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DELVING INTO THE TECHNICAL TEXTILE PHENOMENON: NETWORKING STRATEGIES AND INNOVATION IN MATURE CLUSTERS

Abstract:

Substantial empirical evidence corroborates the advantages brought about by spatial colocation and networking for firms´ innovativeness in the textile industry. But firms benefit from these advantages depending on their portfolio of relationships. Consequently, cluster firms build their networks according to their specific characteristics in terms of resources and innovation activities. Within this framework, using social network analysis techniques, this study aims to identify the foundations of networking practices in textile clusters and to derive managerial and policy implications. Empirical evidence obtained in the Valencian textile cluster show how the profile and specificities of firm's innovation activities shape its relational practices. Most innovative firms focused on technical textiles show higher levels of internal resources and capabilities.

Keywords: Industrial cluster, textile industry, technical textiles, inter-organizational networks, innovation

1. INTRODUCTION

Globalization has triggered an uneven and ever-changing dispersion of innovation and manufacturing activities across the space, with the textile and clothing industry not being an exception (Puig *et al.* 2009). The industry's value chain has globalized, and most textile firms are involved in a complex sequence of activities through a worldwide business network. (Artschwager *et al.* 2009). However, this process has not blurred the robustness of another fundamental fact of the industry, the geographical clustering of textile activities (Dei Ottati 2009, 2014, Crestanello and Tattara 2011, Exposito-Langa *et al.* 2015). In this sense, and following Porter (1990), clusters are defined as "geographic concentrations of interconnected firms, specialized suppliers, service providers, firms in related industries, and associated institutions (i.e., Universities, standards agencies and trade associations) in particular fields that compete but also co-operate".

Although globalization has partially eroded the competitiveness of many textile clusters (Pla-Barber and Puig-Blanco 2009), it has also led to greater innovation and flexibility through collaboration of cluster firms with knowledge-intensive international actors. The right combination of local anchoring and global drive can allow local firms to move up into more knowledge-intensive textile activities (Puig and Marques 2011).

Previous research has explained the benignities of clustering on the fact that spatial proximity favors lower transaction cost, enhanced access to a specialized labor force and, particularly the spread and exchange of knowledge (Maskell and Malmberg 1999). Several empirical studies provide evidence on the positive effects of co-location on innovation (Audretsch and Feldman 1996, Baptista and Swann 1998, Beaudry and Breschi 2003). Using quantitative data collected in the Italian cluster of Prato, Signorini (1994) corroborated the positive effects of clustering for textile firms with regard to productivity and privileged access to resources.

Albeit fruitful, this view has been recently questioned because spatial proximity "per se" is neither a necessary nor a sufficient condition for knowledge spillovers. The exploitation of the innovation potential of a cluster largely depends on the solidness of its local network (Giuliani 2007).

Instead of just focusing on the traditionally overestimated cluster benefits derived from the automatic access to this knowledge "floating in the air" thanks to colocation (Orsenigo 2006), scholars are paying increasing attention to local networks to explain the innovation trajectories of firms and clusters. Networks can be considered as intangible structures within clusters which allow their firms to selectively diffuse and share knowledge with other cluster firms through planned and structured relationships. In this way, the underlying idea of this alternative approach is that knowledge is not freely available in the cluster atmosphere, but mostly embedded in cluster actors who exchange and cultivate it through relations or social capital (Lorenzen 2007). To the extent that innovation is a collaborative process of several actors in which common knowledge generation, accumulation and diffusion are crucial ingredients (Asheim *et al.* 2011), the metaphor of clusters as networks of interdependent organizations linked to each other in systemic knowledge creation processes, allows a more refined analysis of the effect of colocation on innovation.

Although this "network thinking" has helped to overcome the limitations of pre-published empirical works, the way clusters influence innovation is still being unraveled. While certain consensus exists on the idea that networks are a key factor for firms' innovation in clusters (Bathelt et al. 2004; Giuliani 2007; Belso-Martínez et al. 2017; Exposito-Langa et al. 2015 for the textil industry), empirical evidence suggests that not all network structures foster innovation to the same extent (Stam and Elfring 2008).

The textile industry is a paradigmatic example of how the effects of stagnating demand and hardening competition have forced an intense process of restructuring and modernization through the assimilation of new knowledge. Particularly in developed countries, to the extent of their capabilities, textile firms have accentuated the incorporation of technical novelties to orientate towards new market niches with high potential for knowledge-intensive strategies, such as the technical textiles (Puig *et al.* 2013). Being aware of the relevance of networks for the acquisition of knowledge necessary to innovate, technical textile manufacturers appear to be particularly concerned about the creation and management of their portfolio of relationships (Danskin *et al.* 2005).

EU firms have taken up a leading position in several technical niches such as non-woven and composite textiles, whose manufacture has risen by 75% and 60% respectively since 2000. In 2015, technical textiles represented about 30% of the EU entire textile industry and a large share of the exports, with an increase of 5.3%. This excellent economic climate continued during 2016 when the production of non-woven textiles grew by 3% and other technical textiles by 4%, according to Euratex.

Many Spanish textile firms have also reacted by adopting strategies based on technology and the reorientation towards technical textiles (Costa and Duch 2005). Nowadays, the technical sector is composed of about 225 companies and accounts for 16% of total industry. In 2016, the production of Spanish technical textiles grew by 4.9% in 2016, thereby catching up with leading countries such as France, Germany or Italy. Approximately 75% of these firms are concentrated on the Mediterranean coast, specifically in Catalonia and the Valencian Community. Their responsibility in the resilience of the sector makes the comparative analysis of this group of technical textile firms (TTFs) versus the traditional manufacturers or non-technical textile firms (NTTFs), regarding networking and other innovation-related aspects extremely attractive for academics, practitioners or policy makers.

Challenged by the above premises and the lack of unequivocal evidence on the effects of networks on innovation, this research elucidates how a firm´s relational architecture affects innovation in the textile clusters. Paying attention to the magnitude of the technical textile phenomenon in the recent evolutionary trends of the industry, our comparative analysis between TTFs and NTTFs contributes to this emerging paradigm by: a) elucidating the structural differences and similarities between their networks; b) unraveling how these network configurations explain disparities in innovation performance. Our findings not only improve the academic state of the literature, but also provide insights for efficient management local networks at the firm level and for a more tailored design of innovation policies in clusters.

Using data collected in the Textile cluster of Valencia and applying Social Network Analysis, our study reveals the major role for the nature of a firm's manufacturing activities in shaping its relational practices. Precisely, cluster TTFs present marked differences in terms of internal resources and networking behavior, which in turn subsequently shape innovation performance.

This article has been structured in four sections. After this introduction, we present the theoretical foundations and the research questions. Next, the methods and the results are described. Finally, discussion, conclusions and implications close the paper.

2. LITERATURE AND RESEARCH QUESTIONS

The globalization of the textile industry immediately forced textile manufacturers to implement strategies to face increasing pressure from retailers and competitors. Some traditional manufacturers relocated or outsourced production to low-cost countries, while others shifted to design-intensive textiles for fashion or oriented towards the production of technical textiles for the automotive industry, building sector, civil engineering, medicine or health and safety (Pickles *et al.* 2006).

Instead of scale and standardization, this new textile segment requires additional efforts in R&D and a focus on technical innovation (Owen 2000). A firm´s competitiveness appears based on products and technologies whose development relies both on a distinctive set of assets, abilities and routines developed by firms over time (Teece 2010) as well as high-order endowments associated to the cluster. These cluster resources emerge from the embeddedness of firms' routines and capabilities in the territory (Hervás-Oliver and Albors-Garrigós 2007), and transform the industrial system in a place with superior innovative capabilities, where firms easily access shared resources allowing them to outperform competitors.

Beyond external economies, clusters provide collocated firms with privileged access to specific knowledge that is systematically enhanced through knowledge sharing and learning practices within collaborative networks (Maskell and Malmberg 1999, Tallman *et al.* 2004). Some authors (Breschi and Lissoni 2001, Boschma and Frenken 2006, Morrison and Rabellotti 2009) reveal the existence of a cross-over among multiple networks in clusters, and a distinction must be made between them. In this spider web of networks, one of technical knowledge and another of business knowledge are clearly identifiable (Giuliani 2007, Molina-Morales *et al.* 2012, Balland *et al.* 2016). The heterogeneity of network members in terms of strategies, capabilities and knowledge bases (Phelps *et al.* 2012) stimulates the creation of local knowledge (Antonelli 2005).

While there is little doubt about the role of a firm's local network as a source of knowledge positively influencing innovation (Owen-Smith and Powell 2004, Bell 2005), not all networks do so to the same extent. Depending on the network profile, firms have different access to either technical or business-related knowledge (Giuliani and Bell 2005, Boschma and ter Wal 2007, Molina-Morales *et al.* 2012, Balland *et al.* 2016, Belso-Martínez *et al.* 2017). Therefore, not all cluster firms enjoy the same opportunities for knowledge retrieval (Biggiero and Sammarra 2010, Todtling *et al.* 2013). Despite sharing the same location, knowledge is unevenly exchanged and, subsequently, collocated firms present heterogeneous innovation performance.

Research has dug deeper on what and how the characteristics of networks determine a firm's ability to innovate. The network size, defined as the number of relationships a firm has, represents an indicator of the availability of knowledge resources (Powell *et al.* 1996, Ahuja 2000, Baum *et al.* 2000). Firms with more partners are in an advantageous position, not just because of the larger amount of knowledge accessible, but also the dependency on a reduced number of knowledge providers is lessened. Empirical studies highlight the positive effect of network size on innovation (Powell *et al.* 1996, Ahuja 2000).

To a certain point, the mere accumulation of partners may not lead to greater innovation performance. Increasing the number of partners in the network boosts the amount of knowledge available through it, but it also augments the potential for conflicts and the cost of coordination (McFadyen and Cannella 2004). Additionally, larger networks may become harmful due to the cost and difficulty of maintaining multiple relationships (Rothaermel and Deeds 2006). Some previous research (e.g. Deeds and Demirkan, 2013) suggests that either too few or too many members in the firm's network can limit knowledge creation and innovation.

Besides the size of the network, the density or overall connectivity within the firm's network may also shape innovation. A dense network in which members are highly connected to one another induces reciprocity, trust and sanctions against opportunistic behaviors, thus enhancing knowledge sharing (Coleman 1990, Rowley *et al.* 2000), the assessment of partners capabilities (Eisingerich *et al.* 2010) and performance (Ahuja 2000). This is particularly true in clusters where geographical proximity facilitates pervasive interactions (Saxenian 1994a). However, an excess of density may constrain network member's access to novel knowledge available beyond the network. Without new ideas from outside the network, knowledge accessed through the network becomes homogeneous and redundant, hampering innovation. At the cost of sacrificing the benign effects of density, sparse networks provide more diverse and timelier knowledge (Burt 1992). The limited direct connections between partners indicate operations circumscribed to distinct parts of the whole cluster network. This in turn increases the likelihood that these partners carry heterogeneous information, providing the focal firm with informational advantages through which it is more likely to develop innovations (Burt 2004).

Together with the size and the density, other structural features such as the characteristics of the network on the firm-level, can improve understanding on the role of relational resources. The nature of knowledge needed to innovate has implications on the relationships that firms establish (Asheim and Coenen 2005, Plum and Hassink 2011). This lies in the fact that being connected is necessary for cluster firms (Boschma and ter Wal 2007, Morrison and Rabellotti 2009), but it may not be sufficient to benefit from interactions as a certain level of similarity and complementarity in terms of knowledge bases is necessary (Boschma and Frenken 2009). For valuable information transfers, the knowledge base and expertise of partners should be close enough to communicate and process knowledge successfully. If there are too many cognitive differences between the two parties engaged in inter-organizational learning, the absence of a common stock of knowledge and the different interpretation of the business context would make them unable to share and absorb knowledge (Boschma 2005).

Asheim & Coenen (2005) identified three knowledge bases: synthetic (engineering-based), analytical (science-based) and symbolic (artistic-based). Different knowledge bases may coexist in the same industry. Nowadays, the textile industry is a paradigmatic empirical illustration of this phenomenon, as the synthetic base of the NTTFs coexists with the analytical base of the TTFs (Asheim *et al.* 2017). In this vein, for instance, we may expect that firms exhibiting an analytical base where innovation is science-driven will be more prone to interact and share knowledge.

While cognitive closeness in terms of knowledge base may explain the creation of linkages (Cassi *et al.* 2012) and interactive learning (Agrawal *et al.* 2006) in clusters, it may not always be profitable (Boschma and Frenken 2009). Molina-Morales et al. (2015) show how an excess of cognitive closeness may harm networking in a Spanish foodstuff cluster. Too much overlap between knowledge bases may reduce learning and innovation due to the risk of involuntary knowledge spill-overs, cognitive lock-in and the need for certain doses of dissimilarity. Sammarra & Biggiero (2008) evidenced the positive effect of heterogeneity of knowledge bases for collaborative innovation.

When trying to elucidate which features explain firms' innovation in clusters, together with network characteristics, scholars agree on the role of firm's internal capabilities built through accumulated innovation efforts and experiences (Cassiman and Veugelers 2006). Previous innovation efforts enhance a firm's stock of knowledge and the ability to successfully acquire and apply external knowledge (Zahra and George 2002). Cohen & Levinthal (1990) labelled this ability as "absorptive capacity", which allows to recognise the value of new, external information, assimilate it and apply it to commercial ends.

In clusters, absorptive capacity has been proved to be crucial for innovation performance (e.g. Hervas-Oliver and Albors-Garrigos, 2009). Giuliani and Bell (2005) evidenced how absorptive capacity fosters a firm's openness to external knowledge. In their study of the Barletta footwear cluster, Boschma and ter Wal (2007) found the greater relevance of absorptive capacity in the acquisition of technical versus business knowledge. More recently, Expósito-Langa, Molina-Morales and Tomás-Miquel (2015) showed the relevance of relational resources and absorptive capacity for innovation in textile clusters. The cluster's network represents a platform on which interactions enable the acquisition of knowledge that simultaneously fosters innovations and reinforces a firm's capabilities through the enlargement of the stock of resources and competences (Powell *et al.* 1996).

Especially for textile firms and clusters in the EU, where SMEs subject to the liability of smallness prevail, networks have become crucial for the implementation of innovation-based strategies. Therefore, taking a step forward in their comprehension is inevitable to grasp the resilience of the cluster through knowledge-intensive activities such as technical textiles whose outcomes rely on the combination of firm's capabilities and "cluster things".

Based on the above state of the literature on clusters, innovation and the textile industry, some key issues emerge that help to shape the direction of our analysis through the following questions. First, traditional research highlights the relevance of cluster location due to the presence of externalities. However, recent contributions have laid down the foundations for approaching the advantages of clustering, based on network embeddedness to access local resources. We propose that based on this new view, clues as to how textile firms integrate in different local networks can be found within our Textile cluster data.

An interesting point to note is the conspicuous absence of analysis of the implications of firm-level characteristics of the textile firms such as internal resources (absorptive capacity) and the nature of activities (tightly linked to the knowledge base) in their networking behavior. Overall, we posit that nature of manufacturing activities, when understood relative to technical vs non-technical, are important to achieve a complete picture of knowledge diffusion and the innovative trajectory of both the cluster and its members. Additionally, there has yet to be a more detailed comparison between manufacturers implementing traditional versus knowledge-based strategies. We expect that both types of firms could benefit from our findings, particularly with respect to gleaning ways to efficiently design their portfolio of relationships. Thus, the following is the first overriding research question:

RQ_1: *How are TTFs and NTTFs involved in the technical and business knowledge network of the cluster? To what extent do TTFs and NTTFs differ in the way they are involved in the technical and business knowledge network of the cluster?*

There is consensus about the effect of networks on innovation, even for textile clusters. However, to the best of our knowledge, approaching this issue through the lens of the dichotomy TTFs vs NTTFs is still pending. This new approach to the role of different network structures in the textile industry can shed light on the distinct value that embeddedness in local networks can bring to mature industries in developed countries. The second research question addressed in our research is:

RQ_2: *How does the involvement of TTFs and NTTFs in cluster networks influence their innovative performance? Are there any differences between the two groups of firms?*

3. CONTEXT AND METHODS

3.1 The Textile cluster of Valencia

According to the Spanish Inter-Textile Council (CITYC), the textile and clothing industry in 2015 accounted for 6 percent of industrial employment, 3 percent of production and 7 percent of Spanish industrial exports. Production appears concentrated in geographical areas such as the Textile cluster of Valencia, where a myriad of SMEs performs different activities of a fragmented value chain. This cluster, which includes four counties located in the south east of the Iberian Peninsula (L'Alt Vinalopó, La Vall d'Albaida, El Comtat and L'Alcoià), ranks third right behind Barcelona and Madrid in the list of Spanish textile agglomerations. The cluster comprises numerous textile firms employing 22,695 workers with a total revenue of 1,975 million euros, accounting for 19% of the Spanish industry in 2016. Although solid inter-firm linkages and common supporting organizations like the Alcoy Campus of the Polytechnic University of Valencia (UPV) and the technical research institute (AITEX) reveal the compactness of the whole manufacturing area, the four counties have a long-standing tradition in textiles "per se".

The textile cluster is a complex framework in which firms use a wide spectrum of technologies and participate in multiple value chains to address different markets. The activity scope of activity ranges from the preparation and spinning of fibers, to textile weaving and finishing, to the manufacture of knitted and crocheted articles, or elaboration of embroidery. For decades, the production and commercialization of home-textiles such as blankets, duvets, upholstery or curtains predominated. However, restructuring pressures forced many of these firms to delocalize labor-intensive processes or specialize within the value chain by increasing knowledge-based activities (Tomás-Miquel *et al.* 2012).

Technical textiles have become one of the priorities for the Spanish textile industry in the past year. According to AITEX, about 40% of these companies are located in the Textile cluster of Valencia. This sub-group of manufacturers is responsible for the resilience of a cluster that has experienced a 13% increase in turnover and of about 20% in exports over the 2012-2016 period.

3.2 Data and sample issues

Our field work in the Textile cluster of Valencia was conducted during the first half of 2017. In a preliminary stage, interviews held with two key manufacturers and a panel of experts from local institutions (UPV, Regional textile association ATEVAL, AITEX, etc.) enabled us to obtain information on several aspects of the industry and cluster. The information acquired was used for a pilot questionnaire, data collection and discussion of the final outcomes. Once certain modifications derived from a pre-test made with our firms and members of the panel were included, the final version of our questionnaire was ready to be submitted. Furthermore, the information gathered from key manufacturers and experts from local institutions jointly with the directory of Spanish and Portuguese firms (SABI database[1]) allowed us to determine the population of firms in the cluster. This database also provided us detailed information, such as firm's location, main activities, income, financial performance and number of employees. Due to the wide range of manufacturing processes, around 300 firms were identified. Considering the final aim of our research, following indications by our panel of experts, we removed micro-enterprises and mere traders of home textiles that largely lack innovation activities and do not participate significantly in the local knowledge buzz. After applying this refinement, a final list of 125 companies was established. Despite micro-enterprises being underrepresented in the sample, the distribution of firms by size classes does not differ significantly from the size distribution in the population of cluster firms.

Interviews with firms' managers/owners represented the main data sources of this study. Given the large amount of data to be collected from them and the time required to do so, it could lead to errors in data collection due to manager's fatigue, limited time available, etc. In consequence, we opted to develop the entire data collection process in 2 phases separated by an interval of one month.

[1] SABI is a directory of Spanish and Portuguese companies that collects general information and financial data. In the case of Spain, it covers more than 95 percent of the companies of the 17 Spanish regions.

In a first stage, to map the relational activity at the cluster level, we opted for the so-called Roster-Recall method (Wasserman and Faust 1994). Methodological considerations (Ter Wal and Boschma 2009, Giuliani and Pietrobelli 2016) and previous research (Giuliani 2007, Morrison and Rabellotti 2009, Ramírez-Pasillas 2010, Balland *et al.* 2016) make this strategy extremely advisable. During the interview, each firm was confronted with a complete list of local manufacturers and suppliers and asked to specify from whom they received or transferred technical or business advice. Respondents would also be invited to add any more firms (competitors, customers or suppliers) with whom they had contact but did not appear on the list. The relational data captured the existence of linkages based on a subjective perception, and allowed a reliable reconstruction of the both the technical and the business knowledge networks[2]. CEO and entrepreneurs of 107 firms from the final list answered the questionnaire to a skillful technician during a 40-50 minutes face to face interview. In our opinion, the interviewer's profile decisively contributed to the robustness and reliability of the field work. The response rate represents 86% of the total firms populating the cluster. Our panel of experts confirmed that no relevant firms were missing and firms interviewed epitomize the cluster network, as well as practically all of its different knowledge flows. Relational data were arranged in two matrices corresponding to the technical and the business knowledge network respectively. Each 107 by 107 data matrix in which cell *ij* was coded ‘1’ when any of the respondents of firm *i* reported a knowledge tie with firm *j*.

Finally, in a second stage, we interviewed again the CEO of each of the 107 textile firms with a twofold aim. Firstly, by means of a structured questionnaire, to collect data related to the other firms’ variables required for the research, such as innovation performance, absorptive

[2] The respective 4 questions read as follows: a) From which of the firms on the list have you regularly asked for technical information during the last three years?; b) From which of the firms on the list have you regularly asked for business information during the last three years?; c) From which of the firms on the list have you regularly received requests for technical information during the last three years?; d) From which of the firms on the list have you regularly received requests for business information during the last three years?.

capacity, as well as other general variables such as their size or age. Secondly, through semi-structured interviews, to gain a more detailed understanding of the processes, product portfolio, business strategies, and the focus on product innovation developed by textile firms. Furthermore, these interviews enabled us to carefully classify cluster firms into two groups, TTFs and NTTFs. Specifically, firms were asked to corroborate our initial grouping based on quantitative criteria (average production of technical textiles over 30% for the last 3 years). As a result, after completing this final task, a total of 46 TTFs and 61 NTTFs were obtained.

3.3 Variables

Innovation

This variable measures a firm's capacity to incrementally improve processes in the existing products and services by adapting the scale of Jansen et al. (2006) to the particular characteristics of our study. We opted for incremental innovation as a general innovation measure of cluster firms because this type of innovation is the most representative in cluster contexts of medium-low tech industries where SMEs prevail (Forsman and Annala 2011).

Specifically, firms were asked to rate using a 7 point Likert scale 7 questions about the improvement of the existing range of products and services, the regular implementation of slight adaptations to the existing products and services, the introduction of improved products and services in the local market, the efficiency gains in the supplying processes, the increases of economies of scale in existing markets, the provision of services to the existing customers and the relevance of reduction of internal costs. A factor analysis with Varimax rotation was used to condense information obtained from these 7 items in a unique innovation index. Table 1 shows the factor loadings for the items of the variable Innovation. In addition, the explained variance of the extracted factor was 65,33% and the values of Cronbach's Alpha and the KMO measure of adequacy were .910 and .906 respectively. These values are adequate to continue our study, indicating that the use of factor analysis was appropriate to determine the construct of the scale of the Innovation variable.

Table 1**.** Factorial analysis of the variable Innovation

Items	Innovation: Factor load (λ)	Innovation: Reliability
1. Improvement of the existing range of products and services	,729	KMO = ,906 χ^2 = 442,917 p-value = ,000 Cronbach's α = ,910 Total Variance Explained = 65,33%
2. Regular implementation of slight adaptations to the existing products and services	,729	
3. Introduction of improved products and services in the local market	,809	
4. Efficiency gains in the supplying processes	,830	
5. Increases of economies of scale in existing markets	,815	
6. Provision of services to the existing customers	,876	
7. Relevance of reduction of internal costs	,858	

Network variables: connectedness, density and homophily

From the two data matrices, we calculated each firm's network through social network analysis techniques which represent a powerful tool to explore the structural properties of a network (Wasserman & Faust 1994). A firm's network is a part of the whole cluster's network that consists of the firm and its relations to other cluster firms. From an analytical perspective, we adopt this firm-network approach to calculate the different variables because it focuses on the pattern of ties surrounding the firm and its characteristics such as size or density.

Two variables capture firm's connectedness to the technical and to the business knowledge network respectively. Following previous research (Boschma & ter Wal 2007; Belso-

Martinez & Diez-Vial 2018; Demirkan et al. 2012), we estimated the connectedness to the technical network by means of the size of the technical knowledge network of the firm. In the same way, we also estimated the connectedness to the business network by means of the size of the business knowledge network of the firm. In both cases, each network size represents the absolute number of firms that are directly linked to the firm. The larger the size of a firm's technical and business network, the larger its connectedness to these networks.

The density of a firm's network reflects another aspect of its immediate relational structure, and it is a common network structure measure (Marsden 1990, McFadyen *et al.* 2009). This index refers to the proportion of all possible connections in each firm's network that are actually present. Accordingly, we calculated the density of each firm's technical and business knowledge network. The logic underlying these two variables is that the higher percentage of firm's partners that are linked to each other, the higher the density of the firm's network.

Cluster literature highlights the homophily argument, similarity breeds connections (Mcpherson *et al.* 2001), as a powerful driver of network formation. We decided to examine the role of homophily using the principle of similarity in terms of the main firm's product, which is tightly linked to the firm's knowledge base, because cluster firms are more likely to associate themselves with similar others across this dimension (Rosenkopf and Padula 2008, Balland 2012, Broekel and Boschma 2012). To do so, in both the technical and business network networks, we identify the intensity a TTF prefers to be linked with other TTFs and the intensity a NTTF prefers to be connected to other NTTFs. These two homophily coefficients for each firm were obtained by dividing the number of partners with similar products by the total number of the partners in both the firm's technical and business networks.

Absorptive capacity

Following Cohen and Levinthal (1990), many scholars have used R&D-related measures and approaches to proxy absorptive capacity at the firm level (Schmidt 2010). Therefore, we operationalize absorptive capacity using 5 items that reflect a firm's involvement in R&D activities. In line with Jansen, van den Bosch and Volberda (2005), respondents were asked to evaluate: a) the commitment and concern of the firm's managers towards R&D; b) the importance of cooperation for knowledge acquisition. Additionally, we asked interviewees if the firm had engaged in R&D programs during the last three years, the number of technically qualified employees and the R&D expenditures on total sales such as innovation effort. In order to combine information of the 5 items in a unique variable, we ran a factor analysis with Varimax rotation. Table 2 shows the factor loadings for the items of the variable Absorptive capacity. In a first step, two items were eliminated because their factor loadings were less than .5. In a second step, we ran again a factorial analysis without considering those items. The reliability of the items of this new refined scale was assessed by observing that the explained variance of the extracted factor was 64,28% and the values of Cronbach's Alpha and the KMO measure of adequacy were .901 and .647 respectively. These values are considered adequate, indicating that the factor analysis technique was appropriate to determine the construct of the scale of the Absorptive capacity variable.

Table 2. Factorial analysis of the variable Absorptive Capacity

	Absorptive Capacity	
Items	**Factor load (λ)**	**Reliability**
1. Commitment and concern of the firm's managers towards R&D	Eliminated due to low factor loading	KMO = ,647 χ^2 = 67,624 p-value = ,000 Cronbach's α = ,901 Total Variance Explained = 64,28%
2. Importance of cooperation for knowledge acquisition	Eliminated due to low factor loading	
3. R&D programs during the last three years	,717	
4. Number of technically qualified employees	,845	

5. R&D expenditures on total sales such as innovation effort	,837

Control variables

Finally, our model was completed with the inclusion of two control variables, firm's size and age. On the one hand, size was measured through the total number of employees to avoid a high correlation between revenues and R&D intensity. The association between size and innovation has been frequently pointed out in literature (Audretsch and Acs 1991). On the other hand, firm's age was computed as the number of years since it was created, because temporary evolution influences performance in clusters (Pouder and St. John 1996).

3.4 Analysis techniques and results

Together with descriptive statistics and social network analysis, parametric tests (ANOVA Independent simple t-test) were conducted to perform inter-group comparisons. Before, we confirmed that data were normally distributed (Shapiro-Wilk test at the p-value>.05), there was homogeneity of variance (Levene test at the p-value>.05), and there were no outliers (as per inspection of the boxplot).

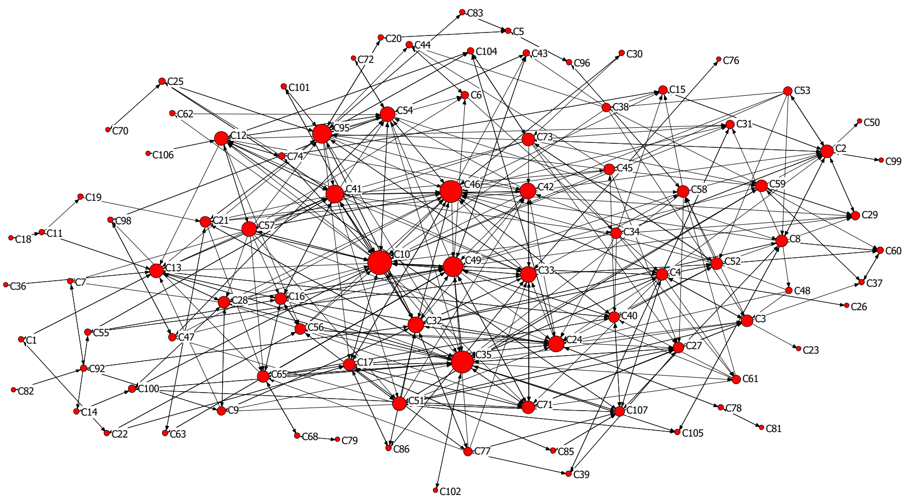

Figure 1. Business knowledge network of Textile cluster

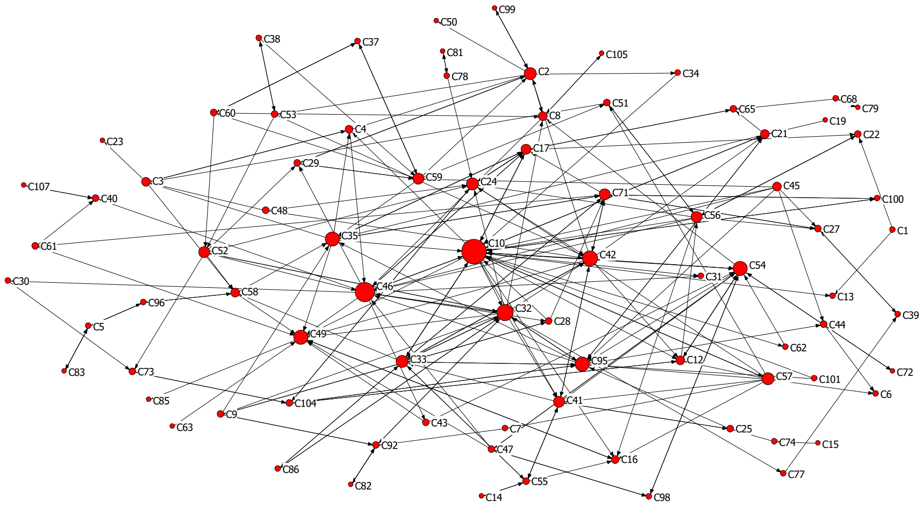

Figure 2. Technical knowledge network of the Textile cluster

Figures 1 and 2 depict the business and the technical knowledge networks in terms of their relations and structure of connectivity. The red circles represent firms while the circle's size is proportional to the number of direct relationships the firm actually has. The higher the amount of direct linkages, the bigger the size of the circle. Lines note the existence of relationships between firms. In our case, these lines are directed giving us an idea of the direction in which the knowledge being exchanged is flowing, with this flow being depicted by an arrow.

At a glance, the differences between the two networks become apparent. The density, defined as the proportion of relationships existing in the whole cluster network to all probable relationships, is higher in the business network. This reveals an increased accessibility and diffusion of business knowledge at the cluster level. Conversely, the sparser structure of the technical network suggests a more selective distribution of this knowledge. Whether in the business network or the technical networks, there is a striking difference in circle size, reflecting important asymmetries in accessing to knowledge.

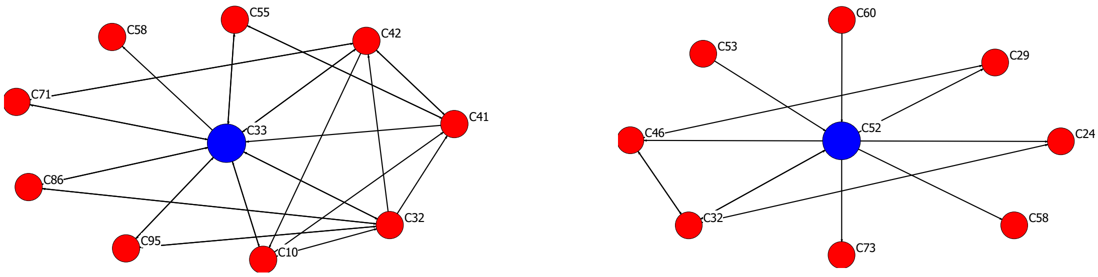

Figure 3. Example of the networks of a NTTF and a TTF respectively

The two networks of the cluster bring together each firm's specific network. Each firm in the cluster possesses its own technical and business network that is a part of the whole cluster relational architecture. Figure 3 shows an example of the representative structure of the individual network of a TTF and a NTTF. Both network structures were obtained by selecting two surveyed firms whose number of partners and connections were close to the average values computed in our statistical analysis. The blue circle is the focal firm and the red circles are the firm's partners. The individual business and technical network of every sampled firm has been used to compute the above explained network variables.

According to the descriptive statistical analysis in Table 3, connectedness values confirm that NTTFs and TTFs are highly involved in the business and technical networks of the cluster, with an average size of the firm's network ranging from 3,440 to 5,930. Both types of firms are more connected on average to the business network of the cluster, while the average density of the NTTFs is always higher than the TTFs. Homophily values are around 60% to 70% in both networks, apparently showing a similarity attraction effect. The two groups have on average about 40-50 employees and 33 years, suggesting that many NTTFs transformed into TTFs. As expected, TTFs exhibit higher average values in terms of innovation and absorptive capacity.

Table 3. Descriptive statistics of the variables

	NTTF		TTF	
	Mean	**Std. dev.**	**mean**	**Std. dev.**
Network variables				
Connectedness (business network)	5.930	5.935	5.87	6.181
Connectedness (technical network)	3.440	3.823	3.480	4.401
Density (business network)	.190	.278	.091	.103
Density (technical network)	.225	.351	.064	.158
Homophily (business network)	.710	.297	.640	.283
Homophily (technical network)	.616	.285	.635	.338
Other variables				
Innovation	-.036	.987	.775	.884
Absorptive capacity	-.410	1.004	.350	1.372
Size	41.440	50.196	48.28	68.028
Age	32.930	18.967	32.98	16.882

To study differences between NTTFs and TTFs in the technical and business networking, Student's t-test was applied using the variables in Table 3. The independent samples t-test evaluates the hypothesis that the difference between the NTTF and TTF samples is equal to 0 (this hypothesis is therefore called the null hypothesis). When the p-value is less than 0.10, the null hypothesis is rejected and the conclusion is that the two means do indeed differ significantly. Positive (negative) values of t imply that the mean values of NTTFs are higher (lower) than the mean values of TTFs.

The results summarized in Table 4 indicate that cluster firms do not show significant differences in their connectedness and homophily either to the technical or the business network. In other words, TTFs and NTTFs exhibit analogous network size and seem to follow the same association logic as the product dimension. In this sense, NTTFs are more likely to establish business and knowledge ties with other NTTFs, and the other way around. Nevertheless, firm's networks significantly differ in terms of density. NTTF networks are denser than those of TTFs both in the technical and the business network.

Table 4. Student's t-tests statistics

Variable	t	Sig.
Network variables		
Connectedness (business network)	.055	.956
Connectedness (technical network)	-.292	.771
Density (business network)	2.303	.023**
Density (technical network)	2.896	.005***
Homophily (business network)	.622	.536
Homophily (technical network)	1.186	.239
Other variables		
Innovation	-4.400	.000***
Absorptive capacity	-3.310	.001***
Size	-.599	.551
Age	-.012	.990

Significant at 0.1 (*); 0.05 level (**); 0.01 level (***)

Furthermore, the results also reveal the existence of significant differences between NTTFs and TTFs in absorptive capacity and innovative performance. In both variables, TTFs show higher values than those of NTTFs, that is, TTFs present greater innovative performance and capabilities for knowledge identification, acquisition and processing. Finally, the results show that NTTFs and NTTFs do not significantly differ in age or size between them.

Once the main differences between NTTFs and TTFs were identified, we studied to what extent the involvement of NTTFs and TTFs in these networks influence firm's innovation. To do so, we analyzed the relation between the firms' network structure (connectedness and density) and their innovative performance, separately for NTTFs and TTFs, and later contrasted the results. To proceed, we initially classified the firms in the technical and business network according to the values of our network variables (connectedness and density). The tertiles split our data into three equal parts. For each of the variables, the first group (G1) was made up of firms with lower values of the variable (bottom tertile). The second group (G2) comprised firms with intermediate values (central tertile), while firm in the upper tertile were brought together in the third group (G3).

Once the NTTFs and TTFs were classified into three groups for our two networks according to their connectedness and density levels, one-way ANOVA was applied to evaluate the differences between the innovative performance of the three groups separately for connectedness and density variables, for NTTFs and TTFs, and also for both the business and the technical knowledge network. Thus, for each network we would have four independent variables or explanatory factors (high, medium or low NTTFs connectedness; high, medium or low TTFs connectedness; high, medium or low NTTFs density; and high, medium or low TTFs density), while firm's innovation performance would be taken as the dependent variable.

Table 5. ANOVA tests statistics

	Network	Firms	G1 mean	G2 mean	G3 mean	F	Sig.
Effect of connectedness on Innovation	Business network	NTTF	-.309	.017	.274	1.987	.146
		TTF	.362	.887	1.106	2.076	.137
	Technical network	NTTF	-.479	.224	.276	4.446	.016**
		TTF	.201	.825	1.530	9.396	.000***
Effect of density on Innovation	Business network	NTTF	-.212	.022	.156	.748	.478
		TTF	.575	.600	1.119	1.944	.155
	Technical network	NTTF	-.473	.377	.179	4.889	.011**
		TTF	.103	1.058	1.097	7.496	.002***

Significant at 0.1 (*); 0.05 level (**); 0.01 level (***)

Following the results obtained in Table 5, we only found significant differences in the mean innovative performance among the different groups in the case of the technical knowledge network, for both NTTFs and TTFs and for both connectedness and density variables. To assess where the differences among the three groups of NTTFs and TTFs were, we performed a Tukey post-hoc analysis through pair-wise comparisons. With regard to the effect of connectedness on innovation, the results in Table 6 show that, for NTTFs, the mean of the innovative performance of the group of firms with lower connectedness (G1) is lower and significantly different to the other (G2 and G3). Thus, the first group would comprise a homogeneous group. On the other hand, the means of the firm's innovative performance in the G2 and G3 groups are higher and do not show statistically significant differences between them. Therefore, we may just conclude that G1 exhibits lower connectedness and innovation compared to G2 and G3.

Table 6. Tukey post-hoc tests statistics (pair-wise comparisons)

		Firms	G1-G2			G1-G3			G2-G3		
			Dif.	Std. error	Sig.	Dif.	Std. error	Sig.	Dif.	Std. error	Sig.
Effect of connectedness on Innovation	Technical network	NTTF	-.703	.291	.049**	-.754	.287	.029**	-.052	.307	.984
		TTF	-.624	.255	.048**	-1.329	.308	.000***	-.705	.290	.049**
Effect of density on Innovation	Technical network	NTTF	-.850	.297	.016**	-.651	.279	.058*	.199	.311	.800
		TTF	-.955	.264	.002***	-.994	.333	.013**	-.039	.306	.991

Significant at 0.1 (*); 0.05 level (**); 0.01 level (***)

Furthermore and with regard to TTFs, the outcomes indicate that the mean of the innovative performance of the group of firms with higher connectedness (G3) is higher than and significantly different from the others (G1 and G2). Thus, this third group would comprise a homogeneous group. Also, the mean of the innovative performance of the firms of the second group is higher and significantly different to those of the first group. Therefore, G1 and G2 would also comprise two other homogeneous groups. So, for TTFs, we may conclude that connectedness systematically improves innovation.

On the other hand, and with regard to the effect of density on innovation, for NTTFs and TTFs, the innovative performance of the firms with lower density (G1) is lower and significantly different to the others (G2 and G3). Furthermore, the G2 and G3 groups of firms do not statistically show significant differences between them with regard to their innovative performance.

4. DISCUSSION, CONCLUSIONS AND IMPLICATIONS

There is an increasing understanding that knowledge is selectively and unevenly exchanged among firms through cluster networks. A firm's innovation can be ascribed to its particular connectedness to these cluster networks together with its absorptive capacity allowing the exploitation of the knowledge acquired. Given the fact that not all cluster firms are equally integrated or positioned in the networks, this research makes a significant contribution on what type of connectedness is necessary to innovate in the textile industry. Answering two relevant open questions through firm-level data collected in the Valencian textile cluster, it represents an additional step forward, as most previous analyses lack insights into the structure of the networks from which the benefits for innovation result.

Our first open question about the involvement of TTFs and NTTFs in the technical and business knowledge network throws light on the networking singularities of a knowledge-based phenomenon in the textile industry. To explore these peculiarities, we used three structural indicators of the firm's network (size, density and homophily). While both groups exhibit analogous connectedness and preference for similar partners, we find that NTTF networks are denser than the TTF networks. Under the light of our firm interviews and previous literature (Saxenian 1994b), traditional textile manufacturers apparently follow widespread relational practices in mature clusters characterized by reciprocity, knowledge sharing and collaborative learning. Geographical proximity fosters face to face interactions and trust, which in turn facilitate transfers of specialized knowledge tightly linked to the territory and embodied in its different actors. Said differently, by promoting density, the resultant network structure fosters the acquisition of specialized knowledge that is often seldom exploited in innovations of the existing product range or processes.

Conversely, also according to interviewees' considerations, TTFs are more concerned about connecting with sources capable of generating or transferring novel knowledge that may engender products or processes with unprecedented performance features. While dense networks provide specialized knowledge of local nature to improve pre-existent products or processes, the implementation of completely novel product lines or manufacturing processes requires the acquisition of different knowledge which is far from the knowledge stock accumulated by cluster firms. The corollary seems evident, consistently with research on textile clusters by Puig and Marques (2011) and Danskin *et al.* (2005), firms need the right combination of local and global sources of expertise to create new knowledge and avoid inertia.

The lack of differences in terms of homophily and connectedness also represent an interesting result. On the one hand, NTTFs or TTFs tend to be connected with similar firms rather than with different alters. This obviously reveals that each type of firm has its own perception, understanding and evaluation of the textile business context. This similarity between partners facilitates knowledge acquisition, but also its assimilation and application through the absorptive capacity of the firm. This finding is consistent with the relevance of cognitive closeness for the creation of linkages observed by Cassi *et al.* (2012) or Balland *et al.* (2016). From the whole cluster perspective, this process is likely to result in two "knowledge clubs" and higher difficulties to access alternative knowledge sources allowing diversification strategies or innovation. On the other hand, the number of partners in the network is not significant. Together with our previous findings, this reveals that the question is with whom rather than the extent to which firms are connected. Again, managers should carefully select their partners and minimize those relationships generating low value.

When we look at innovation performance, some more outstanding results appear. Contrary to the connectedness in the business network, being part of the technical network seems crucial to understand firm's innovation. Undoubtedly, this is tightly linked to our operationalization of innovation performance which mostly relies on product innovation and relegates other organizational or marketing dimensions.

A closer look at the technical network corroborates our expectations that not all cluster network structures foster innovation to the same extent. In line with Exposito-Langa *et al.* (2015), our analysis discloses important differences of density and connectedness depending on the type of firms considered. Connectedness is crucial for both TTFs and NTTFs.

However, while having more sources of knowledge seems always positive for TTFs, the benefits of higher connectedness for NTTFs exist up to certain point after which they practically vanish. Possibly, as qualitative evidences and cluster research reveals (Giuliani and Bell 2005, Boschma and ter Wal 2007, Hervas-Oliver and Albors-Garrigos 2009, Exposito-Langa *et al.* 2015) the higher levels of TTF internal resources (absorptive capacity) allow them to successfully manage, internalize and take advantage of large technical knowledge networks.

The influence of density on innovation also differs between NTTFs and TTFs. As previous research already showed (see Ahuja 2000), frequent interactions characterizing dense networks foster trust and the diagnostic of partners which in turn facilitate knowledge sharing, smooth the absorption of knowledge and enhances innovation performance. However, in light of our findings, there seems to be a “threshold effect” for both types of firms. There is a critical level of density. Once firms get over this threshold, further increases in density does not produce significant effects on innovation. In the case of NTTFs, an excess of density even damages innovation performance. These evidences confirm the risks of an excess of density and redundancies, and the need of different knowledge pointed out by Molina-Morales and Expósito-Langa (2013) or Bathelt *et al.* (2004).

Our analysis has important implications for management. By enhancing the understanding of how and why networks play a role in knowledge transfers and innovation, our insights can help strategic decision making in the management of the firm's portfolio of relationships. Most importantly, our findings underline the importance of network structure. They also show how crucial it is to design and determine the degree of connectedness and density in the light of a firm's characteristics and innovation strategy. For example, in instances where the aim is to develop knowledge-based products such as technical textiles, our findings point to the fact that configuring networks of multiple and diverse knowledge sources is of crucial importance.

Such complexity can only be capitalized if a solid absorptive capacity exists. On the other side of the coin, care should be taken by traditional manufacturers whose weak knowledge bases invite them to relational strategies inducing risky network configurations.

This paper is not exempt of limitations which in turn open avenues for future research. Our data are cross-sectional and circumscribed to a certain geographical location. Although we have little doubt about their robustness and validity, a longitudinal and multi-cluster approach would increase the generalizability of our findings. Moreover, different operationalization of innovation (e.g. radical innovation) may also complement our research. While we have suggested the implications of homophily for the creation of "knowledge clubs", researchers should pay particular attention to the potential advantages of firms´ network positions connecting these clubs.

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