The dynamics of technical and business knowledge networks in industrial clusters: embeddedness, status or proximity?

Pierre-Alexandre Balland
Department of Economic Geography - URU
Utrecht University
Utrecht, The Netherlands
and
CIRCLE
Lund University
Lund, Sweden
p.balland@uu.nl

José Antonio Belso-Martínez
Department of Economics and Finance
Universidad Miguel Hernández de Elche
Elche, Spain

Andrea Morrison
Department of Economic Geography - URU
Utrecht University
Utrecht, The Netherlands
and
CRIOS
Universitá Luigi Bocconi
Milano, Italy

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 knowledge 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 knowledge networks, proximity is more crucial for technical knowledge networks, while embeddedness plays an equally important role in the dynamics of both networks.

Key words:
knowledge networks
industrial clusters
network dynamics
toy industry
Spain

ECONOMIC GEOGRAPHY

1–26. www.economicgeography.org

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, in California, 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 interorganizational ties (e.g., buyer–supplier relations, research and development [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 of their dynamics, that is, how they form and change over time. There are only a few empirical attempts in this area (see Giuliani 2013; Giuliani and Matta 2013), partly because longitudinal network data are rarely available but also because the empirical literature on knowledge networks in clusters is very incipient. 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 describing the structural features of knowledge networks, arguing that clusters are populated by a variety of informational networks (Giuliani and Bell 2005; Vicente, Balland and Brossard 2011); on the other hand, they have analyzed the impact of network positions on the performance of firms or the cluster (Boschma and Ter Wal 2007; Morrison 2008). This article explores this question and contributes to a better understanding of informal knowledge exchanges in clusters, that is, how the local *buzz* is organized (Storper and Venables 2004; Owen-Smith and Powell 2004). Using recent statistical techniques (i.e., actor-based model by Snijders, Van De Bunt and Steglich 2010), we contribute to the empirical literature on networks in clusters by explicitly modeling the microdynamics of technical and business knowledge network formation.

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, de Vaan and Boschma 2013). We explain the formation of informal 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, that is, for the dynamics of technical and business knowledge.[1]

Our multiplex approach constitutes an additional contribution to the literature. We unveil differences that usually remain hidden in most studies on networks in clusters. Indeed, the few studies in this field, which have differentiated between two or more types of networks usually adopt a static approach and focus mainly on structural

[1] We refer in the article to technical and business knowledge networks for informal networks in which technical and business knowledge is exchanged. They are, in this respect, advice networks and not subcontractor networks or networks made of business relationships with customers.

properties (Boschma and Ter Wal 2007; Giuliani 2007; Morrison and Rabellotti 2009). Conversely, those that have recently dealt with the dynamics of knowledge networks (Balland 2012) analyze only one single network. However, there is increasing interest in the literature for multiplex network research (Ahuja, Soda and Zaheer 2012). Our article is the first to analyze commonalities and differences in the dynamics of technical and business knowledge networks.

Prior research has emphasized the role of embeddedness, status, and proximity in accessing external knowledge. Embeddedness of economic actors in a web of social ties (Granovetter 1985) constructs trust and avoids opportunistic behaviors, while status explains why some actors tend to receive requests because of their perceived level of expertise and reputation (Cross, Borgatti and Parker 2001). Besides these configurations, empirical evidence suggests that the proximity between actors also shapes the formation of informal knowledge exchanges (Broekel and Boschma 2012; Balland, Boschma and Frenken 2015). Our theoretical framework discusses the different role played by these latter mechanisms in 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 knowledge networks, while proximity is more crucial for the formation of technical knowledge networks.

We test our hypotheses in the context of a traditional manufacturing cluster: the Toy Valley in the Valencia region of Spain. The Toy Valley emerged in the late nineteenth 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 hypotheses since it represents a paradigmatic example of an industrial cluster specialized in a traditional manufacturing activity involving a large population of small- and medium-sized enterprises. We collected the longitudinal network data by conducting semistructured interviews with 75 firms, which represents 95 percent of the cluster population. To capture the impact of the different network forces, we modeled the dynamics of business and technical advice networks by applying recent statistical techniques in network dynamics (Snijders, Van De Bunt and Steglich 2010). The empirical results indicate that embeddedness, status and proximity do play a different role in the dynamics of business and technical networks.

Our article is structured as follows. In the next, we review the main debates about informal network knowledge in industrial clusters and explain why our work focuses on business and technical knowledge networks. Following this, we present the theoretical hypotheses on embeddedness, status, and proximity, while we illustrate the cluster under investigation and the research design, in particular, focusing on the data collection process in the section that follows. The main features of the statistical model of network dynamics are then presented. The results are illustrated in the penultimate section and discussed, followed by the concluding remarks.

On clusters, networks and knowledge types

The 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). Geographic propinquity, as in industrial clusters, has been often regarded a key factor enhancing local knowledge transmission (Maskell 2001; Pouder and St. John 1996). The latter argument rests on the idea that localized knowledge is usually tacit, hence, its transmission occurs primarily through face-to-face contacts of colocated agents. In addition, clustering also generates local knowledge spillovers (Audretsch and 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. The latter approach suggests that knowledge is *not in the air*, and it does not flow randomly via unplanned spillovers; rather it circulates via (localized) networks among specific actors and communities (Almeida and Kogut 1999; Stuart and Sorenson 2003). In the same vein, it has been disputed whether the local buzz can convey *all* sorts of informational flow to *all* clusters' members (Breschi and Lissoni 2001).

The 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. In particular, two broad types of knowledge networks have attracted the interest of this literature: (1) technical know-how, which has been regarded as the key competitive factor of clusters, since it is sticky and difficult to imitate and transfer outside cluster's boundaries; (2) market information and business knowledge, which has been regarded as a public good shared during informal chit-chat by clusters' entrepreneurs and workers. These studies show that these different types of knowledge circulate along networks of firms and individuals that show distinct structural properties and are, in some instances, overlapping (Vicente, Balland and Brossard 2011; Giuliani 2007; Morrison and Rabellotti 2009; Boschma and Ter Wal 2007; Lissoni and Pagani 2003; Dahl and Pedersen 2004). Following the latter literature, in our article, we distinguish between two types of knowledge: technical know-how, which can be associated with procedural knowledge (Kogut and Zander 1995); and business knowledge, 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 amount of expertise (Kogut and Zander 1992). Its transfer across organizations is less problematic compared to know-how. Business knowledge can be accessed, for example, via subcontracting networks, which are very common in industrial clusters, and convey all sorts of rumors about customer liability, market trends, and 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).

On the other side, 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) (Reagans and McEvily, 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, Lorenz and Lundvall 2002), we acknowledge that technical knowledge can be codifiable and eventually articulated (Lissoni 2001). Our point is that technical know-how, in the form of technical advice shared by firms, can include some substantial tacit component, in particular, as compared to business knowledge. Technical advice is indeed meant to solve technical problems, that is, tasks that might require skills and competences, which remain still highly tacit and embodied in individuals, despite the codification of technical know-how (Balconi 2002).

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 returns 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). The latter mechanism rests on a sociological argument suggesting that cohesive networks enhance trust (Festinger 1954; Coleman 1988).

Embeddedness is a composite concept that can be analytically distinguished in two main dimensions: social embeddedness and structural embeddedness (Cowan, Jonard and Zimmermann 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, thus reducing uncertainty and asymmetric information. Third parties also generate a reputational lock-in, which deters the partner from behaving opportunistically.

The latter type of embeddedness proves to be particularly relevant for sharing technical know-how in industrial clusters (Uzzi 1997). In these contexts, knowledge exchanges are frequent between technicians of competing firms (von Hippel 1987) who share technical information in the form of informal advice, which is not regulated by formal contracts. Therefore, trust is a precondition for these exchanges to be effective and mutually beneficial (Schrader 1991). Besides technical know-how, structural embeddedness allows firms also to cross-check the business knowledge provided by colleagues during informal meetings. To sum up, in a stable set of relations, such as the one prevailing in industrial clusters, knowledge (both business knowledge and technical know-how) can be easily cross-checked, through indirect paths, and deviant and opportunistic behaviors are promptly signaled and eventually sanctioned (McEvily, Perrone and Zaheer 2003). The above considerations lead to the idea that structural embeddedness is important for the formation of new ties in both networks.

Embeddedness can also be constructed through a common social context, with overlapping interpersonal ties often referred to as strong ties (Granovetter 1973), for example, 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 membership in a specific group (e.g., business, religious, political) or social community (e.g., friendship, family) helps entrepreneurs or technicians leverage their social networks to access a variety of resources such as financial capital, business advice, or management support (Asheim 1996; Staber 1997). This is the case for entrepreneurs and technicians who form epistemic communities (Gittelman 2007) or communities of practice (Brown and Duguid 2001), where technical knowledge is usually shared.

Similarly, this sense of belonging is important for exchanging business knowledge, in particular, in the form of know-who. The latter type of knowledge is not easily appropriable; however, it can be as strategic as technical know-how for the competitiveness of a firm. Indeed, information about important clients or on the reliability of suppliers is often kept jealously secret and shared only among a select group of well-trusted entrepreneurs or workers who are part of the stable subcontractor network of the firm (Lissoni 2001).

The above arguments suggest that social embeddedness is important for the formation of new ties in both networks.

To sum up, the discussion presented in this section leads to the following hypotheses:

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

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

Status and network dynamics

Besides achieving higher embeddedness, network relations in clusters can also evolve toward uneven and hierarchical structures (Markusen 1996). This dynamics is highly influenced by the role that *status* plays in the process of knowledge exchange. Robust evidence in the social network literature suggests that actors ask advice from other members of a community who have higher status (Lazega, Mounier, Snijders and Tubaro 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), since they can gain recognition of their status (Blau 1964).

If the exchange dynamics are strongly shaped by status, new ties are established most likely with actors having the highest number of connections (i.e., network status) (Barabasi and Albert 1999) or those with the strongest reputation (i.e., industrial status) (Lazega, Mounier, Snijders and Tubaro 2012), so the network evolves toward a hierarchical structure in which only a few actors are the most prominent. Therefore, we can analytically distinguish between *network status* and *industrial status*. The latter can be regarded as an attribute-based view of status, which is often adopted in the cluster literature, assuming that status descends from the reputation, the recognized expertise, and the visibility a firm builds over the years.[2] The former is instead a structural, degree-related concept that represents the hierarchical dynamics of the network structure. Overall, network status expresses the tendency to ask advice of actors that already receive many requests.

There are several accounts of industrial clusters where few focal actors, those presumably with the highest status and leadership, have contributed either to the genesis of the cluster (Lazerson and Lorenzoni 1999) or its innovative performance (Molina-Morales and Martinez-Fernandez 2004), and more importantly for our argument, the actors have shaped the dynamics of knowledge diffusion (Cantner and Graf 2006; Giuliani 2007; Morrison and Rabellotti 2009).

Based on the above discussion, it can be argued that since knowledge exchanges take the form of trading (in particular as far as technical advice is concerned), firms that are

[2] Although the latter indicator measures the stock of knowledge, a firm has accumulated over time, this formal way of measuring status ignores network structures.

regarded as the most knowledgeable in the cluster will attract a disproportionably higher amount of new contacts. Similarly, as far as business knowledge is concerned, most reputable firms in the cluster, or those that are involved in the biggest subcontracting networks, will receive far more enquiries. Moreover, it cannot be ruled out that, in some cases, where it is difficult to verify the quality of business knowledge, affiliation with reputable actors is used to signal quality (Podolny 1993).

All in all, *status* can positively affect the evolution of knowledge networks toward a hierarchical structure. However, 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 knowledge networks than technical knowledge networks*. Our argument rests on the idea that the dynamics of tie formation are also shaped by the specific type of knowledge transferred. Networks that diffuse technical knowledge are usually stable, reciprocated, and costly to maintain; therefore, over time, highly knowledgeable actors can satisfy only a few additional requests for advice concerning technical knowledge. The implications for the dynamics of the technical knowledge network are that this network will grow at slow pace.

Furthermore, networks that convey business knowledge can be more easily created and nurtured (as well as dissolved). Accordingly, reputable firms, over time, can accept a much higher number of new requests for business advice (as compared to technical know-how advice). This makes the growth dynamics of the business knowledge network similar to the *richer get richer* metaphor of scale-free networks.

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 knowledge network than in the dynamics of the technical knowledge network.

H4: Industrial status plays a more important role in the dynamics of the business knowledge network than in the dynamics of the technical knowledge network.

Proximity and network dynamics

Economic geographers have long debated 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, de Vaan and Boschma 2013). Some studies show that diversity rather than similarity has been found to be relevant in driving the formation of interfirm alliances (Powell, White, Koput and Owen-Smith 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 belonging to the same organizational group are crucial to enhancing knowledge circulation and ultimately innovation.

Early studies have shown that in clusters, geographic propinquity is important to establishing informal collaboration and exchange knowledge (Saxenian 1994). We also suggest that after controlling for other factors, day-to-day interactions require physically close contact with those peers who can provide 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, that is, business knowledge, the latter being 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 with 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 advice might show a higher degree of tacitness than business advice. *Therefore, we expect the two forms of proximity to play a more important role in the dynamics of technical than business knowledge network*. We can formulate the following hypotheses[3]:

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

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

The study setting

The toy valley

The Spanish toy industry is highly concentrated and includes approximately 219 companies and more than 5000 employees. Small and medium businesses predominate, with 96.8 percent of the total establishments having less than 50 employees.[4] These firms account for 57.3 percent of the total industry's revenues and contribute to about 80.7 percent in employment generation. Manufacturing activities concentrate in a few geographic areas in Spain. The region of Valencia is the leading hub, generating 42.80 percent of the industry's revenues and 38.4 percent of the units. Within the Valencia region, the so-called Toy Valley cluster agglomerates 42 toy manufacturers and accounts for more than 98 percent of the total regional production.[5] Located in a natural depression surrounded by mountains, the cluster

[3] In the empirical section, we will control the effects of other forms of proximity, which 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 H2.

[4] Spanish Statistical Institute (www.ine.es) and Asociacion de Fabricantes de Juguetes (www.aefj.es)

[5] Using the Social and Behavioral Instruments (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 the *Asociación Española de Fabricantes de Juguetes* (AEFJ) and the *Instituto Tecnológico del Juguete* (AIJU), lead us to establish the abovementioned number of toy producers.

spreads over 295.83 square meters and four different municipalities (Ibi, Onil, Castalla and Tibi) with 41,729 inhabitants. The origin of the Toy Valley dates back to the late nineteenth century, when families built on their experience and knowledge in handicraft occupations (e.g., tinsmithing activities) to start producing dolls, miniatures, or small cars. The cluster has followed a process of related diversification (Caja and Martí 2014) and continuous technological change and firm creation that was relegated to traditional practices or inputs such as tin or porcelain. In the mid-1970s, the cluster experienced deep transformations as a result of a fierce global competition. Flagship factories badly managed eventually closed, 25 doll producers merged into a big successful company (FAMOSA), productive activities declined, and many toy firms disappeared.[6] From then on, this negative trend ceased, and the population of toy manufacturers started to stabilize again.

The restructuring of manufacturing activities led to a strong fragmentation of the production process, which encouraged the creation of specialized suppliers mostly by local skillful employees. For instance, the switch from metal to plastic toys turned the subcontracting parts or molds to smaller firms into a frequent phenomenon (Belso-Martínez and Escolano-Asensi 2009). As Ybarra and Santa María (2008) highlighted, 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 have 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 centers, 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 types of longitudinal network data are not available in secondary data sources such as patent documents (Ter Wal 2014) 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 were collected in the Toy Valley cluster during the second half of 2011. In a preliminary stage, we conducted a combination of semistructured questionnaires and face-to-face interviews on a sample of eight local manufacturers, researchers, and institutions.[7] Together with inputs from the literature (e.g., Giuliani 2007, 2013; Morrison and Rabellotti 2009), we used this exploratory analysis to carefully design the questionnaire and gather data on four different key dimensions: firm's

[6] The regional Chamber of Commerce reported a decline of 21.9 percent in active units during the period 1996–2005. These figures can be obtained at http://www.alicanteencifras.com

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

characteristics, innovation practices, interorganizational relationships, and economic performance. A pretest was conducted to assess clarity, comprehension, and completion time.

We submitted the survey to the 42 toy manufacturers[8] that design, produce, or sell toys, including subsidiaries of national companies that perform within the cluster as 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 we eliminated sporadic providers and the self-employed, through secondary sources and direct contacts with firms, we asked 38 firms to participate in the survey. Thirty-three accepted our invitation; five refused to fill out the questionnaire. In the end, our population consisted of 75 firms (i.e., toy manufacturers and their suppliers),[9] yielding an appropriate response rate of 95 percent, 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. To ensure respondent accuracy and avoid misinterpretation of the questions, we decided to administer the questionnaire via 40–50 minutes face-to-face interviews with the top managers or business owners of each firm.[10] All interviews were conducted by a technician who had a deep knowledge of this industry and the Toy Valley.[11]

A key issue when analyzing the dynamics of knowledge networks in clusters is to gather longitudinal network data, which can be collected in two ways. In prospective data collection, the researcher designs the study, selects the actors, and then follows them over time to observe their changing relationships (see Giuliani 2013). An alternative approach is based on retrospective data collection, where the researcher collects information on past relationships. Both methods have pros and cons. Although collecting network data in real time provides accurate information on the relationships of each actor, the main limitation of prospective data collection is that subjects might drop out of the study. An employee or manager who was interviewed in 2005 might have moved to another company in 2010. This would be particularly problematic in our case, since we need to collect data on two different networks (business and technical) in two points in time. It is crucial for our study that the set of respondents is constant over time (i.e., no composition change). Asking respondents to report their present and past relationships also ensures homogeneity in their answers. This is why we use the retrospective data collection strategy to gather longitudinal network data. We requested participants to report information about their relationships with others in 2010 and in 2005. Researchers have increasingly emphasized the advantages and validity of retrospective designs (see De Vaus 2001; Featherman 1980; Miller, Cardinal and Glick 1997), and we believe that this strategy offers several avenues for research on network dynamics in clusters.

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

[9] 'Since the data has been collected at the end of the period 2005–2010, we checked the composition change of the network (entry and exit of firms during the period). The SABI database indicates a stable cluster composition with only five firms that have been created and six that exited.'

[10] 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 ensures consistency across firms.

[11] The interviewer is a former employee, responsible for innovation programs at AEFJ.

But, of course, one might argue that a main limitation of retrospective network data collection is potential cognitive distortion such as faulty attributions or lapses of memory (Huber and Power 1985; Golden 1992). In their study of personal networks of people living in the former German Democratic Republic during communism, Völker and Flap (2001) found support for the use of retrospective network data collection, since they report no systematic bias related to cognitive filtering over time. They only found ‘a slight, non-significant tendency to forget weaker ties’ (Völker and Flap 2001, 407).

But, in our case in particular (and for research on networks in clusters more generally), the issue of cognitive filtering is limited. First, the respondents have clear cognitive boundaries that will maximize the accuracy of responses. In our case, respondents had a spatial limit (links with other firms within the cluster), a relational limit (74 other potential partners – the full list was given to them, so it is impossible to forget an actor), and a time limit (five years before). In this delimited context, the potential bias due to inaccurate responses is unlikely, even for the network ties of 2005. Second, 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 investigated concerns trust-based and advice ties, which are typically reoccurring and enduring patters of relationships. Third, since we collected data also on the strength of ties, namely, on weak, medium and strong ties, we checked if omitting weak ties (the one that might be forgotten) from the analysis would affect our results. Our findings show that this is not the case. Finally, 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 (ERGM)) 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 article.[12]

In order to facilitate memory recall, we designed the questionnaire chronologically, associated some specific past events and guided the respondent along the interview. 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 the informants guarantees the accuracy of their records (Miller et al. 1997); an incentive (access to results) was offered to foster a sense that the firms could benefit from 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 relevant time period. These efforts have been proved to increase the effectiveness and accuracy of this methodology (Golden 1992; Miller, Cardinal and Glick 1997).

[12] We thank the referees for suggesting this additional robustness analysis. The social embeddedness variable (H2), industrial status (H4), geographic proximity (H5) and cognitive proximity (H6) variables have exactly the same sign, level of statistical significance and differences of coefficients between the technical (TN) and business (BN) networks with exponential random graph models (ERGMs) and stochastic actor-oriented models (SAOMs). A slight difference concerns 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 the SAOMs), but it is now statistically significant for the TN. Control variables also show the expected sign and significance.

In line with previous studies, we collected network data using a *roster–recall* method (Giuliani and Bell 2005; Boschma and Ter Wal 2007; Morrison and Rabellotti 2009). Each interviewee was provided with a list (roster) on which the names of toy manufacturers and suppliers from the Toy Valley were already given. Each firm was asked to tick off on the list those companies where 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 geographic 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, that is, the business knowledge network and the technical knowledge 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 advice 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.

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 1970s	18 (23,9)
1980s	17 (22,7)
1990s	23 (30,7)
2000s	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 organization 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)

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 the actors choose to ask for advice and assistance, and how this changes over time. 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, Van De Bunt and Steglich 2010). To deal with these econometric issues, the literature has proposed more or less sophisticated statistical models and corrections, including a 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), ERGMs (Robins, Pattison, Kalish and Lusher 2007; Broekel and Hartog 2013) and stochastic actor-oriented models (SAOMs) (Snijders, Van De Bunt and Steglich 2010; Balland 2012).

In this article, we use SAOMs because it is a statistical model for network dynamics that simultaneously allows us to model structural dependencies (like triadic closure for instance) and proximity dimensions, while controlling for heterogeneity of the knowledge bases of the actors. More precisely, we use SAOMs implemented in the RSiena[13] statistical software (Ripley, Snijders and Preciado 2012). It has been acknowledged recently that SAOMs open new areas of inquiries to understand the spatial evolution of networks (Ter Wal and Boschma 2009; Maggioni and Uberti 2011; Broekel, Balland, Burger and Van Oort 2014). So far, SAOMs 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 (2014), and more recently by Balland et al. (2013) on the evolution of the global video games industry. For a general introduction to SAOMs, see Snijders et al. (2010), for more technical details see Snijders et al. (2010).

SAOMs are a class of dynamic models based on Markov random graphs, which induce that change probability only depends on the current state of the network. The change from one state to another, that is, the network dynamics, results from micro-decisions of actors to access the business or technical knowledge of others. These micro-level decisions are based on the preferences, constraints, or opportunities of ego, which 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 advice (create new ties), continue to ask for such assistance (maintain ties), or finally stop asking (dissolve ties).

Estimation of the coefficients is achieved by means of an iterative Markov chain Monte Carlo algorithm based on the method of moments (Snijders, Van De Bunt and

[13] 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/.

Steglich 2010). The stochastic approximation algorithm simulates the evolution of the network and estimates the parameters (for geographic proximity, triadic closure, etc.) that minimize the deviation between observed and simulated networks. Over the iteration procedure, the provisional parameters of the probability model are progressively adjusted in such 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 standard errors. To compare the dynamics of technical and business advice networks, we 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 advice 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 statistic is computed from the particular architecture of advice 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 toward closed triads in advice 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 incoming ties in the network of interest (i.e., the distribution of advice requests actors receive). Therefore, network status is operationalized as a preferential attachment mechanism (Barabasi and Albert 1999), given by $P_i = \sum_j x_{ij} \sqrt{\sum_n x_{nj}}$, and it captures the endogenous construction of status in advice networks (the perceived status grows with the number of advice 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

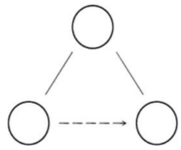
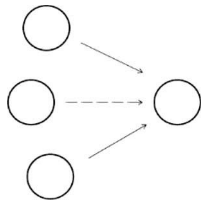
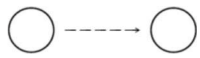
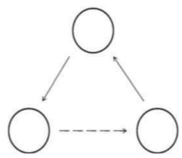
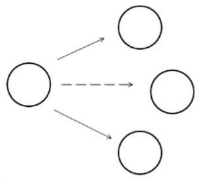
We focus on the geographic (H5) and cognitive (H6) dimensions of proximity. By construction, these variables are dyadic (as social embeddedness). Geographic proximity is obtained by subtracting the physical distance between two firms (in kilometers) to the maximum occurring distance value. Cognitive proximity is a valued measure, corresponding to the number of digits the two companies share in common in their NACE 4 code. Here, we assume that two firms have related knowledge bases (i.e., cognitive proximity) if they operate in the same sector category, which is in line with the literature on related variety (Frenken, Van Oort and Verburg 2007).

Control variables

We first included a set of important variables related to the structural path dependence in network dynamics, that is, explaining how the structure of the network reproduces itself over time (Snijders, Van De Bunt and Steglich 2010; Rivera, Soderstrom and Uzzi 2010). We included the out-degree (density) effect to control for the overall tendency of actors to

Table 2

Structural variables.

	Description	Mathematical formula	Visualization
Structural embeddedness (triadic closure)	Tendency toward 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 who 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 preexisting tie.

form ties (Snijders, Van De Bunt and Steglich 2010). Since we analyzed directed networks, we also expect that actors will only exchange knowledge with those from 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 value 1 if the two actors belong to the same group of firms or if they have formal subcontracting relationships.[14] Institutional

[14] It should be noted that informal, or even secret subcontracting relationships between firms are, by definition, difficult to observe and therefore will not be captured by the organizational proximity variable.

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					
Geographic 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

proximity is a dummy variable, referring to the similarity of the legal status of the companies; for instance, it takes value 1 if both actors are corporations. We included a perceived similarity measure, by asking the actors directly 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, geographic and cognitive proximity, and the other dyadic control variables). In general, these proximity variables are not highly correlated. We also included controls as the firm levels such as R&D intensity, size, and the level of education of employees, but these variables did not significantly influence the dynamics of business and technological networks.[15]

Empirical results

Descriptive statistics and changes in the structure of the technical and business knowledge networks from 2005 to 2010 are found in Table 4. A first observation is that actors of the Toy Valley are more active in asking business rather than technical advice in both periods. On average, actors only ask technical advice to about 14 different actors, while they ask business advice to about 17 different actors. This finding is in line with previous evidence suggesting that business advice, 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 advice (out-degree distribution) and receiving requests (in-degree distribution) is very skewed. Few actors are very active in asking advice (or very popular in receiving requests), while most of the actors ask (or receive) few advice (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

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

Ties created, maintained or dissolved from 2005 to 2010.

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

Table 5

Dynamics of technical and dynamics of business network.

	Technical network (N = 75)			Business network (N = 75)		
	β	SD	p-value	p	SD	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						
Geographic 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.

In order to test our hypotheses and explain how the network structure changes overtime, we apply the statistical model described in 'Econometric Issues and Specification of the Statistical Model.' 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 (t-values < 0.1). The interpretation of β reported is straightforward; they are non-standardized coefficients obtained from logistic regression analysis (Steglich, Snijders and Pearson 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 knowledge network dynamics (right column).[16]

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 knowledge network). Similarly, social embeddedness is also a strong driver of both networks, since 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 knowledge network), suggesting that family ties matter more when interactions deal with business advice. The reason behind it might be that these firms are typically family-owned businesses, so business information is shared prevalently in the inner circles of family owners. Overall, the above findings confirm

[16] 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.

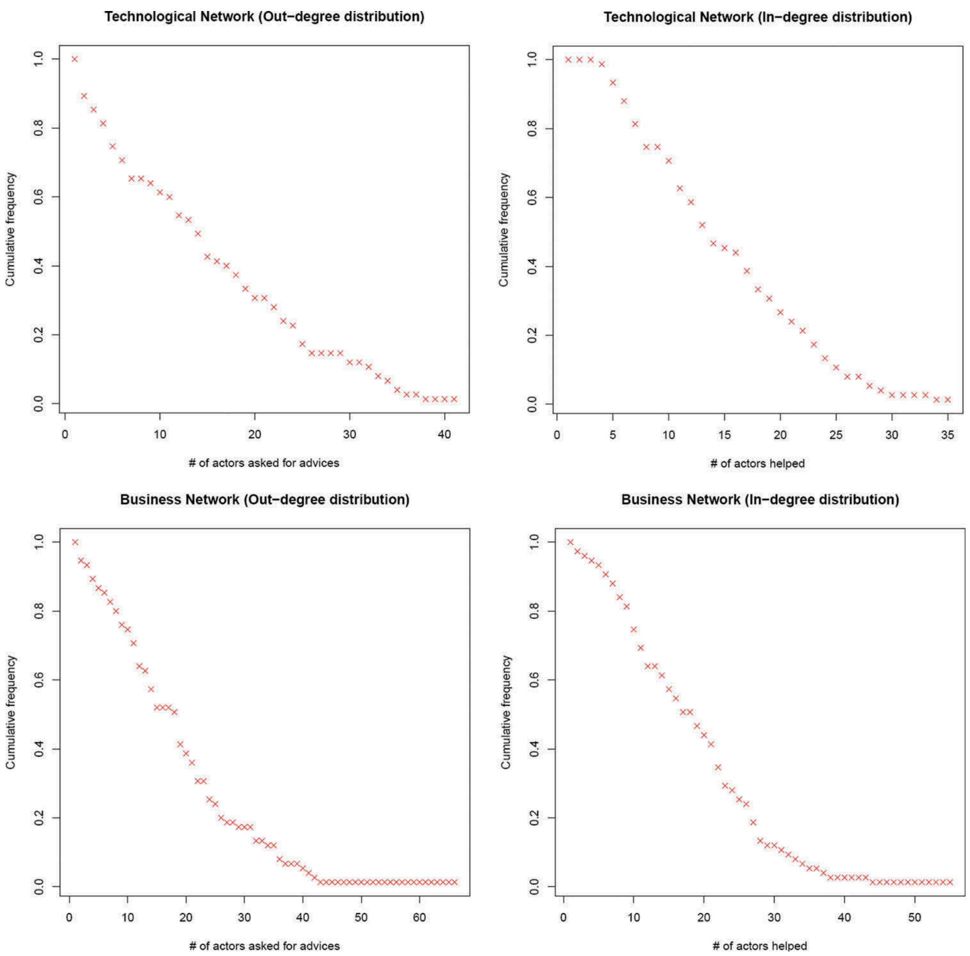


Figure 1. Degree distribution of the technical and business networks.
Note: The different degree distributions are computed from the structure of the technical and business networks in 2010 (dichotomized).

H1 and H2; 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 popularity) is positive and significant for a business knowledge network ($\beta = 0.250$), while it is smaller and not even significant for a technical network ($\beta = 0.035$). Therefore, actors who receive many requests for business advice tend to attract disproportionally new requests in the next period. The latter effect suggests that reputation plays a very important role in business advice sharing. Similarly, industrial status shapes the dynamics of business advice ($\beta = 0.013$), while it is not significant for the dynamics of technical networks. The latter results confirm H3 and H4.

The final set of hypotheses concerns the role of proximity. In this case also, the dynamics of the technical and business knowledge network seem to be driven by different forces. The coefficient for geographic 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 knowledge network (β = 0.023). The same pattern is found for cognitive proximity: positive but not significant in the business knowledge network, while important for technical advice. The latter results confirm H5 and H6.

Concerning the control variables, the *rate parameter* (i.e., stability of the network ties)[17] is lower for the technical network, and *reciprocity* is not significant in the business knowledge network. The latter results seem to confirm that know-how is sensitive to stable, reciprocal links between actors. Common understanding and knowledge transfer require time to be formed and nurtured.

The negative effect of *cyclicity* indicates hierarchy in triads for both networks, that is, that neither business advice nor technical advice 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 knowledge to the other two. 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 who asked a lot of advice in the past tended to ask a lot of advice 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 other words, the latter firm absorbs knowledge from either intra- or extracluster repositories and later diffuses this knowledge between two local partners that are 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 are later 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 knowledge network. In particular, institutional proximity has a positive and significant impact on the formation of technical advice, while it is not significant for business ties. Organizational proximity and perceived similarity are not significant for both networks, but the coefficient has a positive sign in the case of technical networks and a negative sign for business knowledge networks.

Discussion and conclusion

Although networks in clusters have received increasing consideration during the last decade in economic geography, theoretical and empirical research on the dynamics of these networks remains largely underdeveloped (Giuliani 2013). This article explores this question and contributes to a better understanding of informal knowledge exchanges in clusters. Using SAOM (Snijders, Van De Bunt and Steglich 2010), we explicitly model the microdynamics of technical and business knowledge networks formation as an outcome of embeddedness, status, and proximity. We provide evidence of how the latter mechanisms play a different role according to the type of knowledge exchanged (i.e., for the dynamics of technical and business knowledge). 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

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

technical and business interactions. For instance, new toy designs involve codeveloping crucial inputs (e.g., molds), which requires a great deal of information sharing concerning both technical details as well as customer needs. These exchanges are easier if peers are embedded in the same social and structural setting. The latter finding further supports the idea that embeddedness plays a key role in driving the formation of interorganizational networks (Ingram and Roberts 2000) and in particular in clusters (Becattini 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 business advice network. Indeed, the technical advice network shows higher stability and reciprocity than the business knowledge network.

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

Business knowledge networks are characterized by a combination of lack of reciprocity at the 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 to be 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 advice 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 rivalries among competing firms: in such a context, firms avoid sharing information with rivals who might potentially harm their status.

The impact of status on network formation seems to suggest a tendency toward increasing concentration of knowledge in a few hands, which is found in 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 business 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 dynamics of the business knowledge network, but it plays a minor role in 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 geographic 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 the 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 a personal nature). Last, the geographic 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 findings 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). This is in line with Giuliani (2013), who found a positive and significant effect for cognitive proximity[18] (similar to knowledge bases), but different while Giuliani and Matta (2013), who found that both geographic and cognitive proximities do not play a significant role in network dynamics. Such a discrepancy might be due to the specificity of the case studies or the lack of variation in proximity within actors of the clusters. But, we also find instead that proximity plays a limited role in generating business knowledge transfer between local units. While it is true that an important share of the technical advice needed to produce toys is available in the close neighborhood, business knowledge does not necessarily come 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 geographic 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, etc.) also follow different paths. Second, collecting longitudinal data on an informal knowledge network is a very challenging task. Collecting primary data through surveys and interviews 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 a 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 subcontracting 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), which 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 advice, but we did not investigate directly the value of knowledge shared in these informal business and technical networks. In other words, we assumed all knowledge ties to be equal, but it is very likely that some knowledge ties are critical for a firm's performance and

[18] Being slightly significant at the 10 percent level, the author considers that the effect is 'barely significant,' though.

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.

Funding

Andrea Morrison acknowledges the financial support from Nederlandse Organisatie voor Wetenschappelijk Onderzoek (NWO), Innovational Research Incentives Scheme/VIDI project number 452-11-013.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Ahuja, G., Soda, G., and Zaheer, A. 2012. The genesis and dynamics of organizational networks. *Organization Science* 23:434–48.

Almeida, P., and Kogut, B. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Science* 45:905–17.

Asheim B. T. 1996. Industrial districts as 'learning regions': A condition for prosperity. *European Planning Studies* 4:379–400.

Audretsch, D. B., and Feldman, M. P. 1996. R&D spillovers and the geography of innovation and production. *American Economic Review* 86:630–40.

Balconi, M. 2002. Tacitness, codification of technological knowledge and the organisation of industry. *Research Policy* 31:357–79.

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* 46:741–56.

Balland, P. A., Boschma, R., and Frenken, K. 2015. Proximity and innovation: From statics to dynamics. *Regional Studies* 49:907-20.

Balland, P. A., de Vaan, M., and 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* 13:741–65.

Barabasi, A., and Albert, R. 1999. Emergence of scaling in random networks. *Science* 286:509–12.

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

Bell, G. G., and Zaheer, A. 2007. Geography, networks and knowledge flow. *Organization Science* 18:995–72.

Belso-Martínez, J., and Escolano-Asensi, C. 2009. La externalización de actividades como estrategia competitiva en el sector juguetero español. Consideraciones desde una perspectiva espacial. [Outsourcing activities as a competitive strategy in the Spanish toy sector. Considerations from the spatial perspective.] *Economía Industrial* 372:115–27.

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., and 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* 14:177–99.

Breschi S., and Lissoni F. 2001. Knowledge spillovers and local innovation systems: A critical survey. *Industrial and Corporate Change* 10:975–1005.

Breschi S., and Lissoni F. 2009. Mobility of skilled workers and co-invention networks: An anatomy of localized knowledge flows. *Journal of Economic Geography* 9:439–68.
Broekel, T., Balland P. A., Burger, M., and Van Oort, F. 2014. Modeling knowledge networks in economic geography: A discussion of four empirical strategies. *Annals of Regional Science* 53:423–52.
Broekel, T., and Boschma, R. 2012. Knowledge networks in the Dutch aviation industry: The proximity paradox. *Journal of Economic Geography* 12:409–33.
Broekel, T., and Hartog, M. 2013. Explaining the structure of inter-organizational networks using exponential random graph models: does proximity matter? *Industry and Innovation* 20:277–95.
Brown, J. S., and Duguid, P. 2001. Knowledge and organization: A social practice perspective. *Organization Science* 12:198–213.
Burger, M., Van Oort, F., and Linders, G. J. 2009. On the specification of the gravity model of trade: Zeros, excess zeros and zero-inflated estimation. *Spatial Economic Analysis* 4:167–90.
Caja, P., and Martí, J. 2014. La evolución de clusters en España: comparando los casos del juguete-plástico y la cerámica. [The evolution of clusters in Spain, comparing the cases of the toy-plastic and the ceramic-tile.] *Economía Industrial* 391:151–62.
Cantner U., and Graf, H. 2006. The network of innovators in Jena: An application of social network analysis. *Research Policy* 35:463–80.
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* 39:75–87.
Cohendet, P., and Llerena, P. 1995. Diversity and specialisation: An exploration of mechanisms valorising diversity. Unpublished manuscript. University of Strasbourg, France.
Coleman, J. 1988. Social capital in the creation of human capital. *American Journal of Sociology* 94:95–120.
Corredoira, R., and Rosenkopf, L. 2010. Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. *Strategic Management Journal* 31:159–81.
Cowan, R., Jonard, N., and Zimmermann, J. B. 2007. Bilateral collaboration and the emergence of innovation networks. *Management Science* 53:1051–67.
Cross, R., Borgatti, S. P., and Parker, A. 2001. Beyond answers: Dimensions of the advice network. *Social Networks* 23:215–35.
Dahl, M. S., and Pedersen, C. O. R. 2004. Knowledge flows through informal contacts in industrial clusters: Myth or reality? *Research Policy* 33:1673–86.
De Vaus, D. A. 2001. *Research design in social research*. London: SAGE.
Eisenhardt, K. M. 1989. Building theories from case study research. *Academy of Management Review* 14:532–50.
Elfring, T., and Hulsink, W. 2007. Networking by entrepreneurs: Patterns of tie-formation in emerging organizations. *Organization Studies* 28:1849–72.
Featherman, D. L. 1980. Retrospective longitudinal research: Methodological considerations. *Journal of Economics and Business* 32:152–69.
Festinger, L. 1954. A theory of social comparison processes. *Human Relations* 7:117–40.
Frenken, K., Van Oort, F., and Verburg, T. 2007. Related variety, unrelated variety and regional economic growth. *Regional Studies* 41:685–97.
Gittelman, M. 2007. Does geography matter for science-based firms? Epistemic communities and the geography of research and patenting in biotechnology. *Organization Science* 18:724–41.
Giuliani, E. 2007. The selective nature of knowledge networks in clusters: Evidence from the wine industry. *Journal of Economic Geography* 7:139–68.
Giuliani, E. 2013. Network dynamics in regional clusters: Evidence from Chile. *Research Policy* 42:1406–19.
Giuliani, E., and 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., and Matta, A. 2013. Impact evaluation with social network analysis methods, program for supply chain development in the province of Cordoba, Argentina. ATN/ME-8112-AR. Washington, DC: Inter-American Development Bank.
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* 35:848–60.
Grabher, G. 1993. The weakness of strong ties: the lock-in of regional development in the Ruhr-area. In *The embedded firm: On the socioeconomics of industrial networks*, ed. G. Grabher, 255–78. London: Routledge.
Grabher, G. 2002. Cool projects, boring institutions: Temporary collaboration in social context. *Regional Studies* 36:205–14.
Granovetter, M. 1973. The strength of weak ties. *American Journal of Sociology* 78:1360–80.
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* 6:171–80.
Ingram, P., and Roberts, P. W. 2000. Friendships among Competitors in the Sydney Hotel Industry. *American Journal of Sociology* 106:387–423.
Inkpen, A., and Tsang, E. 2005. Social capital networks, and knowledge transfer. *Academy of Management Review* 30:146–65.
Johnson, B, Lorenz, E., and Lundvall, B-Å 2002. Why all this fuss about codified and tacit knowledge? *Industrial and Corporate Change* 11:245–62.
Kogut, B., and Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science* 3:383–97.
Kogut, B., and 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* 10:359–81.
Lazega, E., Mounier, L., Snijders, T., and Tubaro, P. 2012. Norms, status and the dynamics of advice networks. *Social Networks* 34:323–32.
Lazerson, M. H., and Lorenzoni, G. 1999. The firms feed industrial districts: A return to the Italian source. *Industrial and Corporate Change* 8:235–66.
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.
Lissoni, F., and Pagani, M. 2003. How many networks in a local cluster? Textile machine production and innovation in Brescia. In *Cooperation, networks and institutions in regional innovation systems*, ed. D. Fornahl, and T.Brenner,. 220–46. Cheltenham: Edward Elgar.
Maggioni, M., and Uberti, E. 2011. Networks and geography in the economics of knowledge flows. *Quality and Quantity* 45:1065–66.
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 ed. London: Macmillan.
Maskell, P. 2001. Towards a knowledge-based theory of the geographical cluster. *Industrial and Corporate Change* 10:921–43.
McEvily, B., Perrone, V., and Zaheer, A. 2003. Trust as an organizing principle. *Organization Science* 14:91–103.
Miller, C., Cardinal, L., and Glick, W. 1997. Retrospective reports in organizational research: A reexamination of recent evidence. *Academy of Management Journal* 40:189–204.

Mizruchi, M. S., and 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., and Martinez-Fernandez, M. T. 2004. Factors that identify industrial districts: An application in Spanish manufacturing firms. *Environment and Planning A* 36:111–26.

Morrison, A. 2008. Gatekeepers of knowledge within industrial districts: Who they are, how they interact, *Regional Studies* 42:817–36.

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

Nelson, R. R., and 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., and 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., and Sabel, C. F. 1984. *The second industrial divide: Possibilities for prosperity.* New York: Basic Books.

Podolny, J. 1993. A status-based model of market competition. *American Journal of Sociology* 98:829–72.

Pouder, R., and 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., and Owen-Smith, J. 2005. Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences. *American Journal of Sociology* 110:1132–1205.

Reagans, R., and McEvily, B. 2003. Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Science Quarterly* 48:240–67.

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

Rivera, M. T., Soderstrom, S. B., and Uzzi, B. 2010. Dynamics of dyads in social networks: Assortative, relational, and proximity mechanisms. *Annual Review of Sociology* 36:91–115.

Robins, G., Pattison, P., Kalish, Y., and Lusher, D. 2007. An introduction to exponential random graph (p^*) models for social networks. *Social Networks* 29:173–91.

Saxenian, A. 1994. *Regional advantage culture and competition in Silicon Valley and Route 128*. Cambridge, MA: Harvard University Press.

Schrader, S. 1991. Informal technology transfer between firms: Cooperation through information trading. *Research Policy* 20:153–70.

Snijders, T. A. B., Van De Bunt, G. G., and 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* 9:45–64.

Steglich, C. E. G., Snijders, T. A. B., and Pearson, M. 2010. Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology* 40:329–93.

Storper, M., and Venables, A. 2004. Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography* 4:351–70.

Stuart, T., and Sorenson, O. 2003. The geography of opportunity: Spatial heterogeneity in founding rates and the performance of biotechnology firms. *Research Policy* 32:229–53.

Ter Wal, A. L. J. 2014. The dynamics of the inventor network in german biotechnology: geographical proximity versus triadic closure. *Journal of Economic Geography* 14:589–620.

Ter Wal, A. L. J., and Boschma, R. A. 2009. Applying social network analysis in economic geography: Theoretical and methodological issues. *Annals of Regional Science* 43:739–56.

Trapido, D. 2013. Dual signals: How competition makes or breaks interfirm social ties. *Organization Science* 24:498–512.

Uzzi, B. 1996. The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *American Sociological Review* 61:674–98.

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., and Brossard, O. 2011. Getting into networks and clusters: Evidence from the Midi-Pyrenean Global Navigation Satellite Systems (GNSS) collaboration network. *Regional Studies* 45:1059–78.

Völker, B., and Flap, H. 2001. Weak ties as a liability: The case of East Germany. *Rationality and Society* 13:397–428.

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

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

Wasserman, S., and Pattison, P. 1996. Logit models and logistic regressions for social networks. I. An introduction to Markov graphs and p^*. *Psychometrika* 61:401–25.

Winter, S. G. 1987. Knowledge and competence as strategic assets. In *The competitive challenge: Strategies for industrial innovation and renewal*, ed. Teece, D., 159–84. Cambridge: Ballinger.

Ybarra, J., and Santa María, M. 2008. El distrito de juguete de la Foia de Castalla y su evolución. [The toy district of the Foia of Castalla and its evolution.] *Mediterráneo Económico* 13:409–31.