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

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Abstract

Informal knowledge networks have often been regarded as a key ingredient behind the success of both high-tech regions and traditional industrial clusters. Yet few empirical studies have attempted to analyze the dynamics of networks within clusters, and little is known about the determinants of these informal exchanges. In this paper, we address this issue by modeling the evolution of business information and technical advice networks within a Spanish industrial cluster: the toy Valley in the Valencia region. We use recent statistical models of network dynamics to address the econometric issues implied by our research questions. We explain the macro-level dynamics of these two network structures by modeling the micro-level decisions of actors to access external knowledge (based the structure of the network and different proximity dimensions). Empirical results suggest that the type of knowledge (business/technical) influence the dynamics of knowledge ties. Although embeddedness plays an equally important role in the circulation of business and technical knowledge, status is more important for the formation of business networks, while proximity is more crucial for the formation of technical networks.

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 (Almeida and Kogut, 1999; Owen-Smith and Powell, 2004; Uzzi 1996; Ingram and Roberts, 2000; Whittington et al. 2009; 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 dynamic in clusters that are populated by communities of firms and people embedded in dense social relations of overlapping affiliations and obligations (Grabher, 1993; Owen-Smith and Powell, 2004).

Despite the growing interest in informal knowledge networks in clusters, however, there is still relatively little evidence on their dynamics, i.e. how they form and change over time. Changes in informal knowledge networks are, by nature, difficult to track and observe empirically at the cluster level. But 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. As a result we know very little about the dynamics of informal knowledge networks and how the type of knowledge that is exchanged shape the evolution of their structure. To contribute to fill this gap, our study focuses on the dynamics of business and technical knowledge¹ in industrial clusters by explicitly modelling the (micro-level) determinants of their (macro-level) structure. Accessing valuable technical advices and market information is essential to the performance and survival of firms, as technical knowledge refers to how to *make* products or services (know-how) while business knowledge refers on how to get *value* from these products or services on the market² (know-what; know-who). In this paper, we propose to test a theoretical framework in which we develop the idea that the structure of technical and market information networks are driven by different forces and exhibits different dynamics.

Whether geography and cluster membership matter *per se* for accessing technical advices on problem solving or strategic market information has been widely debated in the literature and it appears that firms

¹ In the paper we use the expression ‘business’ and ‘market information’ networks interchangeably.

²Or which new products/services should the firm develop to maximize its profit.

are not equally connected to this invisible web of knowledge (Breschi and Lissoni, 2009; Giuliani, 2007). Prior research on the circulation of informal knowledge 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; Coleman, 1988) construct trust and avoid opportunistic behaviors, while status explains why some actors tend to receive requests because of their perceived level of expertise and reputation (Borgatti and Cross, 2003). Besides these configurations, empirical evidence suggests that the proximity between actors (McPherson et al., 2001; Boschma, 2005) also shape the dynamics of informal knowledge exchange. Our theoretical framework discusses the different role played by these mechanisms on the dynamics of business and technical networks in industrial clusters. Although we expect embeddedness to play an equally important role in the circulation of 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. To test our hypothesis about the different role played by embeddedness, status and proximity we analyze the dynamics of technical and business advices networks in a major toy cluster: the Toy Valley in the Valencia region.

Results indicate that the type of knowledge shapes the structure of networks and 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 organisations (Argote et al., 2003; Ingram and Roberts, 2000; Schrader, 1991; von Hippel, 1987; Uzzi, 1996; Almeida and Kogut, 1999; Owen-Smith and Powell, 2004). Geographical propinquity, as in industrial clusters, has been often regarded a key factor enhancing local knowledge transmission (Saxenian, 1994; Becattini, 1990; Marshall, 1920; Poudier and St. John, 1996). Given that localised knowledge is often tacit, hence difficult to be imitated, it has been claimed that being in a cluster conveys firms additional competitive advantages as compared to non clustered firms (Boisot, 1998; Gertler, 1995). In addition, clustering also generate local knowledge spillovers, which are accessible prevalently to its members (Audretsch and Feldman, 1996). The argument behind the physical proximity effect rests on the idea that knowledge is sticky and personal (i.e. tacit), hence it is primarily shared through face-to-face contacts by people who are by definition co-located. They consist of entrepreneurs, technicians and workers, who usually share cultural or religious values, communication codes, and behavioural norms (Maskell, 2001), and tend to be embedded in cohesive webs of multiple and overlapping social and economic relations. Agglomeration processes give rise to local knowledge spillovers that the literature calls as "industrial atmosphere", local "buzz" and "broadcasting" (Marshall, 1920; Grabher, 2002; Owen-Smith and Powell, 2004; Storper and Venables, 2004). According to this

latter view, information and knowledge circulate more easily and more quickly due to geographical proximity.

Additional arguments have been recently put forward to unravel the role of geographical propinquity for knowledge diffusion and innovation. It has been claimed 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; Steimueller, 2000) 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 (Gittelman et al., 2007; Almeida and Kogut 1999; Leonard-Barton, 1984; Owen-Smith and Powell, 2004; Stuart and Sorenson, 2003). More specifically, it has been maintained that besides physical distance, other forms of proximity affect the diffusion of knowledge and innovation (Boschma, 2005; Bell and Zaheer, 2007). On the same vein, it has been disputed that the local *buzz* can convey *all* sorts of informational flow to *all* cluster's members (Giuliani, 2007; Morrison and Rabellotti, 2009).

More specifically, this literature suggest that different network structures can be associated to different types of knowledge (Vicente et al. 2011; Giuliani, 2007; Morrison and Rabellotti, 2009; Boschma and Ter Wal, 2007; Lissoni and Pagani, 2003; Dahl and Pedersen, 2004). Giuliani (2007) finds that the network of business relations established by entrepreneurs and technicians in a Chilean wine cluster is denser than the one of technical advices. Similarly, Boschma and Ter Wal's (2007) analysis of an Italian footwear cluster shows that market and knowledge informal networks differ in their structural properties, in particular the former tends to be denser than the latter. In a similar vein, Morrison (2008) and Morrison and Rabellotti (2009) provide evidence suggesting that in advice networks reciprocity is higher when technical know-how is exchanged rather than market information.

Also the sociological literature has shown that informal communities can use their professional networks for different purposes: to share information on job opportunities, markets trends, regulations, etc. (Cross et al, 2001; Granovetter 1973; Stuart and Sorenson, 2003; Uzzi, 1997). For example, in sub-contracting relations, which are typical of industrial clusters, it is very common that a subcontractor gains information on market trends or customer needs via its contractors, and possibly share this piece of information via informal ties with other subcontractors.

Evidence from the organization studies literature reaches similar conclusions. For example, Hansen (1999) has shown that complex knowledge can be effectively transferred within an organization when actors are linked by strong rather than weak ties. So, while weak ties might prove to be useful for knowledge searching, knowledge transfer requires closer and more stable relations. In the same vein, the transfer of tacit knowledge across organizations appears to be effective if actors are embedded in a cohesive network (Regan and McEvelly 2003).

Overall the above studies suggest that in order to understand the emergence of networks and their structural characteristics the content of a link (e.g. knowledge vs information flows) matters as much as the type of link (friendship vs organizational relation). More specifically, they provide some robust evidence indicating that the transfer of complex knowledge, that is knowledge which is usually highly tacit and interdependent (Winter, 1987; Zander and Kogut, 1995), requires trusty, stable and reciprocated interactions. Indeed, when two parties trust one another, they are more willing to share resources as they expect no opportunistic behaviour by the other actor (Levine and Cross, 2002; Tsai and Goshal, 1998; McEvily, Perrone, and Zaheer, 2003). Stable and repeated interactions also allow to build relation-specific heuristics, which in turn facilitate mutual understanding and the transmission of tacit knowledge (Uzzi, 1999). Similarly, it has been argued that the exchange of procedural knowledge (i.e. know how) requires more efforts as opposed to declarative knowledge (i.e. know what) (Kogut and Zander, 1992; Zander and Kogut, 1995). Indeed, the former requires continuous feedbacks among the actors involved, which entails also higher costs. So, actors get engaged in such a transfer either if there is some social obligation and cooperative norms (Regan and McEvelly, 2003), or if actors expect some compensation or reward, for example the opportunity to be reciprocated in the future with useful knowledge (Hansen, 1999; Uzzi, 1997; von Hippel, 1994). Technical knowledge concerns production process or product development, which can be associated with procedural or know-how type of knowledge (Kogut and Zander, 1995). Market information (e.g. prices, who knows/has what) can be regarded as declarative knowledge, which does not require specific skills to be understood and reused by somebody in the community who has an average expertise (Kogut and Zander, 1992). The transfer of market information across organizations is less problematic as compared to know-how, as the latter is very firm or context-specific, hence it usually calls for some translation and socialization process (Nonaka, 1994), especially if it travels across organizations.

Overall, the literature reviewed above suggests some important stylized facts : a) informal knowledge networks in clusters take different structures, ranging from the *buzz* representation, where knowledge flows circulate in an unplanned way, to a *network*-based representation, where heterogeneous firms selectively participate to a variety of knowledge networks; b) the dynamic of these knowledge networks is driven by different types of proximities and network configurations. In the next sections we discuss how network properties (i.e. embeddedness and status) and actors' proximities affect tie formation in both technical advice and market information networks, and elaborate some testable hypotheses.

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

Embeddedness and knowledge networks dynamics. A central tenet in studies on industrial clusters is that embeddedness in cohesive webs of relationships yields positive return to its members (Fleming et al.,

2007; Granovetter 1985; Uzzi and Spiro, 2006; Obstfeld, 2005), in particular it fosters the generation and circulation of knowledge through informal contacts (Uzzi, 1996; 1997; Bathelt et al., 2004; Lissoni, 2001; Dahl and Pedersen, 2004). 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 behaviours promptly signalled and eventually sanctioned (Walker et al., 1997; McEvily, Perrone, and Zaheer, 2003). Organisation 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). The preconditions for such exchange are trust, mutual recognition and long term relationships (Carter, 1989). 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; Steinmueller, 2000) and community of practice (Brown and Duguid, 2001; Wenger, 2000), which in geographical bounded clusters are particularly dense and cohesive (Inkpen and Tsang 2005, Lissoni, 2001). 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 (Bathelt et al., 2004). In order to grasp these pieces of information, which is prevalently codified - i.e. understandable to all members of the community, though possibly not written down - (Cowan et al., 2000) firms need to activate a search process, which means they have to look for and identify the right source of information. 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).

To sum up, the above literature indicates that while the transmission of procedural knowledge (i.e. know-how) requires close interactions between the actors involved, declarative knowledge (e.g. market information) can be transmitted over longer distances and through a variety of mechanisms other than face-to-face contacts (e.g. phone calls, e-mails; fax). Since market knowledge 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 tacit knowledge requires additional investment in absorptive capacity (Cohen and Levinthal, 2000), as firms have to move, adapt, incorporate, master and replicate the new piece of knowledge (Hansen, 1999). The role of embeddings 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 equally important for the formation of new ties in the technical advice network and in the market advice network.*

Embeddedness in clusters is a composite concept that can be analytically distinguished in two main dimensions: social embeddedness and structural embeddedness (Cowan, Jonard and Zimmermann, 2007). Within advice networks (i.e. at the structural level), embeddedness is constructed through triadic closure, which is the tendency of actors to form triadic configurations in the advice network (technical or business network). A triad (a sub-set of three actors A, B, C) is closed when two actors that receive or ask advices from the same common actor ($A \rightarrow C$; $B \rightarrow C$) start to exchange advices between themselves ($A \rightarrow B$). 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. It leads to the two following hypothesis:

- **H1:** *Structural embeddedness (triadic closure) is equally important for the dynamics of the business and technical network.*
- **H2:** *Social embeddedness (interpersonal ties) is equally important for the dynamics of the business and technical network.*

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, 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 (Gittelman, 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 and Pagani, 2003; Giuliani, 2007; Morrison and Rabellotti 2009). 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, firms that are regarded as the most knowledgeable in the cluster will attract a disproportionately 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 affects the evolution of knowledge networks towards a hierarchical structure. However, *we expect status to play a more prominent role in the dynamics of business networks than technical networks*. Indeed, asking for market information advices does not require reciprocation and the transfer process is costless, so firms might be more willing to ask. This process is likely to lead to a high hierarchical network structure where the firms with higher status and recognition (the repositories of market information) attract most requests.

We test the different impact of status on the dynamics of market information and technical advice networks by looking at *network status* and *industrial status*. Network status is a structural, degree-related concept based on the incoming advices requests. The status of an actor grows as he receives requests of advice. Industrial status is an attribute of an actor in the industry. We measure it with the experience and knowledge that a firm has cumulated over time. The above discussion leads to the two 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.*

Proximities and network dynamics

The evolution of a network can be driven by different micro dynamics, which ultimately affect the overall structure of a network (Ahuja et al., 2012). Recent theorizing in organisation studies suggests that "similarity between the ego and alter (homophily) or the possibilities of complementarity (heterophily) may cause certain ties to form or dissolve" (Ahuja et al., 2012, p.7). Economic geographers have long debated over the importance of different kinds of proximities other than geographical proximity (Boschma, 2005; Rallet and Torre, 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; Singh, 2005; 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. In this paper, we will focus on the effect of geographical and cognitive proximity³. Recent empirical studies have reported an important effect played by geographical and cognitive proximity in the formation of knowledge networks. Most of the studies, however, focus on R&D networks, co-inventor networks or technical networks. The main argument is that technical, scientific or tacit knowledge is difficult to transfer, and proximity facilitates the transfer of this knowledge. *Therefore, proximity should play a more important role the dynamics of technical networks than business networks.*

Early studies have shown that in cluster 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 highly 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 organisations. Each firm searches in close proximity to its knowledge bases, which makes knowledge cumulative and localised (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 specialisation (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, like the one

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 et al., 2013). We also control for social proximity by including the social relationship variable derived from hypothesis 2.

exchanged through technical advice networks. On the contrary, market information is mostly codified and can be understood without any specific capability, besides those widely available by firms active in the same sector. It leads to the two following hypothesis:

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.

4. The study setting

The Toy Valley

The Spanish toy industry is a highly concentrated sector including approximately 219 companies with more than 5.000 employees. In terms of size, small and medium businesses (SEMs) clearly 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 about 80,7% in employment generation. Manufacturing activities concentrate in some geographical areas, among which the Valencia region is the main one due to representing 42,80% of the industry's revenues and 38,4% of the units. Within this Mediterranean region, the so-called Toy Valley cluster agglomerates 42 toy manufacturers and accounts for more than 98% of the regional production.⁴ Located in a natural depression surrounded by mountains, the cluster spreads over 295,83m² and comprises four different municipalities (Ibi, Onil, Castalla and Tibi) with 41.729 inhabitants. The origin of the Toy valley cluster dates back to the late 19th century, when influenced by external stimuli, some families brought their experience and knowledge acquired through handicraft occupations (e.g. tinsmithing activities) to start producing dolls, miniatures or small cars. Once industrial and business values impregnated the socioeconomic structure of the valley, continuous technological change and firm creation relegated traditional practices or inputs such as tin or porcelain. Since mid seventies, the cluster has experienced deep transformations as a result of a fierce global competition. Flagship factories badly managed closed, 25 dolls producers merged in a big successful company labelled FAMOSA, productive activities declined and many toy firms disappeared (e.g. the regional Chamber of Commerce reported a decline of 21,9% in active units during 1996-2005). From then on, this negative trend ceased and the population of toys manufacturers started to stabilize again.

The restructuring of manufacturing activities lead 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

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

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.

Local institutions, social cohesion and supporting organisations boosted cooperation. On the one hand, the local subcontracting rasher, export consortia and mergers of micro firms serve as examples of how a set of common norms and values emerged. On the other hand, business associations and technical centres have played a crucial role not only by providing advanced services, but also by fostering innovation activities.

The questionnaire

Data were collected in the Toy Valley cluster during second half of 2011. In a preliminary stage, a combination of semi-structured questionnaires and face-to-face interviews were conducted on a sample of 8 local manufacturers, researchers and institutions. Such qualitative evidence was gathered in order to corroborate our quantitative results. Once this preliminary stage was completed, a detailed questionnaire was designed based on inputs from the exploratory analysis and the literature review. The tool tackled four different aspects: firm’s characteristics, innovation practices, inter-organizational relationships and performance. A pre-test was conducted to assess factors such as clarity, comprehension and completion time.

As the particular aim of this paper demands both micro-level and network data, we applied an open “roster-recall” method to identify inter-firm relationships (Giuliani and Bell, 2005; Boschma and Ter Wal, 2007; Morrison and Rabellotti, 2009). According to Giuliani and Pietrobelli (2011) and Ter Wal and Boschma (2009), size of cluster population and data collection process make this methodology suitable. In our research, 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 market information was given/received, and if they benefited from it.

Data collection

Data were collected through a survey submitted firstly to toy manufacturers that design, produce or sell toys, including subsidiaries of national companies that just perform within the cluster a part of the value chain. 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.⁵ Information about providers came from the surveyed manufacturers, since no official register exists. We counted 52

⁵ Further screening through SABI and Key informants was also performed.

suppliers of the toy sector in the cluster. Once discarded sporadic providers and self-employed through secondary sources and direct contacts with firms, 38 firms were surveyed, of which 5 refused to fill the questionnaire. At the end, our population consists of 75 firms (i.e. toy manufacturers and their suppliers)⁶, 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 were considered.

The questionnaire was administered to firms through a 40-50 minutes face-to-face interview conducted by a skillful technician⁷. In order to pool data for different measures over time, we requested respondents to report information at two selected moments 2005 and 2010. Particular emphasis was placed on the retrieval of past experiences during the interview in an attempt to improve reliability. Respondents, who were not working for their companies at the initial moment of the period examined, were persuaded to attend the meeting with somebody else who was already employed.

The respective questions read as follows: a) To which of the following firms on the list did you regularly ask technical advice during the last three years?; b) To which of the following firms on the list did you regularly ask business and market information during the last three years?.

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 $n \times n$ 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.

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5. Econometric issues and specification of the statistical model

⁶Data 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). So reliability of any further analysis seems guaranteed.

⁷The interviewer was selected on the basis of a local origin and a former working experience in AEFJ as responsible of innovation programs. This profile seemed us extremely appropriate because his close relationships with cluster's actors and deep knowledge of the industry could contribute to the verisimilitude and reliability of the fieldwork.

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 RSiena⁸ 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 (2010) 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

⁸ 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/>.

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 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 (Hypothesis 1) and social embeddedness (Hypothesis 2). 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, taking the value 1 if the two actors belong to the same group of firms or if they have formal sub-contracting relationships⁹. 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 *Sociedad Anónima*. We included a perceived similarity, 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 variables). In general, these proximity variables are not highly correlated. The higher degree of correlation can be found between perceived similarity and geographical proximity (0.18), perceived similarity and cognitive proximity (0.16), and finally between social embeddedness and organizational proximity (0.13). 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 networks¹⁰.

--- TABLE 2 ABOUT HERE ---

--- TABLE 3 ABOUT HERE ---

6. Empirical results

⁹It 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.

¹⁰ The full models including these variables are available upon request.

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 firms in 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 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 very straightforward, they are non-standardized coefficients obtained from logistic regression analysis (Steglich et al., 2010)¹¹. 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)¹².

Our first set of hypotheses refers to the role of embeddedness in shaping knowledge circulation in clusters. The coefficient for triadic closure is positive and significant in both cases, and its magnitude is very similar ($\beta=0.048$ for the technical network and $\beta=0.046$ for the business network). Hypothesis 1 is therefore confirmed, structural embeddedness is an equally important driver of the dynamics of the two networks. Social embeddedness is also a strong driver of both networks, as the coefficient for social ties is positive and significant in both cases. However, the coefficient for social ties is substantially lower for technical networks ($\beta=2.310$ for the technical network and $\beta=3.120$ for the business network). Hypothesis

¹¹ 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. One can easily transform the log-odds ratio (β) into odds ratio by computing the exponential form of the coefficients = $\exp(\beta)$, or again into probability by using the following formula = $\exp(\beta) / [1 + \exp(\beta)]$.

¹² 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.

2 is not confirmed, as it seems that social embeddedness plays a more important role for the dynamics of the business network.

Our second set of hypotheses concerns the effects of status. In this case the two networks show a very different dynamics. Although the coefficient for network status (in-degree popularity) is positive and significant for business network ($\beta=0.250$), it is much lower in magnitude and not even significant for technical network ($\beta=0.035$). Therefore, actors that receive many requests of market information tend to attract disproportionately new requests in the next period. This effect suggests that reputation plays a very strong role for market information sharing. Similarly, industrial status (experience of alter) shapes the dynamics of business advices ($\beta=0.013$), while it is not significant for the dynamics of technical networks. These results confirm hypothesis 3&4, but the difference of the role played by status in the dynamics of the two networks is higher than expected.

The final set of hypotheses concerns the role of proximity. In this case again, 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. Also, its magnitude is twice higher for the technical network ($\beta=0.049$) compared to the business network ($\beta=0.023$). The same pattern is found for cognitive proximity, positive but not significant in the business network, while important for technical advices. These results confirm hypothesis 5&6 but again, the difference in the dynamics of the two networks is higher than expected.

Concerning the control variables, the *rate parameter* (i.e. stability of the network ties)¹³ is lower for the technical network and *reciprocity* is not significant in the business network. This result seems 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 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.

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

¹³The 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.

both 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 & conclusion

Although networks in clusters have received increasing consideration during the last decade, theoretical and empirical researches on the dynamics of these networks remains underdeveloped¹⁴. This paper aims at filling this gap by analyzing the dynamics of technical and business networks in the Toy Valley industrial cluster in Valencia (Spain). Due to the dynamic and interdependent nature of networks, we have used an actor-based model for network dynamics (Snijders et al., 2010). The main contribution of the paper concerns the different dynamics of technical and business networks, as being shaped by different forces. In particular, we developed a theoretical framework on the different role played by embeddedness, status and proximity. Empirical findings suggest that embeddedness plays an equally important role for the dynamics of business and technical networks, while status is more preeminent for the formation of business ties and proximity for the formation of technical ties.

Our findings also suggest a number of additional lines of research, which could not be addressed in our work. First, we provide evidence that is circumscribed to a specific cluster and industry. Despite it represents a typical example of traditional manufacturing cluster, further empirical analysis covering different sector and geographical contexts would corroborate and refine our findings. Second, even though we make an attempt to consider network multiplexity within industrial clusters, we might have missed some type of ties which are either more informal (or even secret) or involve other actors in the cluster (e.g. financial sector, public sector) in the complex web of business, technical, social or sub-contracting ties. Third, we do not address the implication of these networks on firm performance, which would be greatly informative about the value of knowledge share in informal networks. Fourth, because network dynamics at both whole- and ego-network, although related, may also differ (Zaheer et al., 2010), future work should pay attention to how ego structures evolve in relation to the whole network approach undertaken in this paper.

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¹⁴One exception being the work by Giuliani (2010).

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Tables and figures

Table 1. Descriptive statistics of the sample

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

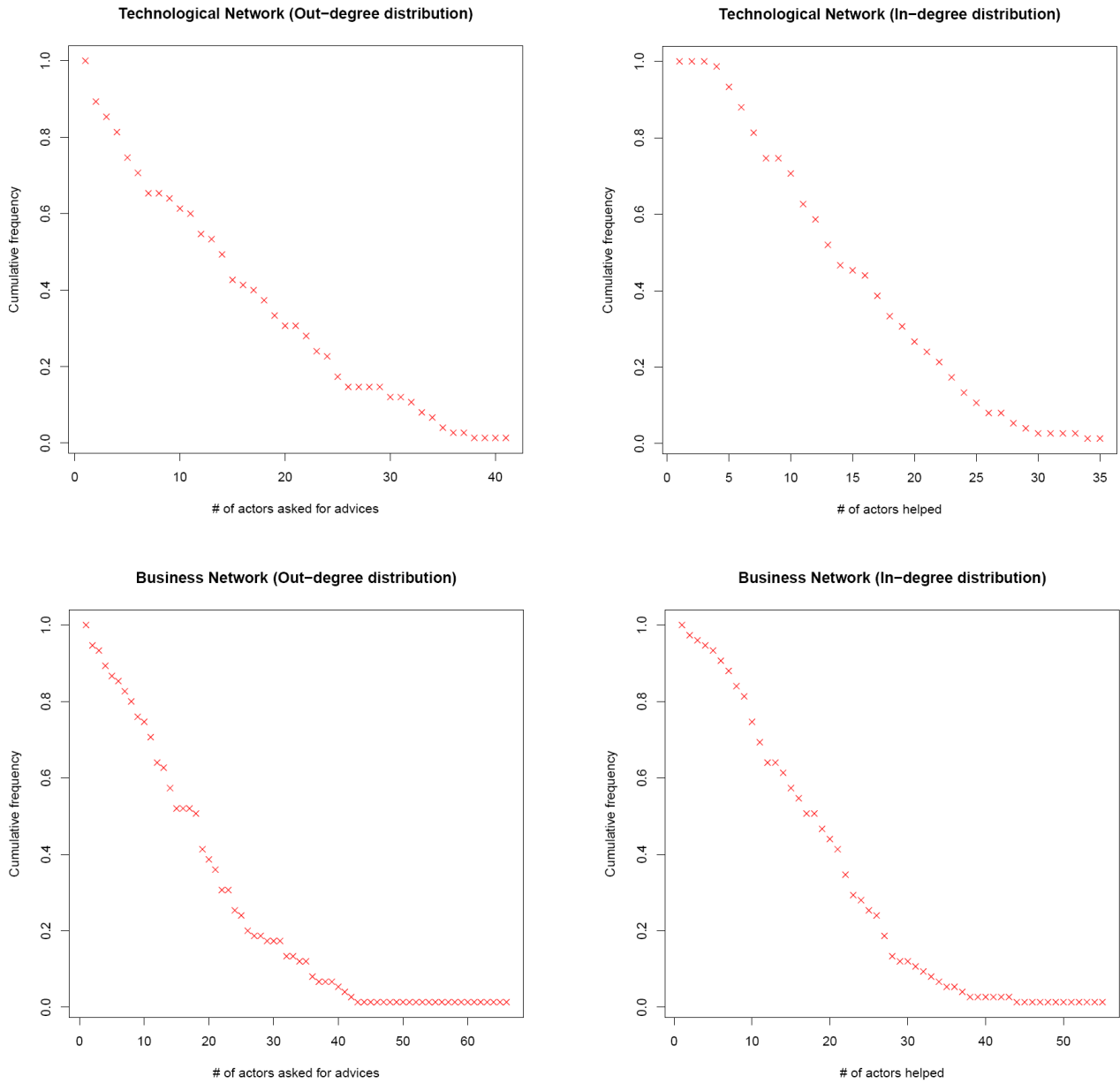
Table 5. Dynamics of Technical and Dynamics of Business Network

		Technical Network (N=75)			Business Network (N=75)		
		β	S.D	p-value	β	S.D	p-value
<i>Embeddedness</i>							
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
<i>Status</i>							
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
<i>Proximity</i>							
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
<i>Control variables</i>							
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
Cyclicality		-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.

<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).