Papers in Evolutionary Economic Geography

14.12

The Dynamics of Technical and Business Networks in Industrial Clusters: Embeddedness, status or proximity?

Pierre-Alexandre Balland, José Antonio Belso-Martínez and Andrea Morrison

Utrecht University
Urban & Regional research centre Utrecht

The Dynamics of Technical and Business Networks in Industrial Clusters: Embeddedness, status or proximity?

Pierre-Alexandre Balland*, José Antonio Belso-Martínez[β], Andrea Morrison[†]

* Department of Economic Geography - URU, Utrecht University, Heidelberglaan 2, 3508 TC Utrecht, The Netherlands
p.balland@uu.nl
Corresponding author. Tel: +31 30 253 2407

[β] Department of Economics and Finance, Universidad Miguel Hernández de Elche, Avenida de la Universidad s/n, Elche 03202, Spain
jbelso@umh.es

† Department of Economic Geography - URU, Utrecht University, Heidelberglaan 2, 3508 TC Utrecht, The Netherlands
KITeS, Universitá Luigi Bocconi, via Sarfatti 25, 20136 Milano, Italy
a.morrison@uu.nl

Abstract: Although informal knowledge networks have often been regarded as a key ingredient behind the success of industrial clusters, the forces that shape their structure and dynamics remain largely unknown. Drawing on recent network dynamic models, we analyze the evolution of business and technical informal networks within a toy cluster in Spain. Empirical results suggest that the dynamics of the two networks differ to a large extent. We find that status drives the formation of business networks, proximity is more crucial for technical networks, while embeddedness plays an equally important role in the dynamics of business and technical networks.

Key words: Knowledge networks, industrial clusters, network dynamics, toy industry

JEL codes: D85, B52, O18

1. Introduction

The transfer of knowledge across organizations plays a critical role in the success of both high-tech regions and more traditional industrial clusters (Asheim, 1996; Owen-Smith and Powell, 2004; Bell and Zaheer, 2007). The higher innovative performance of Silicon Valley compared to Route 128 in the nineties, for instance, has been attributed to the presence of a regional culture of collaboration that fosters knowledge circulation (Saxenian, 1994). Similarly, informal contacts established by technicians and entrepreneurs along buyer-supplier networks in the "Third Italy" have been used to explain its superior performance over the Fordist industrial model (Becattini, 1990; Piore and Sabel, 1984). Informal contacts rapidly and effectively channel information and knowledge across firms otherwise limited to their internal pool of knowledge or bounded by their formal inter-organizational ties (e.g. buyer-supplier relations, R&D collaborations). These informal knowledge networks emerge out of direct and indirect relationships that individuals (e.g. engineers, entrepreneurs) use to access knowledge, and they are particularly important in clusters that are populated by communities of firms and people embedded in dense social relations of overlapping affiliations and obligations (Grabher, 1993).

Despite the growing interest in economic geography about informal knowledge networks in clusters, there is still relatively little evidence on their dynamics[1], i.e. how they form and change over time. Changes in informal knowledge networks are, by nature, difficult to track and observe empirically in clusters. More generally, as recently pointed out by Ahuja et al. (2012), little research has been conducted on the dynamics of networks compared to the impact of networks on economic outcomes. In order to fill this gap, our study focuses on the dynamics of business and technical knowledge[2] in industrial clusters by explicitly modelling

[1] A noticeable exception being the recent paper by Giuliani (2013), in which the author analyzes the formation of new knowledge ties among wineries in a Chilean cluster.

[2] In the paper we use the expression 'business' and 'market information' networks interchangeably.

the micro-level determinants of their macro-level structure. We propose to test a theoretical framework in which we develop the idea that the structure of technical and business networks is driven by different forces and exhibits different dynamics.

Whether geography and cluster membership matter *per se* for accessing advice networks (e.g. on technical problem solving or market information) has been widely debated in the literature. It appears that firms are not equally connected to this invisible web of knowledge (Breschi and Lissoni, 2009) and that the structure and possibly the drivers of these networks differ to large extent (Giuliani, 2007; Boschma and Ter Wal, 2007; Morrison and Rabellotti, 2009).

Prior research has emphasized the role of embeddedness, status and proximity to access external knowledge. Embeddedness of economic actors in a web of social ties (Granovetter, 1985) constructs trust and avoid opportunistic behaviours, while status explains why some actors tend to receive requests because of their perceived level of expertise and reputation (Cross et al, 2001). Besides these configurations, empirical evidence suggests that the proximity between actors also shape the formation of informal knowledge exchanges (Broekel and Boschma, 2012; Balland et al., 2014). Our theoretical framework discusses the different role played by these latter mechanisms on the dynamics of business and technical networks in industrial clusters. Although we expect embeddedness to play an important role in driving the formation of both business and technical knowledge, we argue that status is more important for the formation of business networks, while proximity is more crucial for the formation of technical networks. We test our hypotheses in the context of a traditional manufacturing cluster: the Toy Valley in the Valencia region. The Toy Valley emerged in the late 19th century, when a few families used their experience in handicraft, such as tinsmithing, to produce dolls, miniatures or small cars. This is an interesting case to test our theory and hypotheses since it represents a paradigmatic example of industrial cluster specialized in a traditional manufacturing activity involving a large population of SMEs. We collected the longitudinal network data by conducting semi-structured interviews with 75 firms, which represents 95% of the cluster population. To capture the impact of the different network forces, we modeled the dynamics of market information and technical advice networks by applying recent statistical techniques on network dynamics (Snijders et al., 2010). The empirical results indicate that embeddedness, status and proximity do play a different role in the dynamics of business and technical networks.

2. On clusters, networks and knowledge types

A vast bulk of empirical evidence has shown that informal networks represent effective channels to transfer knowledge across organizations (von Hippel, 1987; Uzzi, 1996; Almeida and Kogut, 1999). Geographical propinquity, as in industrial clusters, has been often regarded a key factor enhancing local knowledge transmission (Maskell, 2001; Pouder and St. John, 1996). This latter argument rests on the idea that localized knowledge is usually tacit, hence, its transmission occurs primarily through face-to-face contacts of co-located agents. In addition, clustering also generate local knowledge spillovers (Audretsch ad Feldman, 1996), which the literature variably defined as "industrial atmosphere", local "buzz" and "broadcasting" (Marshall, 1920; Grabher, 2002; Owen-Smith and Powell, 2004; Storper and Venables, 2004).

Additional arguments have been recently put forward to unravel the relation between clustering, knowledge diffusion and innovation. It has been argued that knowledge is a 'club good' (Breschi and Lissoni, 2001; Capello, 1999), which is shared in cohesive networks of cognitively close professionals, such as 'epistemic communities' (Gittelman, 2007) or communities of practice (Wegner, 2000). This latter approach suggests that knowledge is 'not in the air', and it does not flow randomly via unplanned spillovers, it rather circulates via (localized) networks among specific actors and communities (Almeida and Kogut 1999; Stuart and Sorenson, 2003). On the same vein, it has been disputed whether the local *buzz* can convey *all* sorts of informational flow to *all* cluster's members (Breschi and Lissoni, 2001).

This latter argument has been investigated in a number of recent empirical studies which indicate that informal networks in clusters can be associated with different types of knowledge. They circulate along networks of firms and individuals which show distinct structural properties and are in some instances overlapping (Vicente et al. 2011; Giuliani, 2007; Morrison and Rabellotti, 2009; Boschma and Ter Wal, 2007; Lissoni and Pagani, 2003; Dahl and Pedersen, 2004). Following this latter literature, in our paper we distinguish between two types of knowledge: technical know-how, which can be associated with procedural knowledge (Kogut and Zander, 1995); market information, which can be regarded as declarative knowledge (who knows/has what). The latter does not require specific skills to be understood and reused by somebody in the community who has an average expertise (Kogut and Zander, 1992). Its transfer across organizations is less problematic as compared to know-how. Indeed, technical know-how can be very firm or context-specific (Winter, 1987), hence it usually calls for some translation and socialization process (Nonaka, 1994), especially if it travels across organizations. So, actors get engaged in such a transfer either if there is some social obligation and cooperative norms (as it happens in cohesive networks) (Regan and McEvely, 2003), or when they expect some compensation or reward, for example the opportunity to be reciprocated in the future with useful knowledge (von Hippel, 1987). Although know-how is usually associated with tacit knowledge (Johnson et al. 2002), we acknowledge that technical knowledge can be codifiable and eventually articulated (Lissoni, 2002). Our point is that technical know-how, in the form of technical advices shared by firms, can include some substantial tacit component, in particular as compared to market information. Technical advices are indeed meant to solve technical problems, that is tasks which might require skills and competences that remain still highly tacit and embodied in individuals, despite the codification of technical know-how (Balconi, 2002).

In line with the literature on informal knowledge exchanges we adopt a multiplex perspective to disentangle how heterogeneous actors form different, though possibly overlapping communities who selectively participate to a variety of knowledge networks (e.g. business vs technical). However, different from these studies we go beyond the mere analysis of the structural properties of these networks, we investigate the drivers of network formation. In line with some recent studies that adopt a dynamic perspective (e.g. Giuliani 2013, Giuliani and Matta, 2013), we aim at showing which types of proximities and structural network configurations shape the evolution of the two different networks. In addition to these works, we extend the set of possible determinants of network formation by including a comprehensive list of proximities and structural network properties and as pointed out above, we adopt a multiplex perspective to unravel the different informational flows that are present in clusters. The determinants of network formation will be discussed in details in the next sections and testable hypotheses will be elaborated.

3. The dynamics of technical and business knowledge networks: theory and hypothesis

Embeddedness and networks dynamics. A central tenet in studies on industrial clusters is that embeddedness in cohesive webs of relationships yields positive return to its members (Asheim, 1996; Becattini, 1990), in particular it fosters the generation and circulation of knowledge through informal contacts (Uzzi, 1996; 1997; Grabher, 2002). This latter mechanism rests on a sociological argument suggesting that cohesive networks enhance trust (Festinger 1954; Coleman 1988). Trust emerges in cohesive networks because actors' interactions are prevalently reciprocal, repeated, and frequent. In such a stable set of relations, information can be easily cross-checked, also through indirect paths, and deviant and opportunistic behaviors promptly signalled and eventually sanctioned (McEvily, Perrone, and Zaheer, 2003). Organization studies have indeed shown that knowledge exchanges are frequent also between technicians of competing firms (von Hippel, 1987). They share technical information in the form of informal advices on a mutual basis, so they barter knowledge and expect this exchange to be reciprocated (Schrader, 1991). Moreover, the repeated day-to-day exchange among technicians favours the development of a common background, shared practices, a similar jargon and relation-specific heuristics (Uzzi, 1997). These workers and technicians who share such characteristics form 'epistemic communities' (Gittelman, 2007) and community of practice (Brown and Duguid, 2001), which in geographical bounded clusters are particularly dense and cohesive (Inkpen and Tsang 2005). Besides technical advice, informal contacts established along business relations, like in subcontracting networks, convey also sort of rumours about customer liability, market trends, business opportunities (Capello and Faggian, 2005). In order to grasp these pieces of information firms need to activate a search process, which means they have to look for and identify the right source of information (Hansen, 1999). The acquisition process of information is usually costless and immediate: since information is standardized and does not require any specific training on the side of the receiver (Kogut and Zander, 1992).

Since business information can be more easily transferred, it is more difficult to control its appropriation by other firms. Therefore, trust conveyed by embeddedness is also an important pre-requisite to the formation of business networks to avoid opportunist behaviors. On the contrary, the transfer of technical know-how requires additional investment in absorptive capacity (Cohen and Levinthal, 1990), as firms have to move, adapt, incorporate, master and replicate the new piece of knowledge (Hansen, 1999). The role of embedding is also important then, since the process of transferring knowledge is costly, the relation has to be more balanced and reciprocal. The above considerations lead to the idea that *embeddedness is important for the formation of new ties in both networks.*

Embeddedness is a composite concept that can be analytically distinguished in two main dimensions: social embeddedness and structural embeddedness (Cowan, et al., 2007). Structural embeddedness formally captures the idea that friends of friends become friends (i.e.

triadic closure). These third parties can help to collect high quality information on the reliability of the potential partner, so reducing uncertainty and asymmetric information (Gulati, 1995). They also generate a reputational lock-in, so a deterrent for the partner to behave opportunistically (Gulati and Gargiulo, 1999). As discussed above, structural embeddedness has been proved to be particularly relevant in industrial clusters (Uzzi, 1997). In a recent study, Giuliani (2013) confirms that structural embeddedness is an important driver of network evolution. Embeddedness can also be constructed through a common social context, with overlapping interpersonal ties often referred as strong ties (Granovetter, 1973), such as family ties and friendship. In the case of social embeddedness, the source of trust and the reputational effects come from shared experiences and previous collaborations. In clusters, this sense of belonging and the membership to a specific group (e.g. business, religious, political) or social community (e.g. friendship, family) help entrepreneurs to leverage their social networks to access a variety of resources, such as financial capital, business advices or management support (Asheim, 1996; Staber, 1997).

The above discussion leads to the following hypotheses:

- **H1:** *Structural embeddedness (triadic closure) is important for the dynamics of both the business and technical network (no significant differences are expected).*

- **H2:** *Social embeddedness (interpersonal ties) is equally important for the dynamics of both the business and technical network (no significant differences are expected).*

Status and network dynamics

Besides achieving higher embeddedness, network relations in clusters can also evolve towards a more uneven and hierarchical structure (Markusen, 1996). This dynamics is highly influenced by the role that *status* plays in the process of knowledge exchange. Robust evidence in social network literature suggests that actors ask advice to other member of a community who have higher status (Lazega et al. 2012). On the one side, advice seekers have the incentive to connect to high status people who provide them with valuable information. On the other side, advisors have the incentive to cooperate (i.e. provide advice), as they can gain recognition of their status (Blau, 1964). If the exchange dynamics is strongly shaped by status, new ties are established most likely with actors having the highest number of connections (i.e. network status), so the network evolve towards a hierarchical structure in which only a few actors are the most prominent (Barabasi and Albert, 1999).

Despite industrial clusters have been typically depicted as agglomeration of homogeneous firms that evenly share knowledge and information in an unplanned way (Maskell, 2001), the network literature on clusters has suggested that different, though possibly overlapping communities of firms and people own different capabilities and accordingly share knowledge and information in rather purposeful and selective way (Giuliani, 2007). There are several accounts of heterogeneous clusters in traditional manufacturing industries, where focal actors contribute either to the genesis of the cluster (Lazerson and Lorenzoni, 1999) or their innovative performance (Molina-Morales and Martinez-Fernandez, 2004), or act as brokers to access external knowledge (Cantner and Graf, 2006). Such heterogeneity emerges also in the local communities of entrepreneurs and technicians (Lissoni, 2001). In these contexts, reputation and status play a key role in shaping interactions (Romanelli and Khessina, 2005). Moreover, since knowledge exchanges take the form of trading (in particular as far as technical advice is concerned), firms that are regarded as the most knowledgeable in the cluster will attract a disproportionably higher amounts of contacts. Similarly, as far as market relations are concerned, leader firms, which are involved in bigger subcontracting networks, will receive far more enquiries than firm at the centre of small subcontracting networks. Moreover, it cannot be ruled out that in some cases where it is difficult to verify the quality of market information, affiliation with reputable actors is used to signal quality (Podolny, 1993).

To sum up, the above discussion suggests that *status* can positively affect the evolution of knowledge networks towards a hierarchical structure. But although we expect status to play an important role in advice networks in clusters in general, *we maintain that status plays a more important role in the dynamics of business networks than technical networks*. In fact, ties that are easy to create leads to a more hierarchical network structure (the most hierarchical network structure being the case where all firms ask advices to a single firm). If business information is easier to transfer than technical knowledge, then knowledgeable firms should be able to respond to more business advices requests than technical advices requests. Assuming that firms prefer to ask advices to most knowledgeable firms (i.e. with a highest status and recognition), the structure of the business network will tend to be more asymmetric than the technical network, which on the contrary will be more evenly distributed, also because it is based on reciprocity and trading of resources.

To test the different impact of status on the dynamics of market and technical networks, we distinguish between *network status* and *industrial status*. An attributed-based view of status is often adopted in the cluster literature, assuming that a formal status emerges out of some specific traits and characteristics that differentiate actors. Following this approach, status can be directly expressed by the industrial status of actors, measured in our study by the experience of actors in this industry. Over the years, a firm can establish a reputation, a recognized expertise and visibility that will lead to advices requests, especially from new entrants. Although this latter indicator measures the stock of knowledge a firm has accumulated over time, this formal way of measuring status ignores network structures. Recent network approaches adopted in cluster studies (Giuliani, 2013; Ter Wal and Boschma, 2009; Vicente et al., 2011) allows to go further and develop an analytical distinction between this attributed-based view of status and a more informal construct emerging out of endogenous network effects. Network status can be measured as a structural, degree-related concept which represents the hierarchical dynamics of the network structure. Overall it expresses the tendency to ask advices to actors that already receive many requests. This latter is an outcome-based measure of status at the network level, where the status of an actor grows as she receives advices' requests. The above discussion leads to the following hypotheses:

- **H3**: *Network status (popularity of advisors) plays a more important role in the dynamics of the business network than in the dynamics of the technical network.*
- **H4**: *Industrial status plays a more important role in the dynamics of the business network than in the dynamics of the technical network.*

Proximity and network dynamics

Economic geographers have long debated over the importance of different kinds of proximities other than geographical proximity (Boschma, 2005). The empirical evidence produced so far shows that different proximities matter for the performance of firms (Bell and Zaheer, 2007; Broekel and Boschma, 2012) and for knowledge transfer (Almeida and Kogut 1999; Breschi and Lissoni, 2009; Balland et al., 2013). Some studies show that diversity rather than similarity has been found to be relevant in driving the formation of inter-firm alliances (Powell et al., 2005). Overall, they tend to conclude that beyond co-location, the embeddedness in the same social context, the similarity in terms of knowledge bases, common culture, values, and norms, and the belonging to the same organizational group are crucial to enhance knowledge circulation and ultimately innovation.

Early studies have shown that in clusters geographical propinquity is important to establish informal collaboration and exchange knowledge (Saxenian, 1994). We also suggest that after controlling for other factors, day-to-day interactions require physically close contacts with those peers who can provide with just-in-time advice on urgent, though not necessarily critical problems. However, as discussed above, the transfer of procedural knowledge, like technical know-how, requires closer interactions than the exchange of declarative knowledge, i.e. market information, being the latter usually more codified. Moreover, market information is often exchanged along subcontracting networks, so the sources of information (i.e. contractors) are not necessarily located side by side to their targets (i.e. subcontractors).

Knowledge is in large part personal and idiosyncratic, and resides in the skills of individuals and in the routines of firms (Nelson and Winter, 1982), which makes knowledge difficult to be transferred across organizations. Each firm searches in close proximity to its knowledge bases, which makes knowledge cumulative and localized (Boschma, 2005). Therefore, firms tend to increasingly differ in their knowledge bases and rely on different heuristics to cope with similar problems. Such cognitive diversity is also present in clusters, despite their strong sectoral specialization (Maskell, 2001). Since learning and knowledge creation spring from bringing together complementary bodies of knowledge (Cohendet and Llerena, 1995), firms look for complementary assets. However, when firms are too distant in their knowledge bases, interaction is difficult if not impossible, indeed "information is useless if it is not new, but it is also useless if it cannot be understood" (Nooteboom, 2000: 153). The importance of cognitive proximity appears to be more relevant for mastering knowledge that is tacit and idiosyncratic. As argued above, technical advices might show a higher degree of tacitness than market information. *Therefore, we expect the two forms of proximity to play a more important role in the dynamics of technical than business network*. We can formulate the following hypotheses[3]:

H5. *Geographical proximity plays a more important role in the dynamics of the technical network than in the dynamics of the business network.*

H6. *Cognitive proximity plays a more important role in the dynamics of the technical network than in the dynamics of the business network.*

[3] In the empirical section, we will control for the effects of other forms of proximity that have been found to be relevant for network dynamics such as institutional and organizational proximity (Balland, 2012). We also control for social proximity by including the social relationship variable derived from hypothesis 2.

4. The study setting

The Toy Valley

The Spanish toy industry is highly concentrated and includes approximately 219 companies and more than 5.000 employees. Small and medium businesses predominate, with 96,8% of the total establishments having less than 50 employees. These firms account for 57,3% of total industry's revenues and contribute to about 80,7% in employment generation. Manufacturing activities concentrate in a few geographical areas in Spain. The region of Valencia is the leading hub, generating 42,80% of the industry's revenues and 38,4% of the units. Within the Valencia region, the so-called Toy Valley cluster agglomerates 42 toy manufacturers and accounts for more than 98% of the total regional production[4]. Located in a natural depression surrounded by mountains, the cluster spreads over 295,83 m^2 and four different municipalities (Ibi, Onil, Castalla and Tibi) with 41.729 inhabitants. The origin of the Toy valley dates back to the late 19th century, when families built on their experience and knowledge in handicraft occupations (e.g. tinsmithing activities) to start producing dolls, miniatures or small cars. Continuous technological change and firm creation then relegated traditional practices or inputs such as tin or porcelain. Since the mid seventies, the cluster has experienced deep transformations as a result of a fierce global competition. Flagship factories badly managed eventually closed, 25 dolls producers merged into a big successful company (FAMOSA), productive activities declined and many toy firms disappeared[5]. From then on, this negative trend ceased and the population of toys manufacturers started to stabilize again.

[4] Using the SABI database, Ybarra and Santa María (2008) identified 45 toy manufacturers in 2005. Further refinements through secondary sources (SABI, business directories and other specialized web pages) on recent information provided by AEFJ and AIJU, lead us to establish the above-mentioned number of toy producers.

[5] The regional Chamber of Commerce reported a decline of 21,9% in active units during the period 1996-2005.

The restructuring of manufacturing activities led to a strong fragmentation of the production process, which encouraged the creation of specialized suppliers mostly by local skilful employees. For instance, the switch from metal to plastic toys turned the subcontracting parts or moulds to smaller firms into a frequent phenomenon (Belso-Martínez and Escolano-Asensi, 2009). As Ybarra and Santa Maria (2008) highlight, these fragmentation and diversification processes have culminated in a "know-how subcontracting philosophy" characterized by continuous customizations to satisfy each customer's demands.

Strong technological capabilities, external openness and the joint action of different local actors has allowed deep transformations to overcome different disturbances while maintaining the cluster identity. The industrial base has also evolved and diversified, ranging now from furniture or packing to automotive and aeronautics. Business associations and technical centres such as *Asociación Española de Fabricantes de Juguetes* (AEFJ) and *Instituto Tecnológico del Juguete* (AIJU) have played a crucial role in the cluster, not only by providing advanced services, but also by fostering innovation activities (Holmström, 2006).

Data collection

To test our hypotheses on the underlying mechanisms of network dynamics in clusters, we need to map the informal interaction structure of the Toy Valley (i.e. identify technical and business links) at two different points in time, and collect data on actor's attributes (to construct control variables on actor's heterogeneity but also to derive proximity variables). By nature, these type of longitudinal network data are not available in secondary data sources such as patent documents (Ter Wal, 2013) or formal collaborative projects (Balland, 2012). Therefore, we had to adopt a primary data collection strategy (Ter Wal and Boschma, 2009; Giuliani and Bell, 2005).

Data have been collected in the Toy Valley cluster during the second half of 2011. In a preliminary stage, we conducted a combination of semi-structured questionnaires and face-to-face interviews on a sample of 8 local manufacturers, researchers and institutions[6]. Together from inputs from the literature (e.g. Giuliani, 2007 and 2013; Morrison and Rabellotti, 2009), we used this exploratory analysis to careful design the questionnaire and gather data on four different key dimensions: firm's characteristics, innovation practices, inter-organizational relationships and economic performance. A pre-test has been conducted to assess clarity, comprehension and completion time.

We submitted the survey to the 42 toy manufacturers[7] that design, produce or sell toys, including subsidiaries of national companies that perform within the cluster a part of the value chain. These manufacturers then indicated information on the providers, since no official register exists. We counted 52 suppliers for the toy sector in the cluster. Once discarded sporadic providers and self-employed through secondary sources and direct contacts with firms, we asked 38 firms to fill the survey. 33 accepted our invitation, and only 5 refused to fill the questionnaire. At the end, our population consists of 75 firms (i.e. toy manufacturers and their suppliers)[8], yielding an appropriate response rate of 95%, which is suitable for a whole-network approach (Wasserman and Faust, 1994). Peer debriefing by AIJU's experts confirmed that missing firms were very scarce and all of the most important local players

[6] This preliminary phase is also useful to interpret and corroborate our quantitative results with qualitative evidence.

[7] All the 42 firms surveyed were drawn from the business register of the local technical and business associations (i.e. AIJU and AEFJ), who also helped us to correctly identify the population. Further research through SABI and key informants was also performed.

[8] Data were collected at the end of the period, so an high entry-exit dynamics in the cluster would have limited the validity our dataset. We dispelled any concern about the stability of toy firms using the SABI database. Five firms started operations between 2005 and 2010, while six firms were extinguished. Once discarded multisectorial trading companies, just one firm could be considered as new entrant. However, due to creation in 2005, we treat it as a regular unit along the fieldwork. On the other hand, only two relevant toy firms ceased operations (more than nine employees or sales over one million euros).

were considered.

To insure respondent accuracy and avoid misinterpretation of the questions, we decided to administrate the questionnaire through a 40-50 minutes face-to-face interview with the top managers or business owners of each firm[9]. All these interviews have been conducted by a technician that has a deep knowledge of this industry and the Toy Valley[10]. To gather data at two different points in time, we used retrospective data collection strategy (we requested participants to report information in 2005 and 2010). Researchers increasingly emphasize the advantages and validity of retrospective designs (see de Vaus, 2001; Featherman, 1980; Miller et al., 1997). This strategy offers several avenues for research on network dynamics in clusters. First, it is often a more realistic research design than running interviews twice, from one time period to another. Especially in clusters where linkages are persistent (as it is the case in this study), it would require several years to observe significant change. Second, it offers consistency across observations, because the respondents are the same for the two time periods, so there is no heterogeneity in the nature of their responses.

But of course, the main limit of this strategy is potential cognitive distortions such as faulty attributions or lapses of memory (Huber and Power, 1985; Golden, 1992). So, to obtain reliable longitudinal network data, one first needs to establish clear cognitive boundaries to maximize accuracy of responses. In our case, respondents had a spatial limit (links with other firms within the cluster), an relational limit (only 74 other potential partners - the full list was given to them, so it is impossible to forget an actor) and a time limit (only 5 years before). In this very limited context we can expect accurate responses, even for the network ties from

[9] This strategy is related to the nature of the cluster, mainly made of small and medium-sized firms where top managers are involved in both the technical and market spheres. It also insures consistency accross firms.

[10] The interviewer is a former responsible of innovation programs at AEFJ (Asociación Española de Fabricantes de Juguetes).

2005. Accuracy can also be expected given the nature of the ties in our study. Network research examining retrospective respondent accuracy indicates that actors are more prone to recall enduring patterns of relationships. The type of network we investigate concern trust-based and advice ties, which are typically reoccurring and enduring patters of relationships. Thus, errors related to poor recall will hopefully not adversely affect the construct validity of the networks.

The chronological structure of the questionnaire, the inclusion of cues and the presence of the interviewer contributed to place the informants back in time and rationalize evidences. At the beginning of the meeting, we explained the benefits of the project and granted confidentiality to encourage the provision of precise data (Eisenhardt, 1989). Strong interest of informants guarantees the accuracy of their records (Miller at al. 1997), an incentive (access to results) was offered to foster a sense that the firms would take advantage from a rigorous involvement in the study. The interviewer guided participants through the different questions by prompting specific examples, facts or events. Also, he repeatedly reminded them that questions should be answered based on real situations during the pertinent time wave. These efforts have been proved to increase the effectiveness and accuracy of this methodology (Golden, 1992; Miller et al., 1997).

To rule out any concern about the reliability of the 2005 data, we also ran a specific statistical model of network formation (Exponential Random Graph Model) that only requires 2010 data. We ran this model and compared its results to those of the dynamic model as a robustness check. The results of the static model are in line with the results of the dynamic model reported in the paper[11].

[11] We thank on of the referee for suggesting this additional robustness analysis. The social embeddedness variable (H2), industrial status (H4), geographical proximity (H5) and cognitive proximity (H6) variables have exactly the same sign, level of statistical significance and differences of coefficients between the technical (TN)

In line with previous studies, we collected network data using an open "roster-recall" method (Giuliani and Bell, 2005; Boschma and Ter Wal, 2007; Morrison and Rabellotti, 2009). Each interviewee was confronted with an open list (roster) on which the names of toy manufacturers and suppliers from the Valley were already given. Each firm was asked to tick on the list from which companies technical advice or business information was given/received, and if they benefited from it. The respective questions read as follows: a) To which of the following firms on the list did you regularly ask technical advice in 2005/2010?; b) To which of the following firms on the list did you regularly ask business information in 2005/2010?. The avoidance of free recall procedures reduced the risk of underrepresentation of weak linkages (Lin, 2001; Elfring and Hulsink, 2007).

Table 1 presents descriptive statistics on firm level characteristics, such as size, decade of creation, legal structure, international operations and ownership (whether they are foreign or domestic). Additionally, membership, main business activities and detailed geographical location inside the cluster are reported. Building on this extensive data collection within the toy Valley, we constructed two different networks observed at two points of time, i.e. the business network and the technical network in 2005 and 2010. Each of these networks involves $n = 75$ actors and can be represented as a directed and binary $n*n$ graph $x = (x_{ij})$, where $x_{ij} = 1$ when actor i discloses asking business/technical advices to actor j $(i, j = 1, n)$. The general principles of the statistical techniques we used to model the dynamics of business and technical networks are described in the next section.

---

and business (BN) networks with ERGM and SAOM. A slight difference concern the structural embeddedness variable (H1), which still has the same sign and statistical significance, but is now stronger for the TN. Finally, network status (H3) has the same sign and also has a stronger impact for BN (as for SAOM) but it is now statistically significant for the TN. Control variables also show the expected sign and significance.

--- TABLE 1 ABOUT HERE ---

5. Econometric issues and specification of the statistical model

The statistical model for network dynamics

As discussed in the theoretical framework, a main source of knowledge dynamics within industrial clusters is based on informal contacts between actors to solve technical problems or to address business related issues. To explain how the structure of business and technical networks change over time, the econometric specification needs to model how choice of actors to ask advices and assistance to others change over time in the first place. Therefore, the dependent variable in this analysis is the formation of network ties between actors. It has been identified in the literature that network data violate the basic assumptions of most standard econometric techniques, because such a dependent variable suffers from conditional dependence, excess of zeros and over dispersion (Wasserman and Pattison, 1996; Burger, van Oort, and Linders, 2009; Snijders et al., 2010). To deal with these econometric issues, the literature has proposed more or less sophisticated statistical models and corrections, ranging from fixed effects approach at the dyadic or actor level (Mizruchi and Marquis, 2006; Corredoira and Rosenkopf, 2010), improved specifications of the gravity models of trade (Burger, van Oort, and Linders, 2009), Quadratic Assignment Procedures (Krackhardt, 1988; Broekel and Boschma, 2012), Exponential Random Graph Models (Robins et al., 2007; Broekel and Hartog, 2011) and Stochastic Actor-Oriented Models (Snijders et al., 2010; Balland, 2012).

In this paper, we use Stochastic Actor-Oriented Models (SAOM) because it is a statistical model for network dynamics that simultaneously allows to model structural dependencies (like triadic closure for instance) and proximity dimensions, while controlling for the heterogeneity of knowledge bases of actors. More precisely, we use SAOM implemented in the RSiena[12] statistical software (Ripley et al., 2012). It has been acknowledged recently that SAOM open new areas of inquiries to understand the spatial evolution of networks (Ter Wal and Boschma, 2009; Maggioni and Uberti, 2011). So far, SAOM have been applied to analyze the spatial dynamics of global and regional knowledge networks, for instance by Giuliani (2013) on a knowledge network of a wine cluster in Chile, by Balland (2012) on R&D collaboration networks in Europe, by Ter Wal on invention networks in Germany (2013) and more recently by Balland, de Vaan and Boschma (2013) on the evolution of the global video games industry. For a general introduction to SAOM see Snijders et al. (2010), for more technical details see Snijders et al. (2001).

SAOM are a class of dynamic models based on Markov random graph, which induce that change probability only depends on the current state of the network. The change from one state to another, i.e. the network dynamics, results from micro-decision of actors to access business or technical knowledge of others. These micro-level decisions are based on the preferences, constraints or opportunities of ego that are determined by the previous network structure configuration, their proximity to others, or their internal capabilities and status. More formally, at stochastically determined moments, actors can change their relations with other actors by deciding to ask new business or technical advices (create new ties), continue to ask such assistance (maintain ties) or finally stop asking (dissolve ties).

Estimation of the coefficients is achieved by the mean of an iterative Markov chain Monte Carlo algorithm based on the method of moments (Snijders, 2001). The stochastic approximation algorithm simulates the evolution of the network and estimates the parameters (for geographical proximity, triadic closure…) that minimize the deviation between observed and simulated networks. Over the iteration procedure, the provisional parameters of the

[12] In the SAOM literature, the acronym SIENA is often directly used, which means "Simulation Investigation for Empirical Network Analysis". The RSiena package is implemented in the R language and can be downloaded from the CRAN website: http://cran.r-project.org/web/packages/RSiena/.

probability model are progressively adjusted in a way that the simulated networks fit the observed networks. The parameter is then held constant to its final value, in order to evaluate the goodness of fit of the model and to compute the standards errors. To compare the dynamics of technical and business advices networks, we will run the same model specification (i.e. using the same variables of interests and control variables) to model the dynamics of both networks.

The variables

Embeddedness. To estimate how network cohesion shapes the dynamics of advices networks in clusters, we model the effect of structural embeddedness (H1) and social embeddedness (H2). To operationalize structural embeddedness, we refer to triadic closure. This network-based statistics is computed from the particular architecture of advices ties in the given network of interest (technical or business): $T_i = \sum_{j,h} x_{ij} x_{ih} x_{jh}$. Triadic closure reflects the endogenous evolution of the business/technical network towards closed triads in advices exchanges. Social embeddedness is computed from the direct observation of social ties. Computed at the dyadic level, this dichotomous measure (0/1) indicates the presence/absence of family ties between owners of the different companies.

Status. To further capture the role of status, we operationalize the concepts of network status (H3) and industrial status (H4). Network status is a structural variable (like triadic closure) computed from the distribution of in-coming ties in the network of interest (i.e. the distribution of advices requests actors receive). Therefore, network status is operationalized as a preferential attachment mechanism (Barabasi and Albert, 1999), given by $P_i = \sum_j x_{ij} \sqrt{\sum_h x_{hj}}$ and it captures the endogenous construction of status in advice networks (the perceived status is growing with the number of advices requests). While network status is a structural variable, industrial status is an attribute-based variable, simply constructed from the number of years a given firm has been active in the industry.

Proximity. We focus on the geographical (H5) and cognitive (H6) dimensions of proximity. By construction these variables are dyadic (as social embeddedness). Geographical proximity is obtained by subtracting the physical distance between two firms (in kilometers) to the maximum occurring distance value. Cognitive proximity is a valued measure, corresponding to the number of digits the two companies share in common in their NACE 4 code.

Control variables. We first included a set of important variables related to the structural path dependence in network dynamics, i.e. explaining how the structure of the network reproduces itself over time (Snijders et al., 2010; Rivera et al. 2010). We included the out-degree (density) effect to control for the overall tendency of actors to form ties (Snijders et al. 2010). Since we analyze directed networks, we also expect that actors will only exchange knowledge with whom they already receive knowledge, so we account for reciprocity. The direction of knowledge flows within these triangles is captured by the cyclicity variable. Finally, the hierarchical nature of the out-degree distribution is also tested. All structural-level effects (structural embeddedness, network status and the other structural control variables) and their mathematical formulas are detailed in Table 2. Another set of variables refers to other important proximity dimensions (Boschma, 2005; Balland, 2012). These dyadic variables are either constructed from secondary data or from the perception of actors themselves. Organizational proximity is a dummy variable, taking the value 1 if the two actors belong to the same group of firms or if they have formal sub-contracting relationships[13]. Institutional proximity is a dummy variable, referring to the similarity of the legal status of the companies, for instance it takes the value 1 if both actors are corporations. We included a perceived similarity measure, by asking directly to the actors the degree of similarity they think they have with others (0, 1, 2, or 3). Table 3 presents descriptive statistics of these dyadic variables (social embeddedness, geographical and cognitive proximity and the other dyadic control

[13]It should be noted that informal, or even secret sub-contracting relationships between firms are by definition difficult to observe, and therefore won't be captured by the organizational proximity variable.

variables). In general, these proximity variables are not highly correlated. We also included controls as the firm level such as R&D intensity, size and level of education of employees but these variables did not significantly influence the dynamics of business and technological networks[14].

--- TABLE 2 ABOUT HERE ---

--- TABLE 3 ABOUT HERE ---

6. Empirical results

Descriptive statistics and changes in the structure of the technical and business networks from 2005 to 2010 can be found in Table 5. A first observation is that actors of the Toy Valley are more active in asking market information than technical advices in both periods. On average, actors only ask technical advices to about 14 different actors, while they ask market information to about 17 different actors. This finding is in line with previous evidence suggesting that market information, also due to the lower cost of transfer, circulates more widely than technical know-how (Morrison and Rabellotti, 2009). A second interesting finding, as depicted in Figure 1, shows that the distribution of activity in asking advices (out-degree distribution) and receiving requests (in-degree distribution) is very skewed. Few actors are very active in asking advices (or very popular in receiving requests), while most of the actors asks (or receive) few advices (or requests). This result is in line with previous studies that have shown the hierarchical and uneven nature of knowledge exchanges in clusters (Giuliani, 2007).

--- TABLE 4 ABOUT HERE ---

--- FIGURE 1 ABOUT HERE ---

In order to test our hypotheses and explain how the network structure changes overtime, we apply the statistical model described in section 5. All parameter estimations are based on 2000

[14] The full models including these variables are available upon request.

simulation runs, and convergence of the approximation algorithm is excellent for all the variables of the different models, being the correlation between the two networks around 0,5 (t-values < 0.1). The interpretation of the β reported is straightforward, they are non-standardized coefficients obtained from logistic regression analysis (Steglich et al., 2010). Under the null hypothesis that the parameter value is 0, statistical significance can be simply tested with t-statistics following a standard normal distribution. Therefore, these coefficients are log-odds ratio, corresponding to how the log-odds of tie formation change with one unit change in the corresponding independent variable. Table 5 presents the results of parameter estimations of the model for technical advice network dynamics (left column), but also the results of parameter estimations for business network dynamics (right column)[15].

Our first set of hypotheses refers to the role of embeddedness in shaping knowledge circulation in clusters. As shown in Table 5, the coefficient of triadic closure (i.e. structural embeddedness) is positive and significant in both cases, and its magnitude is very similar (β=0.048 for the technical network and β=0.046 for the business network). Similarly, social embeddedness is also a strong driver of both networks, as the coefficient for social ties is positive and significant in both cases, although it is a bit lower for the technical network (β=2.310 for the technical network and β=3.120 for the business network), suggesting that family ties matter more when interactions deal with market information. The reason behind it might be that these firms are typically family-owned business, so business information is shared prevalently in the inner circles of family owners. Overall, the above findings confirm our Hypotheses 1 and 2, structural embeddedness and social embeddedness are strong drivers of both networks. Our second set of hypotheses concerns the effects of status. In this case the two networks show a very different dynamics. The coefficient for network status (in-degree

[15]Even though the two networks are modeled separately, they are specified with the same techniques and with the same independent variables in order to understand whether the driving forces on technical ties and business ties within industrial clusters are the same.

popularity) is positive and significant for business network (β=0.250), while it is smaller and not even significant for technical network (β=0.035). Therefore, actors that receive many requests of market information tend to attract disproportionally new requests in the next period. This latter effect suggests that reputation plays a very important role for market information sharing. Similarly, industrial status shapes the dynamics of business advices (β=0.013), while it is not significant for the dynamics of technical networks. These latter results confirm hypotheses 3 and 4. The final set of hypotheses concerns the role of proximity. In this case also, the dynamics of the technical and business network seem to be driven by different forces. The coefficient for geographical proximity is positive in both cases, but it is only significant in the technical network. Moreover, its magnitude is twice as much for the technical (β=0.049) than for the business network (β=0.023). The same pattern is found for cognitive proximity: positive but not significant in the business network, while important for technical advices. These latter results confirm hypotheses 5 and 6.

Concerning the control variables, the *rate parameter* (i.e. stability of the network ties)[16] is lower for the technical network and *reciprocity* is not significant in the business network. These latter results seem to confirm that know-how is sensitive to stable, reciprocal links between actors (von Hippel, 1994). Common understanding and knowledge transfer require time to be formed and nurtured.

The negative effect of *cyclicity* indicates hierarchy in triads for both networks, i.e. that neither market information nor technical advices circulate in cycles of the type $i \rightarrow j \rightarrow h \rightarrow i$, but it is more likely that one actor dominates the triad and provides with knowledge the two others. In addition, we observe that in both networks some actors tend to be very active in asking

[16]The rate parameter indicates the speed of change of the dependent variable (tie formation) between 2005 and 2010.The rate parameter of the business network is higher than technical advice network, which indicates that actors tend to change their partners more often when search for market information than when they ask for technical advice.

advice, and the positive activity effect shows that actors that asked many advices in the past tend to ask many advices in the next period. In this type of configuration, two firms share information (regardless of the direction of the information flow), while a third unit gives them advice without being reciprocated in turn. In other words, this latter firm absorbs knowledge from either intra or extra-cluster repositories, and later diffuses this knowledge between two local partners that frequently used it in a synergistic manner. This is confirmed by our interviews with local experts who revealed that toy firms transfer information about new product designs or market trends, which later are shared between input suppliers in order to provide technical solutions to face new challenges.

Turning now to the dyadic control variables, it appears that other proximity variables play a more important role in shaping the technical network than the business network. In particular institutional proximity has a positive and significant impact for the formation of technical advices, while it is not significant for business ties. Organizational proximity and perceived similarity are not significant for bother networks, but the coefficient has a positive sign in the case of technical networks and a negative sign for business networks.

--- TABLE 5 ABOUT HERE ---

7. Discussion and conclusion

Although networks in clusters have received increasing consideration during the last decade in economic geography, theoretical and empirical researches on the dynamics of these networks remains largely underdeveloped (Giuliani, 2013). This paper explores this question and contributes to a better understanding of informal knowledge exchanges in clusters, i.e. how the local "buzz" is organized (Storper and Venables, 2004; Owen-Smith and Powell, 2005). Using recent statistical techniques (i.e. actor-based model by Snijders et al., 2010) we contribute to the empirical literature on networks in clusters by explicitly modelling the micro dynamics of technical and business networks formation. There are only few empirical attempts in this area (see Giuliani 2013 and Giuliani and Matta 2013), partly because collecting longitudinal data is particularly cumbersome, but also because the empirical literature on knowledge networks in clusters is very incipient. So far the literature had first to make the point that local knowledge spillovers do not freely circulate in space, and that social networks play an important role in this process (Breschi and Lissoni, 2001). Accordingly the empirical works in this area have been devoted on the one hand to describe the structural features of knowledge networks, arguing that clusters are populated by a variety of informational networks (Giuliani and Bell, 2005; Vicente et al . 2011); on the other hand, they have analysed the impact of network position on the performance of firms or the cluster (Boschma and Ter Wal, 2007; Morrison, 2008).

We add to the existing studies on network dynamic in clusters (in particular Giuliani 2013) by extending the framework of analysis, which brings together both the structural and the spatial dimensions of networks (Balland et al., 2013). We explain the formation of knowledge networks in clusters as an outcome of embeddedness, status and proximity, and also to what extent these latter mechanisms play a different role according to the type of knowledge exchanges (i.e. for the dynamics of technical and business knowledge).

Our multiplex approach constitutes an additional contribution to the literature. We unveil differences which usually remain hidden in most studies on networks in clusters. Indeed, the few studies in this field that have differentiated between two or more types of network usually adopt a static approach, and focus mainly on structural properties (Boschma and Ter Wal, 2007; Giuliani, 2007; Morrison and Rabellotti, 2009). Conversely, those that have recently dealt with the dynamics of knowledge networks (e.g. Giuliani 2013, Balland, 2012), analyse only one single network. However, there is an increasing interest in the literature for multiplex network research (Ahuja et al., 2012). Our study provides evidence showing that the drivers of knowledge dynamics can be very different. In particular, we demonstrate that some factors exert similar influences in both networks, like structural and social embeddedness, while others (i.e. status, proximity) present remarkable differences. Building ties requires time and efforts in the two gradually changing networks: complementarities, mutual awareness and trust underlie both technical and business interactions. For instance, new toys' designs involve co-developing crucial inputs (e.g. molds), which requires a great deal of information sharing concerning both technical details, as well as about customer needs. These exchanges are easier if peers are embedded in the same social and structural setting. This latter finding further supports the idea that embeddedness plays a key role in driving the formation of inter-organisational networks (Ingram and Roberts (2000) and in particular in clusters (Becattini et al., 1990; Inkpen and Tsang, 2005). Our evidence is also in line with the recent empirical studies on knowledge dynamic in clusters, which show that social ties are important drivers of knowledge diffusion (Giuliani, 2013; Giuliani and Matta, 2013).

Instead, differences emerge in the underlying cost of effectively transferring knowledge, which is usually higher for the technical than for the market information network. Indeed, the technical advice network shows higher stability and reciprocity than the business network.

The lack of reciprocity in the business network is mirrored by the tendency for business advice givers to obtain information from others firms they have not provided advice to. Therefore, *stability* is a peculiar feature of technical knowledge network only, but not of all kind of information-based networks in clusters, as usually claimed in the cluster literature.

Business networks are characterized by a combination of lack of reciprocity at dyadic level, high hierarchy and high industrial status. Firms that gained a solid market position are asked for advice by their local counterparts increasingly often, because of their strategic and market knowledge, valuable experiences and their capabilities. However, while incoming business knowledge from popular firms appears extremely valuable, feedback from less popular units seems to be scarcely appreciated; in other words: advice seekers have little to offer in the eyes of local leaders (i.e. firms with high status). Our interviews to experts in the Toy Valley confirm that top local firms are usually requested to provide advices concerning market diagnostics or business strategies rather frequently. Nevertheless, they refrain from engaging in exchanges that may damage their market position or erode their relative status vis-à-vis other cluster members. Similar findings are found in Trapido (2013), who shows that status might generate rivalry among competing firms: in such a context firms avoid to share information with rivals, who might potentially harm their status.

The impact of status on network formation seems to suggest a tendency towards increasing concentration of knowledge in a few hands, as found by the recent studies on knowledge networks in clusters (see Giuliani, 2013; Giuliani and Matta, 2013). Nevertheless our case shows that the underlying forces that drive this process are not necessarily of a Mertonian nature (i.e. rich get richer). Our approach, by distinguishing between market and technical knowledge and by looking at the diffusion of knowledge in triads is able to illustrate these dynamics on a fine-grained level. We show that preferential attachment is a dominant driving force in the dynamic of the business network, but it plays a minor role for the formation of technical advice networks, which are far more stable and conditioned by proximity factors (see below). These are salient illustrations of the different hierarchal structure of the two networks which can be highlighted only in a multiplex framework of analysis.

The two types of networks also differ in how proximity shapes their formation. The existence of the intimate relationship between proximity and the characteristics of the knowledge shared can be corroborated. Owing to the complex and idiosyncratic nature of technical knowledge, cognitive and geographical proximity become crucial for its diffusion. Likewise, institutional proximity seems to bolster the role of the aforementioned dimensions of proximity. Undoubtedly, a set of common norms and values eases the exchanges of information by generating trust and by resembling the cognitive models and language that firms use to make sense of business world. Following this line of reasoning, the irrelevance of the organizational proximity possibly derives from a displacement effect exercised by trust and institutions. Contracts and control are relegated by less formal rules or social mechanisms as dominant regulators of interactions (mostly of personal nature). Last, the geographical proximity activates and galvanizes institutional, cognitive and social proximities because co-location usually implies common institutional environments, shared views and face-to-face interactions. All the above finding on proximity in technical knowledge networks are in line with the conventional accounts of knowledge diffusion in clusters via informal contacts (Dahl and Pedersen, 2004). Conversely, these results seems to be at odd with Giuliani (2013) and Giuliani and Matta (2013), who found that both geographical and cognitive proximities insignificant. However, such a discrepancy might be due to the specificity of the case study, or also to the different definition of knowledge, which in those studies might sum up different and perhaps confounding effects. We find instead that proximity plays a limited role in generating business contacts between local units. While it is true that an important share of the technical advice needed to produce toys is available in the close neighbourhood, business knowledge does not necessarily comes with proximity.

The idea that business knowledge and technical knowledge do not follow the same dynamics calls for further research. First, we provide empirical evidence that is circumscribed to a specific cluster and industry: the Toy Valley in Spain. Although it represents a typical example of traditional manufacturing cluster, further empirical analysis covering different sector and geographical contexts are needed to corroborate, refine or contrast our findings. It would also be interesting to see whether business and technical knowledge in high-tech sectors (biotech, information technology…) also follow different paths. Second, collecting longitudinal data on informal knowledge network is a very challenging task. Collecting primary data trough survey and interview is time consuming, and it is often not realistic to collect different waves of data if the required interval is too long, which limits the number of studies on network dynamics in clusters. Our strategy, based on retrospective data collecting technique, could open avenues for research on network dynamics in clusters. At this stage, more methodological contributions are needed to carefully collect longitudinal network data and limit recalling bias. Third, the dynamics of business knowledge and technical knowledge might be influenced by other factors related to the complex web of business, technical, social or sub-contracting ties in a cluster. Even though we made an attempt to address network multiplexity within industrial clusters by analyzing a large set of social and organizational ties, it would be worth investigating the role of other type of ties that are more informal (or even secret), that involve other actors in the cluster (e.g. financial sector, public sector) or even external to the cluster. Finally, we analyzed how actors of the clusters learn from each other by asking advices, but we did not investigate directly the value of knowledge shared in these informal business and technical networks. In other words, we assumed every knowledge ties to be equal, but it is very likely that some knowledge ties are critical for a firm's performance and survival while others have very little impact. How the value of knowledge impacts its dynamics in clusters is worth investigating and should be taken up by further research.

8. References

Ahuja, G., Soda, G. and Zaheer, A. (2012) The Genesis and Dynamics of Organizational Networks. *Organization Science,* 23: 434-448.

Almeida, P., Kogut, B. (1999): Localization of knowledge and the mobility of engineers in regional networks. *Management Science,* 45: 905–917.

Asheim B.T. (1996) Industrial districts as 'learning regions': a condition for prosperity. *European Planning Studies,* 4:379-400.

Audretsch, D.B., Feldman, M.P. (1996) R&D spillovers and the geography of innovation and production. *American Economic Review,* 86: 630-640.

Balconi, M. (2002) Tacitness, codification of technological knowledge and the organisation of industry. Research Policy 31: 357–379.

Balland, P.A. (2012) Proximity and the Evolution of Collaboration Networks: Evidence from Research and Development Projects within the Global Navigation Satellite System (GNSS) Industry. *Regional Studies,* 46: 741-756.

Balland, P.A., Boschma, R. and Frenken, K. (2014) Proximity and Innovation: From Statics to Dynamics, Regional Studies, forthcoming.

Balland, P.A., de Vaan, M., Boschma, R. (2013) The Dynamics of Interfirm Networks along the Industry Life Cycle: The Case of the Global Video Games Industry 1987-2007. *Journal of Economic Geography, forthcoming*.

Barabasi, A., Albert, R. (1999) Emergence of Scaling in Random Networks. *Science,* 286: 509–512.

Becattini, G. (1990) The Marshallian industrial district as a socio-economic notion, in Pyke F., Becattini G., Sengenberger W. (eds.) *Industrial districts and inter-firm co-operation in Italy*, pp. 37-51. International Institute for Labour Studies, Geneva.

Bell, G.G., Zaheer, A. (2007) Geography, networks and knowledge flow, *Organization Science,* 18: 995-972.

Belso-Martínez, J., Escolano-Asensi, C. (2009) La externalización de actividades como estrategia competitiva en el sector juguetero español. Consideraciones desde una perspectiva espacial. *Economía Industrial* 372: 115-127.

Blau, P. (1964) *Exchange and Power in Social Life*. New York: J. Wiley

Boschma, R.A. (2005) Proximity and innovation: A critical assessment. *Regional Studies,* 39: 61-74.

Boschma, R.A., Ter Wal, A.L.J. (2007) Knowledge networks and innovative performance in an industrial district: the case of a footwear district in the South of Italy. *Industry and Innovation*, 14: 177-199.

Breschi S., Lissoni F. (2001) Knowledge Spillovers and Local Innovation Systems: A Critical Survey. *Industrial and Corporate Change,* 10(4): 975-1005.

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

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

Broekel, T., Hartog, M. (2013) Explaining the structure of inter-organizational networks using exponential random graph models: does proximity matter?. *Industry and Innovation*, 20:3, 277-295.

Brown, J.S., Duguid, P. (2001) Knowledge and organization: A social practice perspective. *Organization Science*, 12: 198-213.

Burger, M., van Oort, F., Linders, G.J. (2009) On the Specification of the Gravity Model of Trade: Zeros, Excess Zeros and Zero-inflated Estimation. *Spatial Economic Analysis,* 4: 167-190.

Cantner U., Graf, H. (2006) The Network of Innovators in Jena: An Application of Social Network Analysis. *Research Policy,* 35(4): 463-480

Capello, R. (1999) Spatial Transfer of Knowledge in High Technology Milieux: Learning Versus Collective Learning Processes. *Regional Studies,* 33: 353-65.

Capello, R and Faggian, A. (2005) Collective learning and relational capital in local innovation processes. *Regional Studies,* 39 (1): 75-87.

Cohen, W.M., Levinthal, D.A. (1990) Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly,* 35: 128-152.

Coleman, J. (1988) Social Capital In the Creation of Human Capital. *American Journal of Sociology,* 94: 95-120.

Cohendet, P., Llerena, P. (1995) Diversity and Specialisation: an exploration of mechanisms valorising diversity, unpublished paper, University of Strasbourg, January.

Corredoira, R., Rosenkopf, L. (2010) Should Auld Acquaintance Be Forgot? The Reverse Transfer of Knowledge through Mobility Ties. *Strategic Management Journal,* 31: 159-181.

Cowan, R., David, P.A., Foray, D. (2000) The Explicit Economics of Knowledge Codification and Tacitness. *Industrial and Corporate Change,* 9: 211-253.

Cowan, R., Jonard, N., Zimmermann, J. B. (2007) Bilateral collaboration and the emergence of innovation networks. *Management Science,* 53: 1051-1067.

Cross, R., Borgatti, S.P., Parker, A. (2001) Beyond answers: Dimensions of the advice network. *Social Networks* 23: 215-235.

Dahl, M.S., Pedersen, C.O.R. (2004) Knowledge flows through informal contacts in industrial clusters: myth or reality?. *Research Policy,* 33: 1673-1686.

De Vaus, D. A. (2001) Research design in social research. London: SAGE

Dosi, G. (1988) Sources, procedures and microeconomic effects of innovation. *Journal of Economic Literature*, 26: 1120-1171.

Eisenhardt, K.M. (1989) Building theories from case study research. *Academy of Management Review*, 14(4), 532-550.

Elfring, T., Hulsink, W. (2007) Networking by Entrepreneurs: Patterns of Tie—Formation in Emerging Organizations. *Organization Studies*, 28: 1849-1872

Featherman, D. L. (1980) Retrospective longitudinal research: Methodological considerations. *Journal of Economics and Business 32*(2): 152-169.

Festinger, L. (1954) A theory of social comparison processes. *Human Relations,* 7: 117-140.

Gittelman, M. (2007) Does geography matter for science-based firms? Epistemic communities and the geography of research and patenting in biotechnology. *Organization Science*, 18: 724-741.

Giuliani, E. (2007) The selective nature of knowledge networks in clusters: evidence from the wine industry. *Journal of Economic Geography,* 7: 139-168.

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

Giuliani, E., Bell, M. (2005) The Micro-Determinants of Meso-Level Learning and Innovation: Evidence from a Chilean Wine Cluster. *Research Policy,* 34: 47-68.

Giuliani E., Matta, A. (2013) Impact Evaluation with Social Network Analysis Methods, Program for Supply Chain Development in the Province of Cordoba, Argentina. Inter-American Development Bank (ATN/ME-8112-AR).

Golden, B. (1992) The past is the past - or is it? The use of retrospective accounts as indicators of past strategy. *Academy of Management Journal* 35(4), 848-860.

Grabher, G. (2002) Cool projects, boring institutions: temporary collaboration in social context. *Regional Studies,* 36: 205-214.

Grabher, G. (1993) The weakness of strong ties: the lock-in of regional development in the Ruhr-area. In: Grabher, G. (Ed.), The Embedded Firm: on the Socioeconomics of Industrial Networks,pp. 255–278. Routledge, London and New-York.

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

Granovetter, M. (1985) Economic action and social structure: the problem of embeddedness. *American Journal of Sociology,* 91: 481-510.

Hansen, M.T. (1999) The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge Across Organization Subunits. *Administrative Science Quarterly,* 44: 82-111.

Holmström, M. (2006): Globalisation and good work: IMPIVA, a Spanish Project to regenerate industrial districts. *Journal of Economic and Social Geography,* 97: 491-502.

Huber, G. and Power, D. (1985) Retrospective reports of strategic-level managers: Guidelines for increasing their accuracy. *Strategic Management Journal* 6(2), 171–180.

Inkpen, A., Tsang, E. (2005) Social capital networks, and knowledge transfer. *Academy of Management Review*, 30: 146-165.

Kogut, B., Zander, U. (1992) Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science,* 3: 383-97.

Kogut, B., Zander, U. (1995): Knowledge, market failure and the multinational enterprise: a reply. *Journal of International Business Studies,* 26: 417-26.

Krackhardt, D. (1988) Predicting with Networks: A Multiple Regression Approach to Analyzing Dyadic Data. *Social Networks,* 10: 359-381.

Johnson, B, Lorenz, E. and B-Å Lundvall (2002). Why all this fuss about codified and tacit knowledge?. *Industrial and Corporate Change*, 11(2): 245-262.

Lazega, E. , Mounier, L., Snijders, T., Tubaro, P. (2012) Norms, status and the dynamics of advice networks. *Social Networks,* 34: 323-332.

Lazerson, M.H., Lorenzoni, G. (1999) The firms feed industrial districts: A return to the Italian source. *Industrial and Corporate Change,* 8: 235–266.

Lin, N. (2001) Social capital: A theory of social structure and action. Cambridge:
Cambridge University Press.

Lissoni, F. (2001) Knowledge codification and the geography of innovation: The case of the Brescia mechanical cluster. *Research Policy,* 30: 1479–1500.

Maggioni, M., Uberti, E. (2011) Networks and geography in the economics of knowledge flows. *Quality and Quantity*, 45: 1065-1066.

Markusen, A. (1996) Sticky places in slippery space: A typology of industrial districts. *Economic Geography*, 72: 294–314.

Marshall, A. (1920) *Principles of Economics* (8th edition). Macmillan, London.

Maskell, P. (2001) Towards a knowledge-based theory of the geographical cluster. *Industrial and Corporate Change,* 10: 921-943.

McEvily, B., Perrone, V., Zaheer, A. (2003) Trust as an organizing principle. *Organization Science*, 14(1): 91-103.

Miller, C., Cardinal, L., Glick, W. (1997) Retrospective reports in organizational research: A reexamination of recent evidence. Academy of Management Journal, 40(1): 189–204.

Mizruchi, M.S., Marquis, C. (2006) Egocentric, sociocentric, or dyadic? identifying the appropriate level of analysis in the study of organizational networks. *Social Networks*, 28: 187-208.

Molina-Morales, F.X., Martinez-Fernandez, M.T. (2004) Factors that identify industrial districts: An application in Spanish manufacturing firms. *Environment and Planning* A, 36: 111–126.

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

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

Nonaka, I. (1994) A dynamic theory of knowledge creation. *Organization Science*, 5:14-37.

Nooteboom, B. (2000) Learning by Interaction, Absorptive Capacity, Cognitive Distance and Governance. *Journal of Management and Governance*, 4: 69-92.

Owen-Smith, J., Powell, W.W. (2004) Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. *Organization Science*, 15: 5-21.

Piore, M.J., Sabel, C.F. (1984) *The Second Industrial Divide: Possibilities for Prosperity*. Basic Books, New York.

Podolny, J. (1993) A status-based model of market competition. *American Journal of Sociology*,98: 829-872.

Pouder, R., St John, C.H. (1996) Hot spots and blind spots: Geographical clusters of firms and innovation. *Academy of Management Review*, 21: 1192-1225.

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 sciences. *American Journal of Sociology*, 110(4): 1132-1205.

Ripley, R., Snijders, T., Preciado, P. (2012) *Manual for RSiena*, University of Oxford: Department of Statistics, *Version June 6*.

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

Robins, G., Pattison, P., Kalish, Y., Lusher, D. (2007) An introduction to exponential random graph (*p**) models for social networks. *Social Networks,* 29: 173-191.

Romanelli, E., Khessina, O. (2005) Regional industrial identity: cluster configurations and economic development. *Organization Science*, 16: 344–358.

Saxenian, A. (1994) *Regional Advantage Culture and Competition in Silicon Valley and Route 128*. Harvard University Press, Cambridge.

Schrader, S. (1991) Informal technology transfer between firms: Cooperation through information trading. *Research Policy,* 20: 153-170.

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

Staber, U. (1997) An ecological perspective on entrepreneurship in industrial districts. *Entrepreneurship & Regional Development*, 9(1): 45-64.

Steglich, C. E. G., Snijders, T. A. B., Pearson, M. (2010) Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology,* 40: 329–393.

Storper, M., Venables, A. (2004) Buzz: face-to-face contact and the urban economy. *Journal of Economic Geography,* 4: 351-370.

Stuart, T., Sorenson, O. (2003) The geography of opportunity: Spatial heterogeneity in founding rates and the performance of biotechnology firms. *Research Policy,* 32: 229–253.

Ter Wal, A.L.J. (2013) The Dynamics of the Inventor Network in German Biotechnology: Geographical Proximity versus Triadic Closure. *Journal of Economic Geography, forthcoming.*

Ter Wal, A.L.J., Boschma, R.A. (2009) Applying social network analysis in economic geography: theoretical and methodological issues. *The Annals of Regional Science,* 43: 739-756.

Uzzi, B. (1996) The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *American Sociological Review,* 61: 674–698.

Uzzi, B. (1997) Social structure and competition in interfirm networks: the paradox of embeddedness. *Administrative Science Quarterly*, 42: 35–67.

Vicente J., Balland, P.A., Brossard, O. (2011) Getting into Networks and Clusters: Evidence from the Midi-Pyrenean Global Navigation Satellite Systems (GNSS) Collaboration Network. *Regional Studies,* 45: 1059-1078.

von Hippel, E. (1987) Cooperation between rivals: Informal know-how trading. *Research Policy*, 16: 291–302.

Wasserman, S., Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge University Press, New York.

Wasserman, S., Pattison, P. (1996) Logit models and logistic regressions for social networks. I. An introduction to Markov graphs and *p**. *Psychometrika*, 61: 401–425.

Winter, S. G. (1987) Knowledge and competence as strategic assets, in Teece, D.(ed.) The Competitive Challenge: Strategies for Industrial Innovation and Renewal, pp. 159-184. Ballinger, Cambridge.

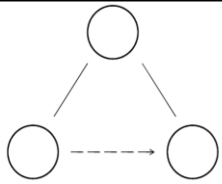
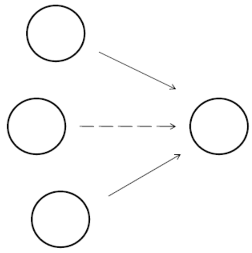
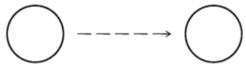
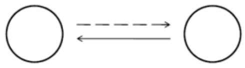
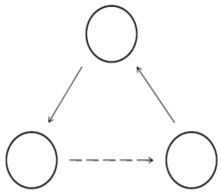
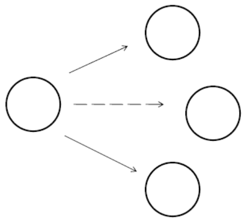
Ybarra, J., Santa María, M. (2008): El distrito de juguete de la Foia de Castalla y su evolución. *Mediterráneo Económico*, 13, 409-431.

Tables and figures

Table 1. Descriptive statistics of the sample

Characteristics	Number of firms (%)
Size (employees)	
Micro	36 (48)
Small	29 (38,7)
Medium	8 (10,7)
Large	2 (2,7)
Ownership	
Domestic	72 (96)
Foreign	3 (4)
Year of creation	
Up to 1970's	18 (23,9)
1980's	17 (22,7)
1990's	23 (30,7)
2000's	17 (22,7)
International operations	
Exporters	16 (21,3)
Exporters/Importers	23 (30,7)
Business activities	
Toy manufacturers	42 (56)
Suppliers	33 (44)
Legal structure	
Corporation	15 (20)
Limited liability	59 (78,7)
Others	1 (1,3)
Local organisations membership	
AIJU (Toy institute)	58 (77,3)
AEFJ (Toy business association)	34 (45,3)
City	
Castalla	6 (8)
Ibi	31 (41,3)
Onil	37 (49,3)
Tibi	1 (1,3)

Table 2. Structural variables

	Description	Mathematical formula	Visualization
Structural embeddedness (triadic closure)	Tendency towards triadic closure in advices exchanges	$T_i = \sum_{j,h} x_{ij} x_{ih} x_{jh}$	
Network status (in-degree popularity)	Tendency to preferentially ask advices to actors that already receive many requests	$P_i = \sum_j x_{ij} \sqrt{\sum_h x_{hj}}$	
Density	Overall tendency of actors to ask advices	$D_i = \sum_j x_{ij}$	
Reciprocity	Tendency to mutually exchange advices	$R_i = \sum_j x_{ij} x_{ji}$	
Cyclicity	Tendency to exchange knowledge in cycles	$C_i = \sum_{j,h} x_{ij} x_{jh} x_{hi}$	
Activity	Tendency to ask advices to many different actors	$A_i = \sum_j x_{ij} \sqrt{\sum_j x_{ij}}$	

Note: The dashed arrow represents the expected tie that will be created if the corresponding structural effect is positive, while the plain arrow represents a pre-existing tie.

Table 3. Descriptive statistics and correlations of the dyadic variables

	Min.	Max.	Mean	SD	Soc.	Geo.	Cog.	Org.	Inst.
Social embeddedness	0	1	0.002	0.042					
Geographical proximity	0	13	8.530	4.061	0.047***				
Cognitive proximity	0	4	1.211	1.753	0.000	-0.022			
Organizational proximity	0	1	0.004	0.063	0.133***	0.037**	0.035**		
Institutional proximity	0	1	0.652	0.476	0.031*	0.034*	-0.039**	-0.026	
Perceived similarity	0	3	0.237	0.727	0.056***	0.180***	0.164***	0.007	0.041**

Table 4. Structural descriptive statistics of the technical and business networks

	Year	Nodes	Ties	Average Degree	Density	Ties created[1]	Ties maintained[1]	Ties dissolved[1]
Technical network	2005	75	1053	14.040	0.190	-	-	-
	2010	75	1009	13.453	0.182	59	950	103
Business network	2005	75	1291	17.213	0.233	-	-	-
	2010	75	1262	16.827	0.227	100	1162	129

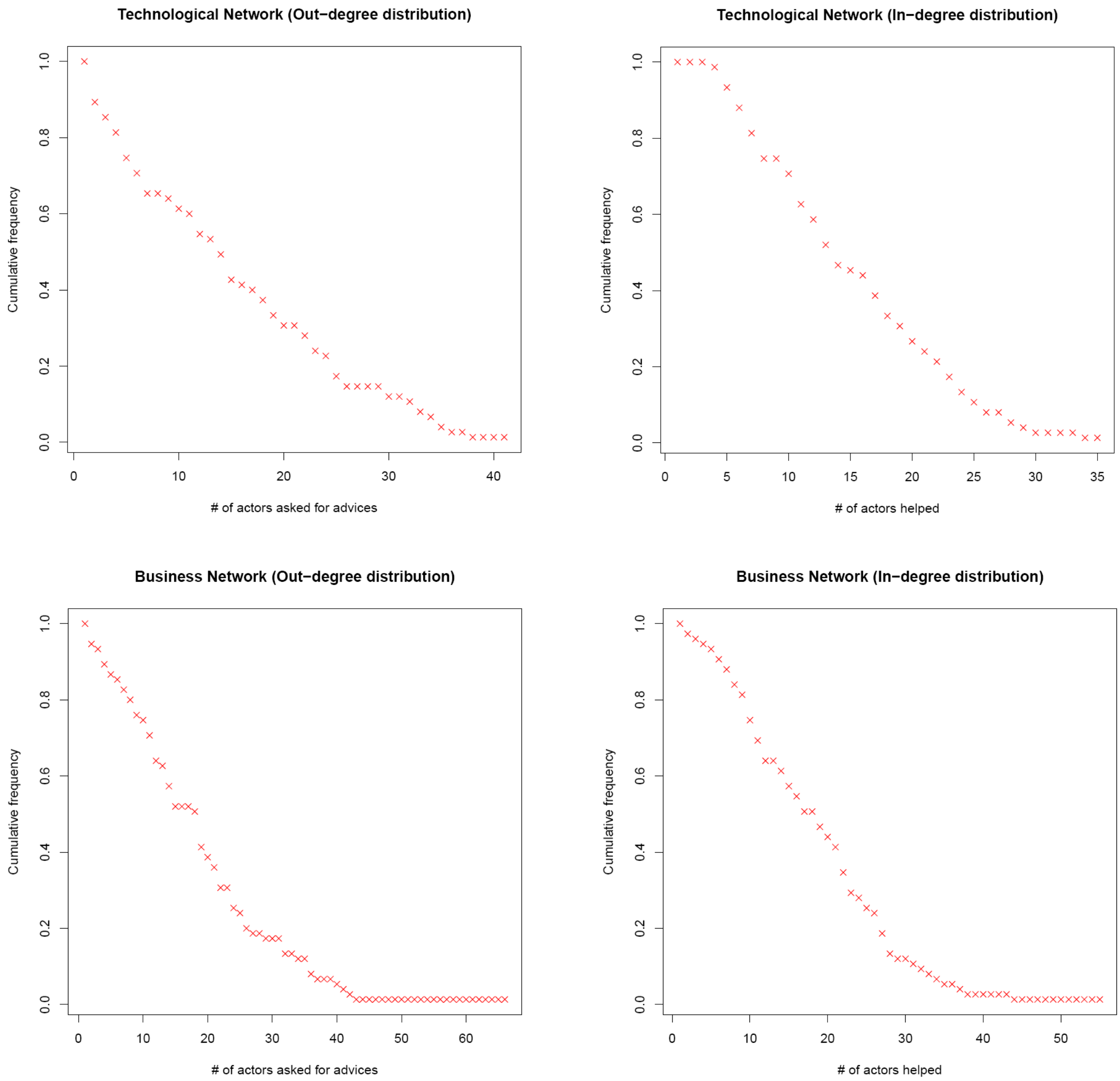
1. Ties created, maintained or dissolved from 2005 to 2010.

Table 5. Dynamics of Technical and Dynamics of Business Network

		Technical Network (N=75)			Business Network (N=75)		
		β	S.D	p-value	B	S.D	p-value
Embeddedness							
Structural embeddedness	(H1)	0.048*	0.025	0.055	0.046**	0.020	0.021
Social embeddedness	(H2)	2.310*	1.219	0.058	3.120**	1.364	0.022
Status							
Network status	(H3)	0.035	0.092	0.704	0.25***	0.071	0.000
Industrial status	(H4)	0.005	0.007	0.475	0.013**	0.006	0.030
Proximity							
Geographical proximity	(H5)	0.049**	0.025	0.050	0.023	0.018	0.201
Cognitive proximity	(H6)	0.083**	0.049	0.090	0.036	0.04	0.368
Control variables							
Density		-2.314***	0.511	0.000	-3.087***	0.503	0.000
Reciprocity		0.885***	0.225	0.000	0.106	0.173	0.540
Cyclicity		-0.089**	0.036	0.013	-0.032**	0.019	0.092
Out-degree activity		0.111*	0.067	0.098	0.136**	0.066	0.039
Organizational proximity		0.139	0.94	0.882	-0.258	0.847	0.761
Institutional proximity		0.479**	0.19	0.012	0.084	0.147	0.568
Perceived similarity		0.089	0.115	0.439	-0.043	0.098	0.661
Rate parameter		2.539***	0.216	0.000	3.527***	0.251	0.000

*Note: β are log-odds ratio. The coefficients are statistically significant at the *p < 0.10; **p < 0.05; and ***p <0.01 level.*

Figure 1. Degree distribution of the Technical and Business Networks



Note: The different degree distributions are computed from the structure of the technical and business networks in 2010 (dichotomized).