospital care and are characterized by technical, economic, and financial autonomy. Teaching hospitals are hospitals linked to universities, and provide education, research, and tertiary care. Private hospitals are partially financed by the regional healthcare service and are investor-owned organizations that provide ambulatory assistance, hospital care, and diagnostic services.

The topography of the Abruzzo region makes the design of an effective supply network of health services a very relevant issue. The region comprises a flat and densely populated coastal area, with cities quickly and easily connected by major roads and infrastructure, and a rather hilly and mountainous internal area, whose cities are far apart, less densely populated, and involving infrastructure that requires longer travel times. The region's hospitals are equally distributed between these two areas.

Why this case

Within this framework, our study setting seems to be particularly appropriate for the purpose of this research. The first reason is that earlier research in this context (Mascia & Di Vincenzo, 2011; Mascia et al., 2012) and our fieldwork show the presence of local networks of collaboration among hospitals, which mainly stem from the sharing of patients between hospitals. Patient sharing occurs when one hospital directly transfers one or more elective patients to another hospital. For example, hospitals that provide only basic services may send patients with more complicated clinical problems to another provider that offers comprehensive specialty care. Patient sharing may also be driven by 'asymmetries' in regional providers' clinical resources or competences: e.g., hospitals may transfer patients to other local providers if they lack the necessary medical equipment (e.g., intensive care unit beds), expertise (e.g., staffing), or supplies. These informal networks become established and can have important implications for organizational performance (Lee et al., 2011; Mascia & Di Vincenzo, 2011).

The second reason is that, given the great strategic and organizational autonomy of our empirical setting, there are no significant external factors that influence the networking process for which we need to control. In the period considered in this study there were no significant policy interventions that substantially altered the institutional framework, the number of providers, or the structure of the local inter-organizational network. Exception is the progressive reduction in the number of beds set by regional authorities, but this reduction has affected proportionally all hospitals.

The third reason for our choice of setting is that the network of hospitals consists of a heterogeneous mix of public, private, and teaching hospitals with different organizational features and different performance. In addition, despite the high degree of autonomy, Abruzzo health care system suffers from a lack of systemic planning and strategy coordination among its hospitals (Lo Scalzo et al., 2009). Unlike some other regions that have fostered inter-hospital collaboration through well-defined and formal collaboration mechanisms (e.g., “hub&spoke” models or clinical pathways for patient referrals), coordination in Abruzzo emerges mainly through patient-sharing among providers (Mascia et al., 2012).

The fourth reason why this is an ideal case to study network dynamics is that especially in regions where systemic planning and organizing of health provision is lacking, collaborative initiatives among hospitals arise and evolve endogenously (Lo Scalzo et al., 2009). These emergent “self-organizing” properties of inter-hospital networks may produce outcomes and behaviors that can be investigated by employing longitudinal models and social network analysis (Snijders et al., 2010).

Data collection and variables description

The analysis draws on a range of rich data. Data on patterns of collaborative interdependencies during the period 01/01/2003–31/12/2008 among all hospitals in the region were extracted from the hospital information system database managed by the Abruzzo Region.

Data on hospital activities, and information on demographics and performance, were taken from the Abruzzo Health Agency archives and yearly reports. These data are collected regularly and archived digitally by the Region for administrative purposes, and by the Health Agency for its operational and reporting activities. Archival sources are generally more precise and detailed than surveys and provided complete information on the network of hospitals: there were no missing data.

We integrated these official data and reports with qualitative data obtained from the responses to a structured questionnaire which provide "both retrospective and real-time accounts by those people experiencing the phenomenon of theoretical interest" (Gioia, Corley & Hamilton, 2013, p. 19). Between May and August 2012 we contacted the medical directors of hospitals operating in the region, and 30 agreed to be interviewed (response rate of 86%). We transcribed the interviews in order not to lose important detail. We obtained information on the patterns of collaboration including the reasons for patient sharing and the criteria used to choose the partner.

Since we are interested in understanding the dynamics of organization collaboration, our dependent variable is inter-hospital collaboration, measured as transfers of patients. Previous studies (Iwashyna et al., 2009; Lee et al., 2011; Lomi & Pallotti, 2012; Mascia et al., 2012) and the interviews with hospital medical directors show that patient flows represent a proper proxy for inter-hospital collaboration networks in the regional health system. Using available data on patient sharing among regional hospitals, as dependent variable, we built six "35x35" dichotomized matrices for the years from 2003 to 2008. The rows and columns of each matrix respectively report the hospitals that sent and admitted at least one patient in the year considered. Because matrices may vary depending on the dichotomization criteria, we conducted separated analyses to assess the effect on our hypotheses of different criteria (i.e. "greater-than" mean value, "greater-than" zero). The results obtained were qualitatively similar.

To measure similarity, we used several different measures as our independent variables. Organizational similarity was measured in terms of staffed beds, in order to indicate the propensity to collaborate with a hospital with a similar number of available beds, and in terms of LHA membership, in order to indicate the propensity to collaborate with hospitals belonging to the same local administrative unit. In line with the previous literature (Mascia et al., 2012), we consider those two variables as good proxies for organizational similarity in the health care sector.

In order to measure the cognitive dimension of similarity we used i) case mix similarity and ii) number of common specialties. These two variables indicate respectively similarity in the complexity of cases (severity of treated cases) handled by each hospital and similarity in the number of medical specialties operating within each hospital. The assumption is that if two hospitals treat – on average – patients with the same level of clinical complexity and have departments with overlapping specialties, they will have similar knowledge bases, use a common language, and possess the same competences.

In line with work that exploits stochastic actor-based models (Giuliani, 2013; Valente, Fujimoto, Palmer & Tanjasiri, 2010), in the estimation we control also for some endogenous effects such as outdegree, transitive mediated triplets, three cycles, balance, indegree-popularity, and out-degree–activity (see Table 1).

Insert Table 1 about here.

Finally, we controlled for organizational-level variables that might influence networking behavior, such as performance (productivity) measured as the total number of admissions and adjusted for case mix, divided by total number of staffed beds (Mascia & Di Vincenzo, 2011) and percentage of emergency admissions (Iwashyna et al., 2009). This last measures the level of uncertainty of input (i.e. patients) faced by the hospital (Lomi & Pallotti, 2012). Each variable was computed yearly, for the six-year period 2003-2008. Table 2 presents the descriptive statistics for the independent variables used in this research. Geographical distance between hospitals, LHA membership and the number of specialties are constant over time, showing the absence of structural policies for the re-designing of the hospitals regional system. The mean of staffed beds reduces over time (such as the percentage of emergency admitted) while the case mix complexity and the productivity indicators slightly increase in the six years analyzed.

Insert Table 2 about here.

Analysis

The R-Siena Software Package (Snijders et al., 2010) allowed us to achieve the first two steps of analysis. First, we performed an analysis of the structural properties of the network in the period considered, based on set of network indicators such as network density, average degree of ties, number of ties' changes. Second, we empirically tested the research hypotheses.

The observed changes can be explained as functions of both individual and dyadic characteristics of actors and structural effects. Specific actor attributes and dyadic characteristics either favor or reduce the probability that two hospitals will transfer patients and so collaborate. For each actor and dyadic attribute, we include several effects in the model specification. As explained by Snijders et al. (2010), for continuous actor covariates (e.g., staffed beds, case mix, productivity, emergency admissions), three kinds of actor-driven mechanisms can be specified. The sender (ego) and receiver (alter) effects evaluate the tendency for organizations with higher attributive value to, respectively, send out more (higher outdegree) or receive more (higher indegree) than others. The “similarity” effect measures whether collaborative relations tend to occur more often between organizations with similar values for a given attribute. Finally, for the categorical actor variables (e.g. LHA membership and specialties), the effects included in the model measure the tendency for ties between actors with the “same” value of that variable. Structural effects represent endogenous network mechanisms that also may influence the probability of interdependence between actors. For a mathematical definition of effects in actor-based models for network dynamics, we refer the reader to Snijders et al. (2010).

In the third step, we applied case study analysis of multiple interviews to obtain a deeper understating of the results we found in the first two steps and to shed further light on the mechanisms underlying the relationships postulated in the hypotheses (Eisenhardt, 1989; Yin, 1994). The qualitative analysis allowed us to observe a common perceived meaning of collaboration and to confirm that patient sharing (i.e. the dependent variable in the stochastic actor based model) is perceived by practitioners as a good proxy for organizational collaborative behavior. More specifically, following Corley and Gioia (2011) approach, we conducted a first-order analysis to capture informant perceptions and meanings related to our research questions. In the second-order analysis we re-categorized these emerging germane categories into relevant theoretical themes. Finally, we built the full set of coded quotes and themes which we were able to aggregate into constructs. The authors conducted the analyses independently and then resolved discrepancies through discussion of the data and by reconciling different understandings and coding approaches (Gioia et al., 2013).

RESULTS

Results of the first step of analysis with R-Siena

Table 3 reports key statistics describing the evolution of inter-organizational collaboration in terms of network density (i.e. ratio of number of collaborative ties observed yearly on the total number of dyads), average degree (i.e. average number of collaborative partners for each node), and total number of ties. With the exception of the year 2009, density and number of ties increased slightly from 11% in 2003 to 12.2% in 2008, and from 131 in 2003 to 145 in 2008 respectively. Also, in the six-year period observed, the average number of collaborative ties increased from 3.743 to 4.143.

To explore the dynamics of inter-organizational collaboration more in-depth, we also consider the collaborative patterns at dyadic level over time (see Table 4). The column labeled 0→0 in Table 4 reports the number of pairs of hospitals that did not develop a collaborative relationship in the observed wave; the column labeled 1→1 in Table 4 indicates the number of dyads that maintained their collaborative interdependence. The other two columns in Table 4 present the number of collaborative ties formed or dissolved from one year to the next. Consistent with the third column in Table 3, also Table 4 shows a growing trend in tie changes: during the period of observation, 213 new collaborative ties were formed and 199 existing relationships were dissolved.

Insert Tables 3 and 4 about here.

Results of the second step of analysis with R-Siena Software

The empirical results of the stochastic actor based model estimations are presented in Table 5. The rate parameters, defined as “the expected frequencies, between successive waves, with which actors get the opportunity to change a network tie” (Snijders et al., 2010, p. 51) are all positive and significant, meaning that the whole collaborative network grows over time.

The analysis of the endogenous effects suggests that collaborative ties do not evolve randomly. Both the significant negative effect of outdegree and the significant positive effect of reciprocity indicate that hospitals tend, over time, to replicate their patterns of collaborative ties. In addition the whole network presents a tendency for indegree popularity and transitive mediate triplets, indicating that hospitals tend to forge new collaborative ties based on existing collaborative relationships.

Insert Table 5 about here.

Our results provide confirmation for Hypothesis 1a (*Organizational similarity in terms of similar institutional context will increase the likelihood of patient transfer between hospitals overtime)*. Specifically, we find that the effect of the variable LHA (same) in Table 5 is positive and significant, meaning that inter-hospital collaboration is more likely to develop between structures belonging to the same LHA. In relation to Hypothesis 1b (*Organizational similarity in terms of similar organization dimension will decrease the likelihood of patient transfer between hospitals overtime)*, the variable staffed beds (alter) is also positive and significant. This result is consistent with our expectations and is explained by the fact that bigger hospitals have a greater propensity to form ties based on receiving patients from smaller hospitals (Lee et al., 2011). The results also provide empirical support for Hypothesis 2 (*Cognitive similarity will increase the likelihood of patient transfer between hospitals overtime*). Case mix (similarity) has a negative impact on inter-hospital collaboration dynamics and N° of specialties (same) is positive and significant. Among the control variables, geographical distance is negative and significant. This implies that there is a proximity effect (Knoben & Oerlemans, 2006), namely that as the distance decreases the propensity of hospital organizations to collaborate through the exchange of patients increases. The significance of the parameters related to the coefficients of % emergency admissions demonstrates that collaborative interdependences are determined by the ability to manage input uncertainty. Finally, in line with previous studies (Lomi & Pallotti, 2012) the coefficients related to productivity show that ties are formed among organizations with similar levels of performance.

Results of the qualitative analysis

We examined hospital medical directors' opinions on inter-hospital collaboration in a three-order of analysis. The semi-structured questionnaire aimed to investigate and discuss about the topic of collaboration in general and patient transfer in detail. Relevant questions are: Q1 What are the forms of collaboration between hospitals? Q2 What are the main reasons of inter-hospital transfers of patients? Q3 How does the transfer process works and what are the main criteria for the choice of a receiver hospital for in-patient transfers? Q4 The transfer of patients represents a learning opportunity for your hospitals? The full questionnaire is available from the authors.

Table 6 presents the main results of the interviews held with respect to the theoretical constructs under investigation.

Insert Table 6 about here.

First, our analysis confirms that patient transfer is an important form of collaboration among the hospitals populating our network: 84% of medical directors consider patient sharing to be a relevant form of collaboration. For example, as SP explained: "... *the most used forms of collaboration among hospitals are patient transfers and consultancies.* TC explained as *"...patient transfer is the main form of collaboration among hospitals and it occurs independently form the existence of a formal agreement among hospital*s".

Second, the analysis of the interviews shows that organizational similarity also matters for explaining collaboration among hospitals. LR and MV said that "… *the first criterion we use to decide where to transfer our patient is that to identify, within our LHA, the hospital structure that better than others can meet the needs for care experienced by the patient".* LM explained as "*…my first criterion in identifying the receiving hospital is the LHA membership; ...in the case the patients express preference for their own personal reasons, I check that the hospital suggested has the skills to deal with the specific clinical condition"*. MM sustained that: "... *once it has manifested the need to transfer a patient given to certain reasons, I usually check the availability of staffed bed placed in one of the hospital within our LHA. If there was no availability in these, I* *check the availability of other regional or - at worst - extra-regional hospitals*".

As regards the research hypothesis concerning cognitive similarity, the interviews showed as that lack of specialties and different levels of structural complexity are determinants of inter-hospital collaboration. AL reported as: "… *we transfer patients to hospitals with medical specialties that we couldn't offer to satisfy patients' needs*". This is in line with LD explanation: "*... the main reason of patient transfers is that my hospital suffers for the lack of specialties such as the physiotherapy unit or the coronary care unit, so we send patients to hospitals which could offer appropriate specialties for patients' pathologies*". Confirmation of what we found in the empirical analysis of this study is also from the statements of FD "…*based on my 20-years experience in this field, I can say that transfers mainly occur from structures of lower complexity to higher complexity ones"* and FT *"... we generally transfer patient in reason of the unavailability in loco of advanced expertise or high-complexity technologies".*

DISCUSSION AND CONCLUSIONS

Despite the large body of empirical research on inter-organizational network ties formation, we know very little about how they evolve over time. This research contributes to filling this gap in the literature by empirically investigating the evolution of the social ties shaping a geographically bounded network of hospital organizations within an Italian region. More specifically, we investigate the role played organizational and cognitive similarity for explaining the networking behavior of organization over time. The opportunity to test our hypotheses and to apply innovative methods of investigation was provided by the availability of very rich data and identification of an ideal and appropriate empirical context in healthcare.

Two main conclusions can be drawn from the results of the present research. First, we found that organization similarity, which represents the extent to which social ties are embedded in an inter-organizational arrangement, explain hospitals' propensities to collaborate. More specifically, testing the impact of our proxies for organizational similarity showed that bigger hospitals have a higher propensity to form more ties, and that belonging to the same Local Health Authority (i.e. administrative unit) has a positive impact on collaboration. These results are in line with recent studies on patient sharing among hospitals (Lee et al., 2011) and confirm their validity using new longitudinal data. Third, we found that cognitive similarity negatively affects hospital collaboration. This contributes importantly to the literature on cognitive similarity, which argues that actors with knowledge, capacities, and expertise in common, perform better (Nooteboom, 2000; Wuyts et al., 2005). Our study shows that the effect of cognitive similarity is strictly dependent on the sector in which the organizations operate. In the case of patient sharing in the health sector, we show that some cognitive distance allows complex problems related to patient illnesses to be better addressed, and ultimately, to enhance patient transfer efficiency (Cohen et al., 2012).

We also found that the formation of collaborative ties between organizations is explained by peculiar forms of structural (or local) configurations, composed of subsets of two or three network actors and the possible ties among them (Madhavan, Gnyawali & He, 2004). These dyadic and triadic micro-processes are not used as direct measures of the network properties. Rather, they are measured statistically to provide evidence on endogenous local forces driving the formation (and evolution) of the network (Mascia & Di Vincenzo, 2013; Robins, Elliott & Pattison, 2001). Among the dyadic configurations, outdegree (the overall tendency of hospitals to exhibit outgoing collaborative interdependence) and reciprocity (the overall tendency of hospitals to exhibit reciprocal interdependence) are both significant, suggesting that the network is not static over time but evolves endogenously. Among the triadic configurations we find that transitive triplets (the tendency toward transitive closure, where collaborative ties are established with partners of partners), and indegree-popularity (the tendency for hospitals experiencing numerous incoming collaborative ties to engage in more collaboration) are significant and add to our understanding of how networks evolve over time.

This study contributes to different streams of literature. It contributes to the literature on network dynamics (Giuliani, 2013; Snijders et al., 2010; Valente et al., 2010) by exploring the evolution of a network over time from a similarity perspective. Testing our empirical results with a mixed methods approach we captured the impact of different dimensions of similarity on the dynamics of organization collaboration. Exploring these heterogeneous dimensions allows a more comprehensive understanding of organizations' networking behavior (Hughes et al., 2014) and the dynamics of intra-group collaboration in a geographically localized network (Kilduff et al., 2006; Lee, 2009).

We contribute also to work in economic geography (Knoben & Oerlemans, 2012; Laursen et al., 2011) by explaining how different dimensions of similarity influence emerging collaborative relationships among hospital organizations. The dynamic approach adopted in this paper allows us to understand that similarity and inter-organizational collaboration come together because of a selection process based on organizations' decisions, which create ties with other organizations on the basis of their organizational and cognitive similarity.

The mixed methods approach adopted in this study provides a further methodological contribution to managerial research. The mixed methods approach combines different qualitative and quantitative data and analysis techniques which increase our understanding of the phenomena through the triangulation of data sources and exploitation of the findings from one method to develop or inform the other method (Creswell, 2003).

Finally, this study contributes to research in healthcare management. Prior research stresses the importance of developing new approaches to enable more accurate analysis of hospital collaboration (Iwashyna et al., 2009) and increase the understanding of hospital administrators and policymakers about the environment in which health care organizations behave and perform.

This study has some limitations which provide opportunities for future research and suggest some caution in interpreting its findings. First, we analyzed one specific relation, i.e. patient transfer among hospitals. Although inter-hospital collaboration is widely used in the literature (Lee et al., 2011; Mascia et al., 2012), and our field experience makes us confident that this relation captures important dimensions of collaboration among hospitals, it is possible that hospitals also collaborate in other ways including exchanges of doctors, cross training of medical staff, and technology transfer. All these methods might reveal the same patterns of collaboration among hospitals. Future studies should pay attention to the multiplexity that inter-organizational collaboration is likely to involve (Lomi & Pattison, 2006). Second, our findings are based on data for a six-year period from hospitals in a single region of Italy and may reflect issues specific to the local context or the time period. We would encourage further research on the dynamics of hospital collaboration to extend the application of social network analyses to other settings to check whether our findings can be generalized.

REFERENCES

Adler, P. S., & Kwon, S. W. (2002). Social capital: Prospects for a new concept. *Academy of management review*, *27*, 17-40.

Ahuja, G., Soda, G., & Zaheer, A. (2012). The genesis and dynamics of organizational networks. *Organization Science*, *23*, 434-448.

Arya, B., & Lin, Z. (2007). Understanding Collaboration Outcomes From an Extended Resource-Based View Perspective: The Roles of Organizational Characteristics, Partner Attributes, and Network Structures. Journal of Management, 33, 697-723.

Becattini, G. (1991). Italian industrial districts: problems and perspectives. International Studies of Management & Organization, 21, 83-90.

Borgatti, S. P., & Foster, P. C. (2003). The network paradigm in organizational research: A review and typology. Journal of management, 29, 991-1013.

Burt, R. S. (1999). Structural holes: The social structure of competition. Harvard university press, Cambridge, MA.

Carmeli, A., & Azeroual, B. (2009). How relational capital and knowledge combination capability enhance the performance of work units in a high technology industry. Strategic Entrepreneurship Journal, 3, 85-103.

Cohen, M. D., Hilligoss, B., & Amaral, A. C. K. (2012). A handoff is not a telegram: an understanding of the patient is co-constructed. *Critical Care*, *16*, 303.

Colombo, M. G., Grilli, L., & Piva, E. (2006). In search of complementary assets: The determinants of alliance formation of high-tech start-ups. *Research Policy*, *35*, 1166-1199.

Corley, K. G., & Gioia, D. A. (2011). Building theory about theory building: what constitutes a theoretical contribution?. *Academy of Management Review*, *36*, 12-32.

Creswell, J. W. (2013). *Research design: Qualitative, quantitative, and mixed methods approaches*. Thousand Oaks, CA: Sage publications.

Dakhli, M., & De Clercq, D. (2004). Human capital, social capital, and innovation: a multi-country study. *Entrepreneurship & regional development*, *16*, 107-128.

Ebers, M. (1999). *The formation of inter-organizational networks*. New York:Oxford University Press.

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *Academy of management review*, *14*, 57-74.

Feldman, M. S. (2000). Organizational routines as a source of continuous change. *Organization science*, *11*, 611-629.

Gilly, J. P., & Torre, A. (2000). Proximity Relations: Elements for an Analytical Framework. In: Green,M. B., & McNaughton, R. B. (Eds), *Industrial Networks and Proximity*. Aldershot: Ashgate Publishing pp.1–16.

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research notes on the Gioia methodology. *Organizational Research Methods*, *16*, 15-31.

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

Gulati, R., Nohria, N., &d Zaheer, A. (2000). Strategic Networks. *Strategic Management Journal 21*, 203–215.

Gulati, R., & Gargiulo, M. (1999). Where do interorganizational networks come from?. *American Journal of Sociology 104*, 1439–1493.

Gulati, R. (1995). Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances.*The Academy of Management Journal, 38*, 85–112.

Hughes, M., Morgan, R. E., Ireland, D. & Hughes, D. (2014). Social Capital and Learning Advantages: A Problem of Absorptive Capacity. *Strategic Entrepreneurship Journal, 8*, 214–233.

Huxham, C. (1996). *Creating collaborative advantage*. Sage Publications, London.

Ingram, P., & Yue, L. (2008). Structure, affect and identity as bases of organizational competition and cooperation. *The Academy of Management Annals, 2*, 275–303.

Inkpen, A. C. & Tsang, E. W. K. (2005). Social capital, networks, and knowledge transfer. *Academy of Management Review, 30*, 146–165.

Iwashyna, T. J., Christie, J. D., Moody, J., Kahn, J. M., & Asch, D. A. (2009). The structure of critical care transfer networks. *Medical care*, *47*, 787-793

Kilduff, M., Tsai, W., & Hanke, R. (2006). A paradigm too far? A dynamic stability reconsideration of the social network research program. *Academy of Management Review*, *31*, 1031-1048.

Kilduff, M., & Tsai, W. (2003). *Social networks and organizations*. London: Sage.

Sage, London.

Knoben, J., & Oerlemans, L. A. (2012). Configurations of inter-organizational knowledge links: Does spatial embeddedness still matter?. *Regional Studies*, *46*, 1005-1021.

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

Laursen, K., Masciarelli, F., & Prencipe, A. (2012). Regions matter: how localized social capital affects innovation and external knowledge acquisition. *Organization Science*, *23*, 177-193.

Lazega, E. (2009). Cooperation among Competitors. Its Social Mechanisms through Network Analyses.*Sociologica, 1*, 1-30.

Lee, B. Y., McGlone, S. M., Song, Y., Avery, T. R., Eubank, S., Chang, C. C., Bayler, R.R., Wagener, D. K., Burke, D.S., Plat, R, & Huang, S. S. (2011). Social network analysis of patient sharing among hospitals in Orange County, California. *American journal of public health*, *101,* 707-713.

Lee, R. (2009). Social capital and business and management: Setting a research agenda. *International Journal of Management Reviews*, *11*, 247-273.

Lomi, A., & Pallotti, F. (2012). Relational collaboration among spatial multipoint competitors. *Social networks*, *34*, 101-111.

Lomi, A., & Pattison, P. (2006). Manufacturing relations: An empirical study of the organization of production across multiple networks. *Organization science*, *17*, 313-332.

Lounsbury, M., & Ventresca, M. (2003). The new structuralism in organizational theory. *Organization*, *10*, 457-480.

Lo Scalzo, A., Donatini, A., Orzella, L., Cicchetti, A., Profili, S., & Maresso A. (2009).Health care system in transition. Italy Health system review. *Health Systems in Transition 11*, 1–216.

Madhavan, R., Gnyawali, D. R., & He, J. (2004). Two's company, three's a crowd? Triads in cooperative-competitive networks. *Academy of Management Journal*, *47*, 918-927.

Mascia, D., & Di Vincenzo, F. (2011). Understanding hospital performance: the role of network ties and patterns of competition. *Health Care Management Review, 36*, 327–337.*Health Care Management Review* 36, 327–33

Mascia, D., & Di Vincenzo, F. (2013). Dynamics of hospital competition: Social network analysis in the Italian National Health Service. *Health Care Management Review*, *38*, 234-247.

Mascia, D., Di Vincenzo, F., & Cicchetti, A. (2012). Dynamic analysis of interhospital collaboration and competition: Empirical evidence from an Italian regional health system. *Health policy*, *105*, 273-281.

Molina-Morales, F. X., García-Villaverde, P. M., & Parra-Requena, G. (2014). Geographical and cognitive proximity effects on innovation performance in SMEs: a way through knowledge acquisition. *International Entrepreneurship and Management Journal*, *10*, 231-251.

Monge, P. R., & Contractor, N. S. (2003) *Theories of Communication Networks*. Oxford University Press, Oxford.

Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *Academy of management review*, *23*, 242-266.

Nelson, R. R., & Winter, S. G. (1982). *An Evolutionary Theory of Economic Change*. Cambridge, MA:Harvard Business School Press,

Ng, T. W., & Feldman, D. C. (2010). The effects of organizational embeddedness on development of social capital and human capital. *Journal of Applied Psychology*, *95*, 696-712

Nooteboom, B. (2000). *Learning and Innovation in Organizations and Economies*Oxford, NY: Oxford University Press,.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative science quarterly*, 116-145.

Powell, W. W., White, D. R., Koput, K. W., & Owen-Smith, J. (2005). Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences1. *American journal of sociology*, *110*, 1132-1205.

Robins, G., Elliott P. & Pattison, P. (2001). Network models for social selection processes. *Social Networks, 23*, 1–30.

Rosenthal, S. S., & Strange, W. C. (2003). Geography, industrial organization, and agglomeration. *Review of Economics and Statistics, 85*, 377–393.

Steensma, H. K. (1996). Acquiring technological competencies through inter-organizational collaboration: an organizazional learning perspective. *Journal of Engineering and Technology Management*, *12*, 267-286.

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

Soda, G., Usai, A., & Zaheer, A. (2004). Network memory: The influence of past and current networks on performance. *Academy of Management Journal, 47*, 893–906.

Torre, A. (2008) On the role played by temporary geographical proximity in knowledge transmission. *Regional Studies, 42*, 869–889.

Torre, A., & Gilly, J. P. (2000). On the analytical dimension of proximity dynamics. *Regional Studies*,34, 169–180.

Valente, T. W., Fujimoto, K., Palmer, P., & Tanjasiri, S. P. (2010). A network assessment of community-based participatory research: linking communities and universities to reduce cancer disparities. *American Journal of Public Health, 100*, 1319–1325.

Wu, W. (2008). Dimensions of social capital and firm competitiveness improvement: The mediating role of information sharing. *Journal of Management Studies, 45*, 122–146.

Wuyts, S., Colombo, M. G., Dutta, S., & Nooteboom, B. (2005). Empirical tests of optimal cognitive distance. *Journal of Economic Behavior & Organization, 58*, 277–302.

Yin, R. K. (1994). *Case Study Research: Design and Methods*. Thousand Oaks, CA: Sage Publications

Yli-Renko, H., Autio, E., & Sapienza, H. J. (2001). Social capital, knowledge acquisition, and knowledge exploitation in young technology-based firms. *Strategic Management Journal, 22*, 587–613.

TABLE 1

Summary of endogenous effects

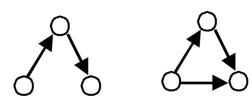
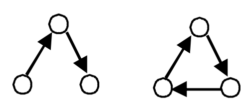
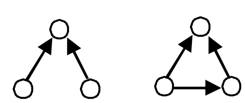
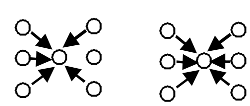
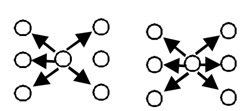
Endogenous effects	**Structural configuration** t_0 t_1	**Interpretation**
Outdegree (density)		The tendency of a hospital to exhibit outgoing collaborative ties.
Reciprocity		The tendency of a hospital to exhibit reciprocal ties.
Transitive mediated triplets		A tendency toward transitive closure. Outgoing collaborative ties are established with partners of direct partners (i.e. '*the friend of my friend, becomes my friend*').
Three-Cycles		The general tendency toward closure and cyclic network structures of collaboration.
Balance		The general tendency to collaborate between hospitals with similar collaborative ties.
Indegree-popularity		The tendency of hospitals experiencing numerous incoming collaborative ties to become more exposed to collaboration.
Outdegree-activity		The tendency of hospitals having many outgoing collaborative ties to become more active in terms of strategic initiatives of collaboration.

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TABLE 2

Descriptive statistics of independent and control variables

Variables	**Changing/ Constant**	**2003**				**2004**				**2005**			
		Mean	StD	Min	Max	Mean	StD	Min	Max	Mean	StD	Min	Max
LHA	*Constant*	3.00	1.81	1.00	6.00								
Staffed beds	*Changing*	183.03	164.68	20.00	730.00	167.83	146.70	20.00	661.00	168.17	145.27	20.00	650.00
Case mix	*Changing*	1.03	0.13	0.81	1.40	1.03	0.13	0.81	1.40	1.02	0.12	0.70	1.42
N° specialties	*Constant (Dyadic)*	33	7.32	1	31								
Productivity	*Changing*	35.65	16.80	5.45	79.40	42.92	23.13	9.21	130.44	50.93	27.10	11.21	136.37
% Emerg. admissions	*Changing*	31.657	25.53	0	71	35.74	24.25	0.00	71.00	37.35	24.54	0	74
Geographic distance	*Constant (Dyadic)*	65.69	29.61	0	133								

Variables	**Changing/ Constant**	**2006**				**2007**		
		Mean	StD	Min	Max	Mean	StD	Mi
LHA	*Constant*							
Staffed beds	*Changing*	167.83	146.70	20.00	661.00	167.83	146.70	20.
Case mix	*Changing*	1.03	0.11	0.66	1.29	0.92	0.20	0.0
N° specialties	*Constant (Dyadic)*							
Productivity	*Changing*	32.49	16.24	5.74	77.16	28.10	14.72	0.0
% Emerg. admissions	*Changing*	34.77	28.07	0	79	34.69	27.44	0
Geographic distance	*Constant (Dyadic)*							

TABLE3

Key statistics of ties evolution

Years	Density (%)	Average degree	Number of ties
2003	11	3.743	131
2004	10.2	3.457	121
2005	11.2	3.800	133
2006	9.5	3.229	113
2007	11.5	3.914	137
2008	12.2	4.143	145

TABLE 4

Number of changes between subsequent observations

Observation waves	0→0	0→1	1→0	1→1
2003-2004	1030	29	39	92
2004-2005	1022	47	35	86
2005-2006	1029	28	48	85
2006-2007	1021	56	32	81
2007-2008	1000	53	45	92
Total	5102	213	199	436

TABLE 5

Results of R-Siena analysis

Rate Function	***Estimates***		***Std Error***
Rate parameter period 1	3.9946		0.7154
Rate parameter period 2	6.0044		1.1455
Rate parameter period 3	4.9225		0.8968
Rate parameter period 4	7.9550		1.6556
Rate parameter period 5	7.6376		1.3636
Endogenous effects			
Outdegree	-3.0054	***	0.2791
Reciprocity	0.6223	***	0.1538
Transitive mediated tripletes	0.1529	*	0.0723
Three-Cycles	- 0.0479		0.0837
Balance	0.0516		0.0484
Indegree popularity	0.0627	**	0.0235
Outdegree activity	0.0330		0.0455
Independent and control variables			
LHA	1.1738	***	0.1409
N° of specialties	0.0169	*	0.0183
Staffed beds (similarity)	0.1546		0.3870
Staffed beds (alter)	0.0030	***	0.0007
Staffed beds (ego)	0.0007		0.0006
Casa mix (similarity)	-0.4315	*	0.0316
Case mix (alter)	-0.6677		0.3867
Case mix (ego)	0.8019		0.4127
% of emergency admissions (similarity)	0.5397	*	0.2435
% of emergency admissions (alter)	0.0055		0.0032
% of emergency admissions (ego)	0.0152	***	0.0031
Productivity (similarity)	1.3909	*	0.6128
Productivity (alter)	0.0014		0.0034
Productivity (ego)	-0.0029		0.0036
Geographical distance (centered)	-0.0111	***	0.0022

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Robustness check shows that model convergence is good (t- ratios are all less than 0.10 for all coefficients) and there are no major problems of multicollinearity.

TABLE6

Results of qualitative analysis from interviews with medical directors

Empirical observations	Theoretical observations	Theoretical constructs
LHA membership "…the first criterion we use to decide where to transfer our patient is that to identify, within our LHA, the hospital structure that better than others can meet the needs for care experienced by the patient" (LR). "…my first criterion in identifying the receiving hospital is the LHA membership; …in the case the patients express preference for their own personal reasons, I check that the hospital suggested has the skills to deal with the specific clinical condition" (LM). "…I usually check the availability of staffed bed placed in one of the hospital within our LHA. If there was no availability in these, I check the availability of other regional or - at worst - extra-regional hospitals" (MM).	**Hierarchical constraints**	**Organizational Proximity**
Specialties unavailability "…we transfer patients to hospitals with medical specialties that we couldn't offer to satisfy patients' needs" (AL). "…the main reason of patient transfers is that my hospital suffers for the lack of specialties such as the physiotherapy unit or the coronary care unit, so we send patients to hospitals which could offer appropriate specialties for patients' pathologies" (LD). "…my hospital usually send patients to hospitals which could offer appropriate specialties to patients' pathologies" (FE). "…we generally transfer patient in reason of the unavailability in loco of specific competencies" (FT). "…we transfer patient in reason of the lack of beds for highly-complex care and advanced technologies" (MV). ***Different levels of complexity*** "…based on my 20-years experience in this field, I can say that transfers mainly occur from structures of lower complexity to higher complexity ones" (FD). "…we usually transfer patient in reason of the unavailability in loco of high-complexity technologies and devices" (MRR). "…here we don't have all medical and surgical competencies; we work as a <<spoke>> who refer patients to regional <<hubs>> according to their major and relevant diseases" (DV).	**Different knowledge / expertise bases**	**Cognitive Proximity**