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How do interorganizational networks and firm group structures matter for innovation in clusters: Different networks, different results

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ABSTRACT
Innovation requires knowledge-intensive processes. In firms, group structures may lead to better innovation practices because knowledge pooled by the members through their networks enhances creativity and innovation processes. Knowledge sourced from networks is shaped by the specificity of the network. Using data on Spanish clusters, this article confirms that both teams and external knowledge contribute to innovation, and that combining external knowledge with team practices is effective. However, the benefits of this combination are contingent on the idiosyncrasies of the network in terms of density and geography. Cluster characteristics also determine the role of networks and teams.

KEYWORDS
Industrial clusters; teams; networks; innovation

Introduction

In today's fiercely competitive economy, the need to innovate in order to survive has never been so apparent. Managers and policymakers embrace this mantra, instilling systematic innovation as the new economic religion. Innovation can occur at the individual, team, or firm level or a combination of more than one of these levels. In addition to the wealth of literature on innovation predictors at both the individual and firm levels, research at the team level is also gaining momentum (Hülsheger, Anderson, & Salgado, 2009). In parallel to companies' inexorable shift toward group-based structures and the greater importance of team innovation (Gibson & Gibbs, 2006; Somech, 2006; Somech & Drach-Zahavy, 2013), researchers have turned their gaze toward the dichotomy of teams and firm innovation (Bresman, 2010; Gebert, Boerner, & Kearney, 2010; Gibson & Gibbs, 2006).

As evidence explaining innovation from a team perspective has grown (Hülsheger et al., 2009; Mathieu, Maynard, Rapp, & Gilson, 2008), the debate has shifted from establishing whether team-level factors matter to understand when and how they affect innovation. Despite these considerable efforts, studies of the impact of teams on innovation have yielded inconclusive

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results, often because teams differ in many ways (Joshi & Roh, 2009; Mathieu et al., 2008). For instance, teams that enjoy a high degree of autonomy are more innovative because having control over their own activities is associated with high levels of responsibility and facilitates knowledge transfer and flexible information processing (Langfred, 2005). This association is particularly true for radical innovation (Patanakul, Chen, & Lynn, 2012) and turbulent environments (Chen, Neubaum, Reilly, & Lynn, 2014).

Understanding how these autonomous teams learn to innovate through the integration of diverse sources of expertise is essential. Accordingly, there is a certain degree of academic consensus about the enabling role of external and internal cooperation for teams to innovate (Smith, Busi, Ball, & Vander, 2008). Despite the theoretical and managerial value previous research of this cooperation, studies have primarily focused on intrateam networks (Adler & Kwon, 2002; Balkundi & Harrison, 2006; Mehra, Dixon, Brass, & Robertson, 2006; Tröster, Mehra, & van Knippenberg, 2014) rather than exploring relational issues pertaining to the external sphere of the firm. Although the scarce evidence endorses a positive association between external relationships and team performance (Reagans, Zuckerman, & McEvily, 2004; Wong, 2008), the mechanisms through which extrafirm relational configurations and teams interact to foster innovation have barely been explored (Alexiev, Jansen, Van Den Bosch, & Volberda, 2010; Chung & Jackson, 2013; Collins & Clark, 2003; Simoni & Caiazza, 2012a).

To address this research gap, we build on the premise that network features and team activity influence firms' innovation by improving the available knowledge and the quality of innovation decisions (Mihalache, Jansen, Van Den Bosch, & Volberda, 2014; Smith, Collins, & Clark, 2005; West & Anderson, 1996). However, the properties of external networks vary, and these variations in turn prompt differences in the knowledge that is accessed by teams as well as their contribution to innovation. Strength and density determine aspects of the relationship such as novelty, depth, and refinement of shared knowledge (Ozman, 2009, 2015), especially in industrial clusters, whose potential to generate knowledge is based on patterns of interfirm connections (Mota & de Castro, 2004). Unlike the traditional view that focuses on the relevance of proximity for network creation, the recent literature on sparse extracluster networks emphasizes the value of building distant relationships to innovate (Fitjar & Rodríguez-Pose, 2011).

Using data from three prominent Spanish clusters, we provide a refined understanding of the role of teams and external networks in innovation. Responding to recent calls for cross-level or multilevel approaches (Anderson, Potočnik, & Zhou, 2014), we make three valuable contributions to the literature. First, we explore the mechanisms through which teams and external knowledge sources act together to support innovation. Drawing on the social capital approach, the literature explains the varying impact of cohesive internal networks versus sparse external networks (Alexiev et al., 2010; Chung & Jackson, 2013). Yet there is a lack of empirical evidence on whether the influence of external relationships is still relevant as these networks become denser through pervasive interactions in situations of proximity. Therefore, we extend previous research by testing whether the contribution of these knowledge sources is contingent on the characteristics of the relational architecture.

Second, although few empirical studies have addressed this topic, the literature acknowledges the positive effect of autonomous teams on innovation (Eisenbeiß & Boerner, 2010). However, their effectiveness depends on aspects such as environmental turbulence (Chen et al., 2014) and radical innovation (O´Connor, 2008; Patanakul et al., 2012). We provide novel insights by examining the conditional effect of autonomous teams throughout the cluster life cycle (Menzel & Fornahl, 2010). We thus evaluate knowledge recombination from internal knowledge sources and locational benefits (Bell, 2005; Pouder & St. John, 1996) from a novel perspective. Additionally, we extend research on human management systems and innovation in clusters (Belso-Martinez, Palacios-Marqués, & Roig-Tierno, 2018; Laursen & Foss, 2003; Martínez-del-Río, Céspedes-Lorente, & Pérez-Vall, 2013; Zhou, Hong, & Liu, 2013) by opening the black box to assess the exact contribution of autonomous teams.

Third, we add to the sparse literature on the contingent nature of the influence of network structures on innovation throughout the cluster life cycle (Balland, De Vaan, & Boschma, 2013; Østergaard & Park, 2015; Ter Wal, 2014). Whereas most research has focused on a unique cluster or has compared clusters within a single industry (see Bell & Giuliani, 2007 or Giuliani, Morrison, Pietrobelli, & Rabellotti, 2010 in the wine industry), our study provides a pioneering intercluster comparison using a unified multi-industry methodological approach. Moreover, it represents an initial attempt to measure how much the combination of internal and external innovation practices matter for innovation throughout the cluster life cycle. Major implications for strategic organizational design and public innovation programs can be derived. After presenting the theoretical framework and the hypotheses in the next section, we describe the method, econometric approach, and main findings. Finally, conclusions, limitations and implications at different levels close the study.

Literature

Knowledge, networks, and clusters

Firms increasingly dissolve their boundaries to foster learning and knowledge sharing in order to survive. Conceiving ideas requires extensive interactions between firms and external actors. The literature on social capital largely focuses on the characteristics and role of interfirm networks across three interrelated dimensions (Nahapiet & Ghoshal, 1998).[1]

The structural dimension of the social capital approach differentiates dense, cohesive networks (Coleman, 1988) from sparse networks based on the theory of structural holes (Burt, 1992). Highly interconnected network structures provide firms with social control mechanisms. Partners are inclined to perform according to each other's expectations and cooperate honestly because opportunism or deviant behaviors are quickly punished. The trustful atmosphere of cohesive networks fosters intense interactions, enabling a better understanding, exchange, and application of knowledge. Even density enables refined knowledge transfers. It may lead partners to feel compelled to maintain traditional relationships, generating cognitive lock-in (Grabher, 1993), may result in smaller spaces for cultivating new relationships due to high costs (Gargiulo & Benassi, 2000), and may create redundancies (Burt, 1992; Molina-Morales & Expósito-Langa, 2013).

In view of the potential detrimental effects of cohesiveness, proponents of the theory of structural holes highlight the benefits of sparse networks and nonredundant ties. Network members should act as bridges that connect otherwise disconnected actors to fill the structural holes of the relational structure (Burt, 1992). Nonredundant ties offer advantages in terms of privileged access to novel knowledge from different sources, which encourages exploration, particularly when codified knowledge prevails (Rowley, Behrens, & Krackhardt, 2000). The debate surrounding the two approaches to the structural dimension has resulted in a rich stream of research. Arguments for the benefits of both cohesiveness and looseness have received widespread empirical support (Ahuja, 2000; Hargadon & Sutton, 1997; Obstfeld, 2005; Uzzi & Spiro, 2005). Although some authors suggest that these positions are complementary and beneficial for performance, most recent research has provided evidence of a contingent trade-off between these positions based on conditions and mediating factors (see Ozman, 2015 for a recent review).

Industrial clusters are a special case of interwoven organizations (Sorenson, 2003), where place (location) and flows (networks) overlap considerably (Boschma & Ter Wal, 2007; Ter Wal & Boschma, 2009). In these systems, the spatial proximity of partners enhances interorganizational knowledge flows (Maskell & Malmberg, 1999; Whittington, Owen-Smith, & Powell, 2009), particularly in the case of complex tacit knowledge, whose transmission requires the dense networks and trust that result from constant face-to-face interactions enabled by regular co-location (Audretsch & Feldman, 1996; Maskell & Malmberg, 1999). This need for dense networks

[1]The *structural dimension* is based on elements such as density, hierarchy, and connectivity. The *relational dimension* focuses on the normative infrastructure underlying a network (norms or obligations). The *cognitive dimension* is defined by resources that afford a shared basis for interpretations and representations.

and trust is especially strong when firms are at risk of opportunism, unexpected knowledge leaks, or imitation by other companies located nearby (Simoni & Caiazza, 2012b).

Local interactions cannot be understood in isolation from translocal linkages that enrich and challenge territorialized knowledge resources (Bathelt, 2006). New knowledge introduced through sparse networks (McEvily & Zaheer, 1999) helps overcome the negative effects of obsolescence and rigidities (Asheim & Coenen, 2006; Martin & Sunley, 2006). Within translocal linkages, transfers of tacit knowledge become arduous unless supported by information and communication technologies (Bathelt & Turi, 2011). Thus, exchanged knowledge becomes more codified (Ter Wal, 2014). Additionally, geographical distance hinders the development of goodwill trust because contacts are more formal, periodic, and computer mediated (Morgan, 2004).

Teams, knowledge, and innovation

For decades, the individual nature of creativity and innovation has been taken for granted (Gupta, Tesluk, & Taylor, 2007). Nowadays, firms should also promote precise organizational structures (Tidd & Bessant, 2013) and efficiently mobilize knowledge resources (Powell, Koput, & Smith-doerr, 1996). Because of the increasing complexity and the number of inputs involved (van der Vegt, Bunderson, & Kuipers, 2010), teams have become crucial units in the response to innovation demands (Powell et al., 1996) through dynamic relationships within (van der Vegt et al., 2010) and beyond their boundaries. Thus, scholars have shifted their attention from a focus on the lone innovator (Singh & Fleming, 2010) toward a focus on teams (Lungeanu & Contractor, 2015).

The teams literature (for example, Yu & Hang, 2010) shows that groups are conducive to practices leading to innovation for two main reasons: (a) creativity and effectiveness (Dew & Hearn, 2009) and (b) outstanding innovativeness that stems from greater access to a broader range of knowledge (Smart, Bessant, & Gupta, 2007). The human resource perspective corroborates teams' additional benefits resulting from the integration of heterogeneous knowledge from different employees and better use of local knowledge (Laursen & Foss, 2014). This finding is consistent with the importance of team diversity for innovation. Unobservable cognitive differences between team members (for example, knowledge-based differences) encourage novelty that stems from alternative combinations of diverse knowledge stocks (Guimera, 2005; Milliken, Bartel, & Kurtzberg, 2010; Taylor & Greve, 2006).

Networks of teams provide opportunities for diversity, knowledge acquisition (Podolny & Baron, 1997), and trust (Nahapiet & Ghoshal, 1998). Using original data on 766 teams, Ruef (2002) linked innovation to team members' ability to access diverse information and sustain an atmosphere of goodwill through frequent interaction with others in the firm (internal networks) or outside the firm (external networks). Besides aspects of team structure such as size or heterogeneity, Ruef (2002) observed that the analysis of a team's innovativeness must address the characteristics of internal and external networks.

Whereas internal networks provide opportunities to exploit information that the firm already has, members form external networks with other firms to exchange specific knowledge (Caiazza, Cannella, Phan, & Simoni, 2018). In their study of boards, Simoni and Caiazza (2012b) found that interpersonal ties between members of multiple corporate boards create interfirm relationships through which valuable resources can be obtained. Such team-based external collaboration ties for innovation can be established with customers (to gather knowledge about markets and opportunities), suppliers (to keep knowledge about technology updated), or other knowledge organizations such as universities or research centers (Johnsson, 2017). According to Birkinshaw, Bessant, and Delbridge (2007), it could be valuable to seek these networks in distant areas to identify potential unusual strategic partners when striving to innovate.

Network-based approaches to teams seek to understand and distinguish between the relational configurations that facilitate or constrain knowledge flows and build trust among team members (Mehra et al., 2006). They are rarely related to discovering how these network patterns at the intrateam level affect innovation (Balkundi & Harrison, 2006; Tröster et al., 2014). This issue remains open to debate (Crawford & Lepine, 2013). Using insights from the social capital literature, Chung and Jackson (2013) found that relationships between networks of people within the team and networks between team members and other parts of the firm exert a significant effect on team performance. As mentioned earlier, the effect of different extrafirm relational configurations on innovation from the team perspective remains relatively unexplored.

Hypothesis development

Problem solving and innovation in complex settings call for collective actions leading to interactive value creation across organizational borders (Brödner, 2013). Thus, despite being contingent on their inherent characteristics, team-based structures in firms are useful for innovation (Sivasubramaniam, Liebowitz, & Lackman, 2012; Stewart, 2006). Their contribution stems from fact that the range of knowledge is broader than that of individuals, which stimulates new ideas and the spread of knowledge (Smart et al., 2007).

Team autonomy, the degree to which a team is allowed to make its own decisions about the content and outcomes of the innovation process (Du Chatenier, Verstegen, Biemans, Mulder, & Omta, 2009), improves the team's capacity to develop new ideas and experiment, which in turn promotes innovation (Das & Joshi, 2007). The underlying logic is simple. Autonomy increases perceived self-determination and hence intrinsic motivation of team members, which causes creativity to flourish (Zhou, 1998). At the team level, autonomy promotes high levels of ownership and responsibility, and facilitates knowledge transfer, flexible information processing, and collaboration, all of which enhance innovation. Empirical evidence shows how autonomy may shape collaborative knowledge creation in teams (Camelo Ordaz, Fernández Alles, & Martínez Fierro, 2006; Govindarajan & Trimble, 2005; O'Connor, Paulson, & DeMartino, 2008), particularly favoring radical innovation (Patanakul et al., 2012) in turbulent environments (Chen et al., 2014).

The geographical clustering of firms has been widely recognized as conducive to innovation and growth (Audretsch & Feldman, 1996; Capello & Faggian, 2005). Nevertheless, rather than co-location itself, it is the combination of the networks generated throughout the cluster (Owen-Smith & Powell, 2004) and certain internal capabilities that make a firm innovative. These internal capabilities, particularly absorptive capacity (Cohen & Levinthal, 1990), are critical to benefit from externally acquired knowledge. In the cluster literature, absorptive capacity is cited as essential for acquiring, understanding, or using knowledge to innovate (Giuliani & Bell, 2005; Hervas-Oliver & Albors-Garrigos, 2009). The network of relationships among co-located firms is typically characterized as a web of dense, overlapping ties, where knowledge is rapidly diffused (Molina-Morales & Expósito-Langa, 2013). Through these local networks and the necessary absorptive capacity, firms located in an industrial cluster acquire knowledge from co-located partners and exploit this knowledge in an innovative way (Presutti, Boari, & Majocchi, 2011).

These local relationships are influenced by extracluster knowledge introduced through external linkages, which renews locally generated knowledge (Bathelt, Malmberg, & Maskell, 2004). The most innovative firms do not limit themselves to local knowledge; instead, they build networks with distant customers or suppliers to acquire updated technological or market information (Li, Veliyath, & Tan, 2013). Doing so enables the acquisition of innovation capabilities and a wide variety of novel solutions. According to the conceptualization of the cluster, distant networks connecting firms beyond the cluster boundaries are sparse and exist under conditions of structural holes (McEvily & Zaheer, 1999; Molina-Morales & Expósito-Langa, 2013).

The positive effect of teams on firms' innovation is reinforced when extrafirm connections are used to gather valuable information to enhance performance (Ancona & Caldwell, 1992; Brion, Chauvet, Chollet, & Mothe, 2012; Büchel, Nieminen, Armbruster-Domeyer, & Denison, 2013; Drach-Zahavy, 2011; Faraj & Yan, 2009; Hülsheger et al., 2009; Marrone, Tesluk, & Carson, 2007; Somech & Khalaili, 2014; Vissa & Chacar, 2009). For instance, interlocking boards that create bonds to exchange resources and benefits when a board member of Company A is also a board member of Company B (Caiazza & Simoni, 2015) help firms exchange knowledge and outperform rivals (Simoni & Caiazza, 2013). Openness to knowledge in innovation processes is correlated with team autonomy, particularly in decisions (Stock, 2014). Therefore, it would seem that the combination of networks and the implementation of autonomous team structures should enhance firms' innovation. Collective efforts and decisions in contexts of autonomy should be more likely to creatively transform knowledge from dense localized networks or sparse distant networks into novelty. Therefore, we hypothesize the following:

Hypothesis 1 (H1): The interaction between dense local networks and autonomous teams is positively related to a firm's innovation performance such that firms with autonomous teams benefit from dense local networks.

Hypothesis 2 (H2): The interaction between sparse distant networks and autonomous teams is positively related to a firm's innovation performance such that firms with autonomous teams benefit from sparse distant networks.

Networks may contribute differently to firms' innovation performance depending on costs and the characteristics of knowledge access. Geographical proximity lowers the cost of identification of partners, face-to-face interactions, and the transmission of knowledge (Audretsch & Feldman, 1996; Tallman, Jenkins, Henry, & Pinch, 2004). In particular, location in industrial clusters allows trade and nontrade inputs to be provided at a lower cost (Baptista & Swann, 1998). Tacit complex knowledge is widely acknowledged as a necessary ingredient for innovation. Together with lower costs, co-location facilitates transfers of tacit knowledge, which is best conveyed through constant personal interactions (Maskell, 2001) and is systematically refined within cluster boundaries (Bathelt et al., 2004). Additionally, local networking encourages the development of partner-specific absorptive capacity, enabling enhanced common learning and knowledge sharing (Maskell, 2001; Mcevily & Marcus, 2005).

Trust-based relationships are known to be a prerequisite for innovation because they reduce the risk of unpredictable behaviors, extending the firm's willingness to share knowledge (Kogut & Zander, 1992; Simoni & Caiazza, 2012b). To the extent that dense local networks allow teams to better monitor external partners and contribute to feelings of trust (Bronfenbrenner, 1986), they facilitate the effective transfer of the complex knowledge that is necessary to innovate (Obstfeld, 2005) and the emergence of a climate that is conducive to innovation (Smith et al., 2008). These knowledge transfers are further strengthened if there is a shared understanding of the experiences and symbols between the team and external partners (Caiazza et al., 2018). Dense network structures support the formation and operation of such systems of codes and symbols (Obstfeld, 2005) and make task coordination easier (Gargiulo & Benassi, 2000). In short, teams in firms located in clusters access and absorb complex knowledge more easily through dense local networks. Therefore, we hypothesize the following:

Hypothesis 3 (H3): The interaction between networks and autonomous teams is more pronounced in dense local networks than in sparse nonlocal networks such that the contribution to innovation of dense local networks of firms with autonomous teams is greater than the contribution of sparse nonlocal networks of firms with autonomous teams.

The literature shows the advantage of geographical clustering for stimulating interactive learning and innovation clusters and developing sustained competitiveness (Maskell, 2001; Tallman et al., 2004). Some scholars have challenged this view by suggesting that dense networks of mature clusters may cause a systemic suboptimal evolutionary trajectory because of over-embeddedness (Grabher, 1993; Martin & Sunley, 2006; Pouder & St. John, 1996). For instance, firms in such clusters tend to deal with the same suppliers or share the same cognitive map and common values, making it hard for them to react to exogenous shocks. Networks that are too local, too closed, and too rigid may suffer from an entropic deterioration that eventually degrades the knowledge resources available in the cluster (Li et al., 2013).

To avoid negative contexts, firms may change the blend of competitive and cooperative relationships (Simoni & Caiazza, 2012b). In mature clusters, it is common for firms to increasingly build linkages with nonlocal firms to ensure competitiveness (Bathelt et al., 2004; Owen-Smith & Powell, 2004). Through extracluster linkages, firms may obtain the latest technological information, learn of changes in market demand, and adjust their product designs (Giuliani & Bell, 2005). Although local and nonlocal relationships may complement each other, recent studies have shown that intracluster networks may be progressively replaced by distant ones in the production of knowledge and innovation (Menzel & Fornahl, 2010; Ter Wal & Boschma, 2011). Because sparse extracluster networks allow access to a more varied set of knowledge that is not locally available (Ahuja & Katila, 2004), we hypothesize the following:

Hypothesis 4 (H4): The interaction effect between local networks and cluster characteristics is negatively related to a firm's innovation performance such that firms in mature clusters benefit from dense local networks less than firms in nonmature clusters.

Hypothesis 5 (H5): The interaction effect between nonlocal networks and cluster characteristics is positively related to a firm's innovation performance such that firms in mature clusters benefit from sparse nonlocal networks more than firms in nonmature clusters.

Adopting the characteristics of autonomy, teamwork, and participative decision-making can improve firms' innovativeness. Teamwork and information sharing allow team members to undertake tasks more efficiently and develop problem-solving skills, which improve learning and innovativeness (Forrester, 2000; Yeung, Lai, & Yee, 2007). Although teams are likely to enhance innovation activity, they may not be equally effective across different sectors. In dynamic knowledge-based industries, the uncertainty surrounding innovation success is greater than in traditional manufacturing sectors because of higher rates of change and less certainty over the way technologies will develop. Drawing on arguments from the organizational literature, Laursen (2002) noted that organic structures (flexible, decentralized, informal, team based, and highly integrated) suit knowledge-based industries because such structures cope better with uncertainty. In a study of Swedish firms, Laursen (2002) observed that team-based practices were associated with innovation in industries that were more knowledge based. Considering the positive effect of the simultaneous implementation of human resource management practices in clusters (Belso-Martinez et al., 2018; Martínez-del-Río et al., 2013; Zhou et al., 2013), we hypothesize the following:

Hypothesis 6 (H6): The interaction effect between autonomous teams and cluster maturity is negatively related to a firm's innovation performance such that firms in mature clusters benefit from autonomous teams less than firms in nonmature clusters.

Method

Selection of industrial clusters

This empirical study covered three industrial clusters located in the south of the region of Valencia (Spain): toys, foodstuffs, and biotechnology. We selected these clusters for three reasons. First, the availability of network data and the workable sizes of the clusters facilitated the fieldwork. Second, the industries differed in terms of their history, international openness, and managerial practices, enabling interesting cross-sector comparisons. Third, the clusters comprised both large firms and small and medium-sized enterprises (SMEs), enabling the exploration of the effect of certain intraorganizational structures that typically do not exist in micro and small enterprises. Table 1 displays the characteristics of the analyzed firms by cluster.

Sample and data collection

We conducted a cross-case study using mixed qualitative and quantitative methods (Cameron & Molina-Azorin, 2011). We first explored the history and status of the three clusters using documents, materials, and a combination of semistructured and in-depth interviews with six academic experts, seven representatives of prominent business associations, and three members of the associated technological institutes.[2] Based on these insights and our literature review, a questionnaire was designed to collect data on firm characteristics, networking, organizational practices (teams/groups), and innovation. A draft version of the questionnaire was pretested with five firms per cluster. The pretest was conducted to assess clarity, comprehension, and completion time. Feedback from the pretest helped us refine the questionnaire prior to the final data collection process.

A total of 147 firms based in the clusters were identified using local business associations and SABI-Bureau Van Dijk data files.[3] In view of the complexity of the phenomenon under study, top-level managers and business owners from each organization were invited to respond to the questionnaire. To ensure the accuracy of responses and avoid misrepresentation of the questions, we administered the questionnaire in 45-minute face-to-face interviews with the top managers and business owners of each firm. Interviews were conducted by an expert with extensive knowledge of these industries.

At the beginning of the meeting, we presented the project and guaranteed respondents' confidentiality to encourage the provision of accurate data (Eisenhardt, 1989). Access to the results was also offered to encourage engagement in the study (Miller, Cardinal, & Glick, 1997). These measures have been shown to increase effectiveness and accuracy (Miller et al., 1997). With guidance on how to respond to each question, 139 participants completed the questionnaire in their facilities between late 2012 and early 2013, yielding a response rate of 95 percent. Following the approach by Podsakoff,

[2]The business associations were *Asociacion Española de Fabricantes de Juguetes* (toys), *Asociación de Empresas de Biotecnología de Alicante* (biotech), and *Asociacion de Fabricantes de Turrón y Derivados* (foodstuffs). The technological institutes were *AIJU* (toys) and *Consejo Regulador del Turrón de Jijona* (foodstuffs). Insights from this preliminary phase were also used to interpret and corroborate our quantitative results using qualitative evidence.

[3]SABI is a directory of Spanish and Portuguese companies that provides general information and financial data. It covers more than 95 percent of companies in all 17 Spanish regions with total annual revenues of 360,000 to 420,000 euros or more.

Table 1. Characteristics of the firms in each cluster.

Characteristic	Foodstuffs Cluster	Toy Cluster	Biotech Cluster
Company size			
Small	75.0%	86.7%	89.3%
Medium	16.7%	10.7%	7.1%
Large	8.3%	2.7%	3.6%
Legal structure			
Corporations	47.2%	20.0%	75.0%
Limited liability	41.7%	78.6%	25.0%
Others	11.1%	1.4%	
Exporters	44.4%	21.3%	
Industrial activities	Foodstuffs manufacturers and suppliers (chemicals, technology, and ingredients)	Toy manufacturers, auxiliary industry (injectors or molds), and suppliers of raw materials.	Red biotech (health), green biotech (environment) and white biotech (industry).
Towns	Xixona	Ibi, Onil, Castalla, Biar	Alicante-Elche
Sample size	36	75	28

MacKenzie, Lee, and Podsakoff (2003), we discarded the possibility of common method bias using a single-factor test. The analysis revealed six factors accounting for 63.27 percent of the total variance. The largest factor did not account for the majority of the variance (26.34 percent).

Although the 95 percent response rate reduced the risk of nonresponse bias, further analysis showed the absence of relevant differences between our sample (n = 139) and a control group from the industry (n = 260) obtained from business associations and SABI-Bureau Van Dijk data files. We compared the average number of employees and total revenues using a Student's t test. We did not find significant differences for either metric (p-value = .193; p-value = .337, respectively).

Measures and constructs

We constructed a dependent variable to measure each firm's innovation behavior and investigated the effect of four independent variables. We also used two control variables and considered five interaction effects.

Dependent variable

There is no universal approach to measuring a firm's innovation. All alternatives have certain limitations. For instance, patents are among the most frequently applied indicators. However, there are several well-documented reasons that many companies do not use patents to protect their knowledge outputs (Grant, 1996). Aware of the difficulties involved in simultaneously assessing innovation in different contexts, we linked innovation to new product or process creation in terms of business units (Tushman & Nadler, 1986). Specifically, the indicator that we used was drawn from the literature on innovation and clusters (Boari, Molina-Morales, & Martínez-Cháfer, 2016; Expósito-Langa, Molina-Morales, & Tomás-Miquel, 2015; Molina-Morales, Belso-Martinez, & Mas-Verdú, 2016).

Innovation

In this study, innovation was evaluated by combining information from eight items obtained from the official questionnaire of the Innovation in Companies Survey conducted annually by the Spanish National Statistics Institute.[4] The questions in Table 2 captured whether the firm introduced a new product or service in the past three years; implemented new operational practices in manufacturing, logistics, or support activities; made advances in terms of organizational procedures, structure, or knowledge sharing; and made changes in areas such as packaging, promotion, or

[4]The Innovation in Companies Survey provides up-to-date information on the structure of the innovation process, companies' technological strategies, factors influencing companies' capability to innovate, and performance. The survey follows the methodology set forth in the Oslo Manual (OECD and Eurostat, 2007).

Table 2. Constructs and measures.

Innovation (*Cronbach's alpha* = .84)

Over the last three years, has your company introduced any of the following innovations?

- New or improved goods or services before competitors (Y/N)
- New or improved products or services already available from competitors (Y/N)
- New or improved manufacturing methods (Y/N)
- New or improved practices to support processes (Y/N)
- New or improved organizational structures (Y/N)
- New or improved organizational procedures (Y/N)
- Significant changes in product packaging and promotion strategies (Y/N)
- New strategies for market positioning (Y/N)

Size

What is the average number of employees in your company over the last three years?

R&D Efforts

What is the average R&D expenditure as a percentage of total revenues in the last three years?

Local Network

Over the last three years, has your company cooperated in innovation activities with any of these actors located in your town/region?

- Suppliers of equipment, materials, components, or software (Y/N)
- Customers from the private or public sector (Y/N)
- Competitors or other companies from the same branch of activity (Y/N)

Non-Local Network

Over the last three years, has your company cooperated in innovation activities with any of these firms located outside your town/region?

- Suppliers of equipment, materials, components, or software (Y/N)
- Customers from the private or public sector (Y/N)
- Competitors or other companies from the same branch of activity (Y/N)

Team

Regarding the organization of innovation activities over the last three years, express your agreement or disagreement with the following statement:

- Your company frequently creates autonomous work teams (Y/N)

Cluster

Ordinal variable taking the value 1 if the firm belongs to the biotech cluster, 2 if the firm belongs to the toy cluster, and 3 if the firm belongs to the foodstuffs cluster

positioning (see Table 2). Scores on the individual items were factor analyzed using maximum likelihood estimation (Kaiser-Meyer-Olkin Index (KMO) = .777; p-value < .01). The unique factor had acceptable internal consistency (Cronbach's alpha = .84). Because the questions in our construct were taken from a widely applied scale that follows the guidelines of the Spanish Statistical Institute, we were confident of its validity. Even so, the opinions collected from our panel of experts corroborated that our instrument effectively reflected a firm's innovation behavior.

Control variables

We controlled for research and development (R&D) effort and firm size to isolate the independent variables' effects in the model. Following the approach of Cohen and Levinthal (1990) and Mowery, Oxley, and Silverman (1996), we operationalized the variable *R&D effort* as the average R&D expenditure as a percentage of total revenues over the past three years. Size is frequently used as a control variable. According to the literature, a positive association between size and innovation may be expected (Audretsch & Acs, 1991; Mowery et al., 1996). *Firm size* was measured as the average number of employees over the past three years. Data for both variables were gathered directly from the firms during the fieldwork.

Independent variables

To measure knowledge networks for innovation through cooperation with local and nonlocal firms, we created two composite variables using the procedure described by Laursen and Salter (2004). Composite variables created by summing dichotomous items have been used extensively to evaluate firms' networking behavior in clusters (Boari et al., 2016; Molina-Morales et al., 2016). The variable *Local network* was a count of questionnaire answers on the existence or absence of relevant intracluster linkages with suppliers, customers, and competitors in the past three years. Questions were obtained from the Innovation in Companies Survey (see Table 2). Each response on local partners in innovation was codified as a binary variable and later aggregated into a single index. The final variable ranged from 0 if no relationship existed to 3 if the firm had valuable linkages with the three groups of actors. The greater the number of local partners identified by respondents, the greater the degree of intracluster networking. Similarly, the variable *Non-local network* was built by aggregating answers on the existence or absence of relationships with suppliers, customers, and competitors located outside the cluster boundaries. Again, answers to these questions, which were taken from the Innovation in Companies Survey (see Table 2), were dichotomized and summed to form a single index ranging from 0 to 3. Higher values of this index represented higher levels of extracluster networking.

Moderating variables

To evaluate the role of innovation teams, firms were asked to think about their teamwork and indicate whether the firm's innovation teams were autonomous regarding working activities and decisions (see Table 2). Answers were codified using a binary variable labeled *Team* taking the value 1 when the respondent agreed, and 0 otherwise. To explore the effect of the stage of the life cycle and maturity, we created the variable *Cluster*. The variable took the value 1 if the firm was located in the biotech cluster, 2 if the firm belonged to the toy cluster, and 3 if the firm belonged to the foodstuffs cluster. Based on previous research, we assumed that the most mature cluster was the foodstuffs cluster (March, Adamè, & Escrig, 2007; Molina-Morales, Belso-Martinez, Mas-Verdu, & Martinez-Chafer, 2015) followed by the toy cluster (Balland, Belso-Martínez, & Morrison, 2016; Holmström, 2006). The biotech cluster was considered to be in the early stages of its life cycle (Belso-Martinez & Diez-Vial, 2018; Belso-Martínez, Mas-Tur, & Roig-Tierno, 2017).

Consequently, higher values of this variable indicated higher degrees of maturity of the cluster.

Regression analysis and results

We ran ordinary regression analysis, which is the method used to test most actor-level hypotheses. Specifically, three models were used to assess the exploratory power of each set of variables and empirically confirm the theoretical hypotheses derived from the literature review. Figure 1 illustrates the relationships between the variables. The models may be specified as follows:

- **Model 1**: Innovation = β_1Size + β_2R&D effort
- **Model 2**: Innovation = β_1Size + β_2R&D effort + β_3Cluster + β_4Team + β_5Local networks + β_6Non-local networks
- **Model 3**: Innovation = β_1Size + β_2R&D effort + β_3Cluster + β_4Team + β_5Local networks + β_6Non-local networks + β_7Local networks*Team + β_8 Non-local networks*Team
- **Model 4**: Innovation = β_1Size + β_2R&D effort + β_3Cluster + β_4Team + β_5Local networks + β_6Non-local networks + β_7Local networks*Cluster + β_8Non-local networks*Cluster
- **Model 5**: Innovation = β_1Size + β_2R&D effort + β_3Cluster + β_4Team + β_5 Team*Cluster

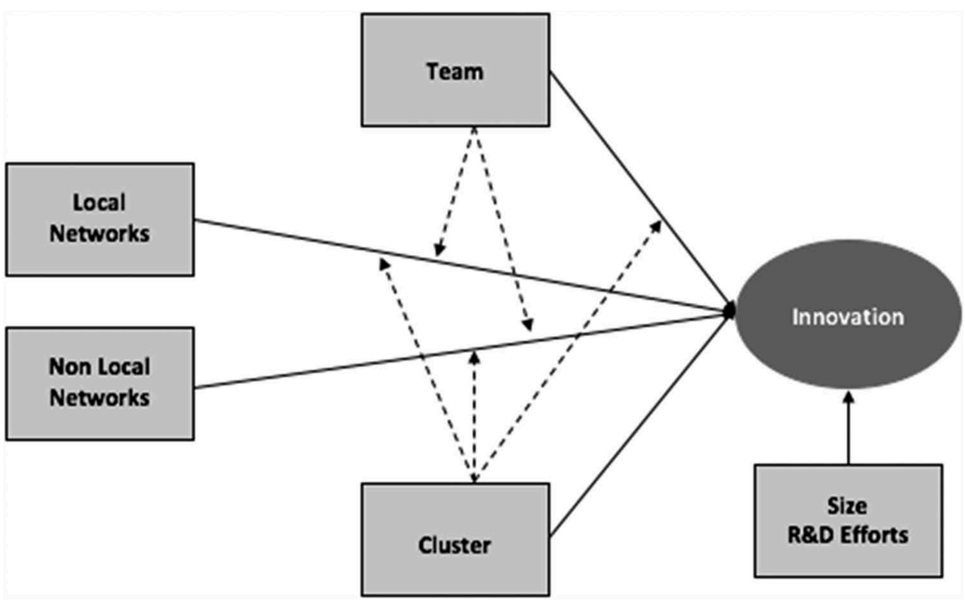

Figure 1. The model.

Table 3. Main descriptive statistics and correlations.

Variable	*Mean*	*SD*	*N*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Innovation	.0	1	139	1						
(2) Cluster	2.023	.680	139	***−.300	1					
(3) Size	30.387	54.006	139	***.303	.106	1				
(4) R&D effort	16.338	22.543	139	***.338	***−.495	***.671	1			
(5) Team	.446	.498	139	***.273	***−.465	***.439	***.336	1		
(6) Local networks	2.237	.757	139	*.156	***−.168	.067	−.043	*.159	1	
(7) Non-local networks	1.899	1.031	139	***.333	***-.471	***.349	**.187	***.249	. 003	1

Significance level: ***.01, **.05, *.10.

Table 4. Regression results.

Term	Model 1 *B* (sig.)	Model 2 *B* (sig.)	Model 3 *B* (sig.)	Model 4 *B* (sig.)	Model 5 *B* (sig.)
Intercept	***−.459	***−1.117	*−.451	*−2.029	*−1.881
Size	***.006	***.006	***.006	***.005	***.006
R&D effort	***.016	***.013	**.011	.006	.006
Cluster		−.041	−.063	.454	.284
Team		.223	**−1.226	.097	***1.120
Local networks		*.188	−.091	***.667	*.180
Non-local networks		**.183	.151	**.160	***.200
Local networks*Team			***.501		
Non-local networks*Team			.156		
Local networks*Cluster				***−.614	
Non-local networks*Cluster				.058	
Team*Cluster					***−1.039
F-statistic (sig.)	***19.299	***9.699	***8.399	***9.700	***10.425
R^2	.228	.314	.350	.413	.367
Adjusted R^2	.216	.282	.308	.371	.332
ΔR^2	***.228	***.050	***.036	***.063	***.053
N	139	139	139	139	139

Significance level: ***.01, **.05, *.10.

Descriptive statistics and the Pearson correlation coefficient for all variables are presented in Table 3. Detailed analysis of the data in Table 3 led to dismissal of the possibility of multicollinearity because correlations did not exceed .70. Even so, the variance inflation factors (VIF) obtained in the regression equations were less than 5, far below the cutoff of 10 proposed in the literature (Hair, Anderson, Tatham, & Balck, 1998). Hypothesis testing was conducted using ordinary least squares.

Table 4 shows the results of the regression analysis. Model 1 comprised only the control variables so that we could observe changes in the explanatory power of the models when more variables were added. As expected, R&D effort had a positive effect on innovation (p-value < .01). Model 2 was the base model, containing all the control variables and the four independent variables. This model provided information on all the main effects of the independent variables. Consistent with our literature review, we observed that both local networks and nonlocal networks were positively associated with innovation, with p-values of less than .10 and less than .05, respectively. Surprisingly, this was not the case for teams, where the main effect was positive but not significant (p-value < .190).

Models 3, 4, and 5 were used to separately test our hypotheses. Each model added the interaction terms to the previous main effects model. Model 3 enabled testing of H1, H2, and H3, Model 4 enabled testing of H4 and H5, and Model 5 enabled testing of H6.

In Model 3, the coefficient for the interaction between local networks and teams was positive and significant (p-value < .05), once the change of R^2 had been accounted for. Thus, H1 is supported. Knowledge from intracluster linkages had a stronger effect on firm innovation when processed through groups focused on organizational innovation. However, the interaction effect of nonlocal networks and teams was not statistically significant, so H2 is not supported. Although this finding requires further examination, the level of codification or lack of trust may offer an explanation.

Figure 2 shows that the significant contribution of local networks is pronounced for firms with teams. The positive impact on innovation of local networks grows as firms implement organizational structures that pool knowledge from different intracluster sources. The regression curves indicate that this trend does not hold for firms without teams. This finding might owe to the greater difficulties in pooling and managing knowledge. Firms should therefore be aware of the relevance of these organizational structures when designing their innovation strategies.

Model 4 included the interactions between local networks and clusters and nonlocal networks and clusters. H4 is confirmed because the interaction between local networks and clusters was negative and significant, consistent with our expectations (p-value < .01). This coefficient corroborates the dampening effect of cluster maturity on the positive relationship between local networks and innovation. In contrast, H5 is not confirmed. We did not observe significant interactions in the case of nonlocal networks. Regarding the interaction effects, Figure 3 reflects the relationship between local networks and clusters. Dense local networks had a stronger negative relationship with innovation in more mature clusters. For clusters with low levels of maturity, increases were not related to innovation.

Model 5 was used to test the interaction effect described in H6. The interaction of clusters with teams was negative and significant, thereby supporting our hypotheses. Thus, high levels of maturity and a strong presence of teams reduce firms' innovation performance. Figure 4 graphically shows the significant effect of the interaction between clusters and teams. In general, team contributions decrease as the maturity of the cluster increases, and vice versa.

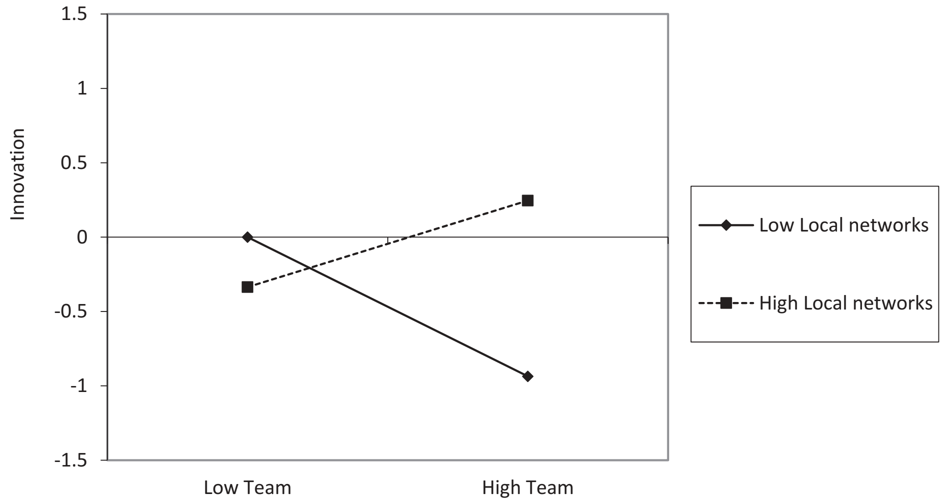

Figure 2. Two-way interaction effect of local networks and teams on innovation.[a] [a]Although the characteristics of our control variables lead to inaccurate values of the dependent variable, the plot allows for a robust comparison of the curves and a sound interpretation of the results (Dawson, 2013). To avoid potential misunderstandings, we modified the intercept value to reflect the marginal effect of the interaction on the dependent variable.

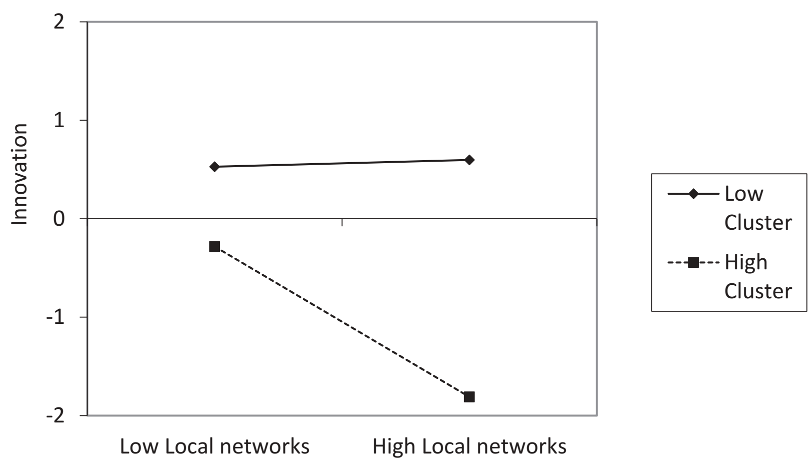

Figure 3. Two-way interaction effect of local networks and clusters on innovation.

Discussion and conclusions

As discussed in the literature (Smith et al., 2008), teams have become a key way to generate new ideas and solutions that depend on other factors such as openness, collaboration, and management style. Innovation-related research has shown that both dense local networks, based on constant face-to-face interactions, and sparse distant networks, where technology-mediated communication prevails, give life to the new knowledge that is necessary for

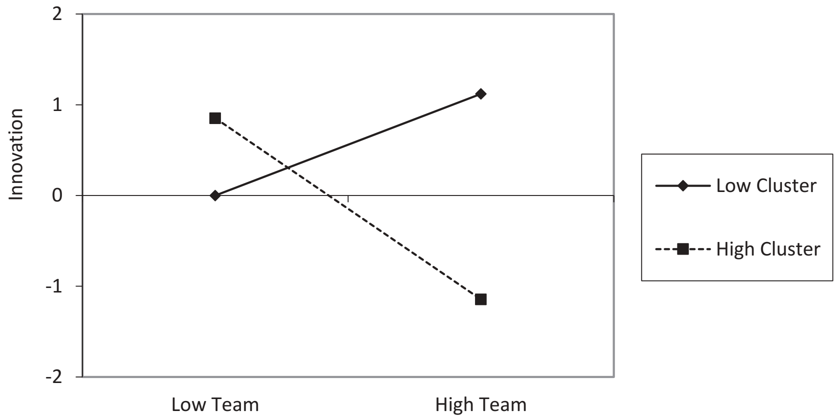

Figure 4. Two-way interaction effect of cluster and team on innovation.

innovation and decision-making. However, research has also shown that the advantages of each type of network are contingent. Team-based structures benefit particularly from this external knowledge to the extent that teams have a certain degree of independence in terms of decision processes and self-organization.

In this article, we draw on insights from the social capital, cluster, and management literatures to investigate the role of autonomous teams and extrafirm knowledge sources in firms' innovation. Our goal is to enrich the conventional firm-level versus individual-level dichotomy by proposing an intermediate structure that has been relatively overlooked by scholars (Bresman, 2010; Gebert et al., 2010; Gibson & Gibbs, 2006; Hülsheger et al., 2009). We go beyond the traditional single-level focus, centering on the interaction between the organization and the team to uncover new complex effects that are likely to occur between different levels of analysis (Anderson et al., 2014). Data on three Spanish clusters and moderated regression analyses yield findings that provide additional insight rather than simply reconfirming the key role of autonomous teams and external knowledge in innovation.

First, our findings add to the literature on the benign effects of human resource management practices that consider internal context and external collaboration (Zhou et al., 2013). Complementing the theoretical and empirical research that shows the positive influence of simultaneously implementing different human resource management practices in clusters (Belso-Martinez et al., 2018; Martínez-del-Río et al., 2013; Zhou et al., 2013), our results shed light on the effect of a specific management practice. According to the innovation literature, autonomous teams are expected to improve innovation performance systematically (Eisenbeiß & Boerner, 2010). However, we do not find complete support for this prediction because the main effect is not statistically significant in all models.

Research has shown that the effect of autonomous teams is stronger in knowledge-intensive projects that pursue radical innovation (Patanakul et al., 2012) and in technologically turbulent environments (Chen et al., 2014). Similarly, when interaction effects are considered, our study shows that autonomous teams are less effective in mature clusters. Even though the cluster life cycle may differ from industry to industry, the importance of autonomy and teams for innovation is shared in different contexts. Besides issues linked to our research design (for example, the small size of the firms surveyed and the low diversity within teams), these findings suggest the existence of numerous mechanisms and enablers of innovation from a team perspective, as Johnsson (2017) reported in a recent literature review.

Second, these findings are aligned with those reported in the literature on the relevance of extrateam relationships for organizational performance (Ancona & Caldwell, 1992; Brion et al., 2012; Büchel et al., 2013; Drach-Zahavy, 2011; Marrone et al., 2007; Mol & Birkinshaw, 2009; Somech & Khalaili, 2014; Vissa & Chacar, 2009). In addition to confirming their value for knowledge practices (Faraj & Yan, 2009) and innovation (Hülsheger et al., 2009), we detect different network configurations that may make varying contributions to innovation in teams and link these network configurations to the geographical dimension. Consistent with Ruef (2002) and Büchel et al. (2013), who observed the positive influence of density and trust on team performance, we found that dense external networks foster the transfer of more useful and complex knowledge for innovation. As could be expected from the theory, we enrich this research stream by showing the role of spatial proximity in creating behavioral pressures that support the development of trust and the transfer of complex knowledge. Also, consistent with Vissa and Chacar (2009) and Büchel et al. (2013), we show the value of sparse networks that provide opportunities to access nonredundant information and innovate. However, whereas Vissa and Chacar (2009) reported that this effect is contingent on certain features of the team such as cohesion and strategic consensus, we did not observe team autonomy to have the same conditional effect.

Third, we respond to calls to identify mediators and moderators and thereby develop integrative models that improve our understanding of the dynamics of the team's external network – in innovation. Scholars have tested the conditional effect of extrateam linkages (for example, Stock, 2014) and the extent to which team contribution depends on contextual factors (Faraj & Yan, 2009; Joshi & Roh, 2009), structural conditions (Somech & Khalaili, 2014), task routines (Chung & Jackson, 2013), and psychological safety (Faraj & Yan, 2009). The results reported here reveal that group structures and extrafirm knowledge networks reinforce each other in support of innovation. More specifically, the knowledge richness provided by external relationships provides opportunities to design more creative solutions and well-crafted decisions. Furthermore, collective structures can make better use of larger amounts of diverse knowledge furnished by the firm's networks. In essence, our results are consistent with those reported by Alexiev et al. (2010), who highlighted the preference and effectiveness of external advice versus internal advice at the firm and team levels.

However, the synergistic effects of this mutually reinforcing relationship are not the same for all types of external networks. Reflecting the crucial role of trust for teams and innovation (Büchel et al., 2013; Johnsson, 2017; Ruef, 2002), the interaction between dense local networks and autonomous teams has a significant effect on innovation performance. Nevertheless, the interaction between sparse distant networks and autonomous teams does not behave in the same way. This finding may be attributed to factors such as limited trust in the source due to the lack of face-to-face interactions and the characteristics of the knowledge that is accessed. Although the theoretical reasoning would suggest that diversity of knowledge should be extremely beneficial for a team's creativity, our results show the preference for dense trust-based local networks of homogeneous partners. For team members, trust and the quality of the transferred information seem to be what matters for collective diagnostics and decision processes.

In the long term, these localized relationships may rely exclusively on knowledge that travels back and forth between the same partners, failing to allow for new ideas and leading to stagnation. As observed by Chung and Jackson (2013) at the intrateam level, too much internal trust prevents members from sharing knowledge that contradicts the team's common perceptions and may lead to inertia. Therefore, these fruitful local networks should be accompanied by a certain openness to nonlocal relationships. Consequently, consistent with Anderson et al. (2014), we advocate the use of models that integrate not only the team and organizational factors (see Somech & Drach-Zahavy, 2013), but also the firm's external networks. This integrative approach enables the precise identification of the relationship between team composition, team processes, networks, and innovation.

Fourth, our findings on cluster characteristics show the contingent nature of both extrafirm networking and teams. By revealing the declining importance of dense networks in mature clusters, we confirm the risks of redundancies caused by an excess of local involvement, reflecting the findings reported by Ter Wal and Boschma (2011) and Molina-Morales and Expósito-Langa (2013). This valuable insight is consistent with evidence from the cluster life cycle perspective (Balland, 2012; Østergaard & Park, 2015; Ter Wal, 2014). However, contrary to our predictions, our findings show that sparse networks do not generate benefits for pursuing innovation. In addition, our findings indicate that firms in knowledge-intensive clusters obtain greater benefits from the use of teams. Through teams, firms in knowledge-intensive clusters deal better with the uncertainty of highly dynamic contexts. Considering the differences observed across industries (Alexiev et al., 2010) and their moderating role (Joshi & Roh, 2009), our insights support the need for multi-industry approaches that boost our understanding of firms' innovation from a team-level perspective.

Implications for managers and policymakers

For managers, our study provides guidelines for the design of organizational structures and the use of networks when firms aim to boost innovation. Overall, it provides a powerful analytical framework describing the sources of external knowledge. Group-based processes and innovation practices are influenced by fine-grained knowledge provided by dense local networks built on trust and ease of communication rather than by sparse networks characterized by geographical distance and codification. This finding has major practical implications. Networks support group practices and decisions. Therefore, top-level managers should devote additional efforts to design and manage the firm's relational assets. In particular, managers should focus on avoiding a potential excess of network density and proximity. Regarding sparse networks, care should be paid to implement tools and mechanisms capable of generating trust and smooth knowledge endogenization (for example, information and communication technologies). These actions would require resources and would strengthen the firm's networking capability, which is built on repetitive experience and training.

Our study also highlights the need for caution in organizational transformation efforts that attempt to implement group structures. Our results show that teams are more important for innovation in knowledge-intensive sectors than in mature sectors. Managers should be aware not only of the value of teams when operating in uncertain and risky environments, but also of their cost when strategic organizational decisions are made in mature contexts. For policymakers, we encourage the promotion of team-based structures as powerful organizational advances that should lead to higher innovation rates. Care should also be taken when designing networking policies in clusters. Programs should be tailored according to the cluster life cycle rather than being based on a standard approach. Particularly in mature clusters, policymakers should promote selective networking behaviors to avoid inertia and lock-in.

Limitations and future research

This research has certain limitations that open avenues for future research. Two main considerations limit the generalizability of our results. First, we focused on firms located in three clusters where innovation activities and relationships are intense and concentrated. Therefore, while our results hold for these three Spanish clusters, care should be taken when extrapolating our findings to other contexts. The widespread diffusion of these open innovation practices across many industries and geographies calls for an extension of the scope of our research. Also, networks are built between individuals rather than at the interfirm level (for example, Collins & Clark, 2003). Future research should consider more refined approaches based on multilevel networks.

Second, we simply distinguish between firms that use autonomous teams to deal with innovation threats and decisions and those that do not. However, member characteristics (Hülsheger et al., 2009; Somech & Drach-Zahavy, 2013) and intrateam networks (Chung & Jackson, 2013; Crawford & Lepine, 2013) have been proposed as accompanying factors of innovativeness. A different questionnaire and alternative operationalization of the variable might help open the black box. Likewise, social network analysis techniques would enable a more nuanced reconstruction of firm networks. Future research should also consider the strength and overlap of interfirm linkages. In addition, the influence of information and communication technologies and temporary co-location on networks should be addressed because these mechanisms may act as powerful substitutes of traditional face-to-face interactions in generating trust and complex knowledge transfers (Bathelt & Turi, 2011; Gibson & Gibbs, 2006).

Care has been taken with causality and endogeneity concerns. The sequential nature of the fieldwork and the tests we conducted guarantee the robustness and reliability of our research. However, empirical analysis performed using longitudinal data would be welcome. Finally, we used a unique indicator of innovation performance. Differentiating between types of innovations might lead to a more sophisticated view of the phenomenon under study. Moreover, our indicator refers to innovation as an overall concept that encompasses creativity and implementation (Hülsheger et al., 2009). Scholars should evaluate potential changes across different phases of the innovation process.

References

Adler, P. S., & Kwon, S.-W. (2002). Social capital: Prospects for a new concept. *Academy of Management Review*, *27*(1), 17–40. doi:10.5465/amr.2002.5922314

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly*, *45*(3), 425–455. doi:10.2307/2667105

Ahuja, G., & Katila, R. (2004). Where do resources come from? The role of idiosyncratic situations. *Strategic Management Journal*, *25*(89), 887–907. doi:10.1002/(ISSN)1097-0266

Alexiev, A. S., Jansen, J. J. P., Van Den Bosch, F. A. J., & Volberda, H. W. (2010). Top management team advice seeking and exploratory innovation: The moderating role of TMT heterogeneity. *Journal of Management Studies*, *47*(7), 1343–1364.

Ancona, D. G., & Caldwell, D. F. (1992). Bridging the boundary: External activity and performance in organizational teams. *Administrative Science Quarterly*, *37*(4), 634. doi:10.2307/2393475

Anderson, N., Potočnik, K., & Zhou, J. (2014). Innovation and creativity in organizations: A State-of-the-science review, prospective commentary, and guiding framework. *Journal of Management*. doi:10.1177/0149206314527128

Asheim, B. T., & Coenen, L. (2006). Contextualising regional innovation systems in a globalising learning economy: On knowledge bases and institutional frameworks. *Journal of Technology Transfer*, *31*(1), 163–173. doi:10.1007/s10961-005-5028-0

Audretsch, D. B., & Acs, Z. J. (1991). Innovation and size at the firm level. *Southern Economic Journal*, *57*(3), 739–744. doi:10.2307/1059787

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *American Economic Review*, *86*(3), 630–640.

Balkundi, P., & Harrison, D. A. (2006). Ties, leaders, and time in teams: Strong inference about the effects of network structure on team viability. *Academy of Management Journal*, *49*(1), 49–68. doi:10.5465/amj.2006.20785500

Balland, P. A. (2012). Proximity and the evolution of collaboration networks: Evidence from research and development projects within the Global Navigation Satellite System (GNSS) Industry. *Regional Studies*, *46*, 741–756. doi:10.1080/00343404.2010.529121

Balland, P. A., Belso-Martínez, J. A., & Morrison, A. (2016). The dynamics of technical and business knowledge networks in industrial clusters: Embeddedness, status, or proximity? *Economic Geography*, *92*(1), 35–60. doi:10.1080/00130095.2015.1094370

Balland, P. A., De Vaan, M., & Boschma, R. A. (2013). The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987-2007. *Journal of Economic Geography*, *13*(5), 741–765. doi:10.1093/jeg/lbs023

Baptista, R., & Swann, P. (1998). Do firms in clusters innovate more? *Research Policy*, *27*(5), 525–540. doi:10.1016/S0048-7333(98)00065-1

Bathelt, H. (2006). Geographies of production: growth regimes in spatial perspective 3 – toward a relational view of economic action and policy. *Progress in Human Geography*, *30*(2), 223–236. doi:10.1191/0309132506ph603pr

Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1), 31–56. doi:10.1191/0309132504ph469oa

Bathelt, H., & Turi, P. (2011). Local, global and virtual buzz: The importance of face-to-face contact in economic interaction and possibilities to go beyond. *Geoforum*, *42*(5), 520–529. doi:10.1016/j.geoforum.2011.04.007

Bell, G. G. (2005, September). Clusters, networks, and firm innovativeness. *Strategic Management Journal*, *295*, 287–295. doi:10.1002/smj.448

Bell, M., & Giuliani, E. (2007). Catching up in the global wine industry: innovation systems, cluster knowledge networks and firm-level capabilities in Italy and Chile. *International Journal of Technology & Globalization*, *3*(2/3), 197–223. doi:10.1504/IJTG.2007.014333

Belso-Martinez, J. A., & Diez-Vial, I. (2018). Firm's strategic choices and network knowledge dynamics: how do they affect innovation? *Journal of Knowledge Management*, *22*(1), 1–20. doi:10.1108/JKM-12-2016-0524

Belso-Martínez, J. A., Mas-Tur, A., & Roig-Tierno, N. (2017). Synergistic effects and the co-existence of networks in clusters. *Entrepreneurship & Regional Development*, *29*(1–2), 137–154. doi:10.1080/08985626.2016.1255429

Belso-Martinez, J. A., Palacios-Marqués, D., & Roig-Tierno, N. (2018). Building resilient clusters through HRM systems: a multiple mediator model. *Management Decision*, *56*(6), 1398–1416. doi:10.1108/MD-02-2017-0175

Birkinshaw, J., Bessant, J., & Delbridge, R. (2007). Finding, forming, and performing: Creating networks for discontinuous innovation. *California Management Review*, *49*(3), 67–84. doi:10.2307/41166395

Boari, C., Molina-Morales, F. X., & Martínez-Cháfer, L. (2016). Direct and interactive effects of brokerage roles on innovation in clustered firms. *Growth and Change*, *48*(3), 336–358. doi:10.1111/grow.12170

Boschma, R. A., & Ter Wal, A. L. J. (2007). Knowledge networks and innovative performance in an industrial district: The case of a footwear district in the South of Italy. *Industry & Innovation*, *14*(2), 177–199. doi:10.1080/13662710701253441

Bresman, H. (2010). External learning activities and team performance: A multimethod field study. *Organization Science*, *21*(1), 81–96. doi:10.1287/orsc.1080.0413

Brion, S., Chauvet, V., Chollet, B., & Mothe, C. (2012). Project leaders as boundary spanners: Relational antecedents and performance outcomes. *International Journal of Project Management*, *30*(6), 708–722. doi:10.1016/j.ijproman.2012.01.001

Brödner, P. (2013). Reflective design of technology for human needs. *AI and Society*, *28*(1), 27–37. doi:10.1007/s00146-012-0389-z

Bronfenbrenner, U. (1986). Ecology of the family as a context for human development. Research perspectives. *Developmental Psychology*, *22*(6), 723–742. doi:10.1037/0012-1649.22.6.723

Büchel, B., Nieminen, L., Armbruster-Domeyer, H., & Denison, D. (2013). Managing stakeholders in team-based innovation: The dynamics of knowledge and trust networks. *European Journal of Innovation Management*, *16*(1), 22–49. doi:10.1108/14601061311292841

Burt, R. S. (1992). *Structural holes: The social structure of competition*. Cambridge, MA: Harvard University Press.

Caiazza, R., Cannella, A. A., Jr, Phan, P. H., & Simoni, M. (2018). An institutional contingency perspective of interlocking directorates. *International Journal of Management Reviews*. Online. doi:10.1111/ijmr.12182

Caiazza, R., & Simoni, M. (2015). Directors' role in inter-organizational networks. *Corporate Governance*, *15*(4), 508–516. doi:10.1108/CG-05-2014-0059

Camelo Ordaz, C., Fernández Alles, M., & Martínez Fierro, S. (2006). Influence of top management team vision and work team characteristics on innovation: The Spanish case. *European Journal of Innovation Management*, *9*(2), 179–201. doi:10.1108/14601060610663569

Cameron, R., & Molina-Azorin, J. F. (2011). The acceptance of mixed methods in business and management research. *International Journal of Organizational Analysis*, *19*(3), 256–271. doi:10.1108/19348831111149204

Capello, R., & Faggian, A. (2005). Collective learning and relational capital in local innovation processes. *Regional Studies*, *39*(1), 75–87. doi:10.1080/0034340052000320851

Chen, J., Neubaum, D. O., Reilly, R. R., & Lynn, G. S. (2014). The relationship between team autonomy and new product development performance under different levels of technological turbulence. *Journal of Operations Management*, *33–34*, 83–96.

Chung, Y., & Jackson, S. E. (2013). The internal and external networks of knowledge-intensive teams: The role of task routineness. *Journal of Management*, *39*(2), 442–468. doi:10.1177/0149206310394186

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152. doi:10.2307/2393553

Coleman, J. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, *94*, S95–S120. doi:10.1086/228943

Collins, C. J., & Clark, K. D. (2003). Strategic human resource practices,top management team social networks,and firm performance. *Academy of Management*, *46*(6), 740–751.

Crawford, E. R., & Lepine, J. A. (2013). A configural theory of team processes: Accounting for the structure of taskwork and teamwork. *Academy of Management Review*, *38*(1), 32–48. doi:10.5465/amr.2011.0206

Das, S. R., & Joshi, M. P. (2007). Process innovativeness in technology services organizations: Roles of differentiation strategy, operational autonomy and risk-taking propensity. *Journal of Operations Management*, *25*(3), 643–660. doi:10.1016/j.jom.2006.05.011

Dawson, J. F. (2013). Moderation in management research: What, why, when, and how. *Journal of Business and Psychology*, *29*(1), 1–19. doi:10.1007/s10869-013-9308-7

Dew, R., & Hearn, G. (2009). A new model of the learning process for innovation teams: Networked nominal pairs. *International Journal of Innovation Management*, *13*(4), 521–535. doi:10.1142/S136391960900239X

Drach-Zahavy, A. (2011). Interorganizational teams as boundary spanners: The role of team diversity, boundedness, and extrateam links. *European Journal of Work and Organizational Psychology*, *20*(1), 89–118. doi:10.1080/13594320903115936

Du Chatenier, E., Verstegen, J. A. A. M., Biemans, H. J. A., Mulder, M., & Omta, O. (2009). The challenges of collaborative knowledge creation in open innovation teams. *Human Resource Development Review*, *8*(3), 350–381. doi:10.1177/1534484309338265

Eisenbeiß, S. A., & Boerner, S. (2010). Transformational leadership and R&D innovation: Taking a curvilinear approach. *Creativity and Innovation Management*, *19*(4), 364–372. doi:10.1111/j.1467-8691.2010.00563.x

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, *14*, 532–550. doi:10.5465/amr.1989.4308385

Expósito-Langa, M., Molina-Morales, F. X., & Tomás-Miquel, J. V. (2015). How shared vision moderates the effects of absorptive capacity and networking on clustered firms' innovation. *Scandinavian Journal of Management*, *31*(3), 293–302. doi:10.1016/j.scaman.2015.06.001

Faraj, S., & Yan, A. (2009). Boundary work in knowledge teams. *Journal of Applied Psychology*, *94*(3), 604–617. doi:10.1037/a0014367

Fitjar, R. D., & Rodríguez-Pose, A. (2011). When local interaction does not suffice: Sources of firm innovation in urban Norway. *Environment and Planning A*, *43*(6), 1248–1267. doi:10.1068/a43516

Forrester, R. H. (2000). Capturing learning and applying knowledge: An investigation of the use of innovation teams in Japanese and American automotive firms. *Journal of Business Research*, *47*(1), 35–45. doi:10.1016/S0148-2963(98)00049-6

Gargiulo, M., & Benassi, M. (2000). Trapped in your own net? Network cohesion, structural holes, and the adaptation of social capital. *Organization Science*, *11*(2), 183–196. doi:10.1287/orsc.11.2.183.12514

Gebert, D., Boerner, S., & Kearney, E. (2010). Fostering team innovation: Why is it important to combine opposing action strategies? *Organization Science*, *21*(3), 593–608. doi:10.1287/orsc.1090.0485

Gibson, C. B., & Gibbs, J. L. (2006). Unpacking the concept of virtuality: The effects of geographic dispersion, electronic dependence, dynamic structure, and national diversity on team innovation. *Administrative Science Quarterly*, *51*(3), 451–495. doi:10.2189/asqu.51.3.451

Giuliani, E., & Bell, M. (2005). The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster. *Research Policy*, *34*(1), 47–68. doi:10.1016/j.respol.2004.10.008

Giuliani, E., Morrison, A., Pietrobelli, C., & Rabellotti, R. (2010). Who are the researchers that are collaborating with industry? An analysis of the wine sectors in Chile, South Africa and Italy. *Research Policy*, *39*, 748–761. doi:10.1016/j.respol.2010.03.007

Govindarajan, V., & Trimble, C. (2005). Organizational DNA for strategic innovation. *California Management Review*, *47*(3), 47–76. doi:10.2307/41166306

Grabher, G. (1993). The weakness of stronf ties: the lock-in effect of regional development in Ruhr area. In G. Grabher (Ed.), *The embedded firm: On the socio-economics of industrial networks* (pp. 255–277). London, UK: Routledge.

Grant, R. M. (1996). Toward a knowledge-based view of the firm. *Strategic Management Journal*, *17*(52), 109–122. doi:10.1002/smj.4250171110

Guimera, R. (2005). Team assembly mechanisms determine collaboration network structure and team performance. *Science*, *308*(5722), 697–702. doi:10.1126/science.1106340

Gupta, A. K., Tesluk, P. E., & Taylor, M. S. (2007). Innovation at and across multiple levels of analysis. *Organization Science*, *18*(6), 885–897. doi:10.1287/orsc.1070.0337

Hair, J., Anderson, R., Tatham, R., & Balck, W. (1998). *Multivariate data analysis*. Englewood Cliffs, NJ: Prentice-Hall.

Hargadon, A., & Sutton, R. I. (1997). Technology brokering and innovation in a product development firm. *Administrative Science Quarterly*, *42*(4), 716–749. doi:10.2307/2393655

Hervas-Oliver, J.-L. J.-L., & Albors-Garrigos, J. (2009). The role of the firm's internal and relational capabilities in clusters: when distance and embeddedness are not enough to explain innovation. *Journal of Economic Geography*, *9*(2), 263–283. doi:10.1093/jeg/lbn033

Holmström, M. (2006). Globalisation and good work: Impiva, a Spanish project to regenerate industrial districts. *Tijdschrift Voor Economische En Sociale Geografie*, *97*, 491–502. doi:10.1111/tesg.2006.97.issue-5

Hülsheger, U. R., Anderson, N., & Salgado, J. F. (2009). Team-level predictors of innovation at work: A comprehensive meta-analysis spanning three decades of research. *Journal of Applied Psychology*, *94*(5), 1128–1145. doi:10.1037/a0015978

Johnsson, M. (2017). Innovation enablers for innovation Teams-A review. *Journal of Innovation Management*, *5*(3), 75–121. doi:10.24840/2183-0606_005.003

Joshi, A., & Roh, H. (2009). The role of context in work team diversity research: A meta-analytic review. *Academy of Management Journal*, *52*(3), 599–627. doi:10.5465/amj.2009.41331491

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, *3*(3), 383–397. doi:10.1287/orsc.3.3.383

Langfred, C. W. (2005). Autonomy and performance in teams: The multilevel moderating effect of task interdependence. *Journal of Management*, *31*(4), 513–529. doi:10.1177/0149206304272190

Laursen, K. (2002). The importance of sectoral differences in the application of complementary HRM practices for innovation performance. *International Journal of the Economics of Business*, *9*(1), 139–156. doi:10.1080/13571510110103029

Laursen, K., & Foss, N. J. (2003). New human resource management practices, complementarities and the impact on innovation performance. *Cambridge Journal of Economics*, *27*(2), 243–263. doi:10.1093/cje/27.2.243

Laursen, K., & Foss, N. J. (2014). Human resource management practices and innovation. In M. Dodgson, D. Gann, & N. Phillips (Eds.), *The Oxford handbook of innovation management* (pp. 1–44). Oxford, UK: Oxford University Press.

Laursen, K., & Salter, A. (2004). Searching high and low: What types of firms use universities as a source of innovation? *Research Policy*, *33*(8), 1201–1215. doi:10.1016/j.respol.2004.07.004

Li, W., Veliyath, R., & Tan, J. (2013). Network characteristics and firm performance: An examination of the relationships in the context of a cluster. *Journal of Small Business Management*, *51*(1), 1–22. doi:10.1111/jsbm.2013.51.issue-1

Lungeanu, A., & Contractor, N. S. (2015). The effects of diversity and network ties on innovations: The emergence of a new scientific field. *American Behavioral Scientist*, *59*(5), 548–564. doi:10.1177/0002764214556804

March, I., Adamè, C., & Escrig, A. (2007). Aplicación de un modelo de caracterización de la competitividad al sector de fabricación de turrón. *Revista Valenciana de Economía y Hacienda*, *14*(1), 111–135.

Marrone, J. A., Tesluk, P. E., & Carson, J. B. (2007). A multilevel investigation of antecedents and consequences of team member boundary- spanning behavior. *Academy of Management Journal*, *50*(6), 1423–1439. doi:10.5465/amj.2007.28225967

Martin, R., & Sunley, P. (2006). Path dependence and regional economic evolution. *Journal of Economic Geography*, *6*(4), 395–437. doi:10.1093/jeg/lbl012

Martínez-del-Río, J., Céspedes-Lorente, J., & Pérez-Vall, M. (2013). Relación entre las prácticas de recursos humanos, la innovación y el rendimiento en clústeres geográficos. *Cuadernos de Economía y Dirección de la Empresa*, *16*(4), 238–249. doi:10.1016/j.cede.2013.02.001

Maskell, P. (2001). Towards a knowledge-based theory of the geographical cluster. *Industrial and Corporate Change*, *10*(4), 921–943. doi:10.1093/icc/10.4.921

Maskell, P., & Malmberg, A. (1999). Localised learning and industrial competitiveness. *Cambridge Journal of Economics*, *23*(2), 167–185. doi:10.1093/cje/23.2.167

Mathieu, J., Maynard, M. T., Rapp, T., & Gilson, L. (2008). Team effectiveness 1997-2007: A review of recent advancements and a glimpse into the future. *Journal of Management*, *34*(3), 410–476. doi:10.1177/0149206308316061

Mcevily, B., & Marcus, A. (2005). Embedded ties and the Acquisition of Competitve Capabilities. *Strategie Management Journal Strat. Mgmt. J*, *26*, 1033–1055. doi:10.1002/smj.484

McEvily, B., & Zaheer, A. (1999). Bridging ties: a source of firm heterogeneity in competitive capabilities. *Strategic Management Journal*, *20*, 1133–1156. doi:10.1002/(ISSN)1097-0266

Mehra, A., Dixon, A. L., Brass, D. J., & Robertson, B. (2006). The social network ties of group leaders: Implications for group performance and leader reputation. *Organization Science*, *17*(1), 64–79. doi:10.1287/orsc.1050.0158

Menzel, M.-P., & Fornahl, D. (2010). Cluster life cycles–dimensions and rationales of cluster evolution. *Industrial and Corporate Change*, *19*(1), 205–238. doi:10.1093/icc/dtp036

Mihalache, O. R., Jansen, J. J. P., Van Den Bosch, F. A. J., & Volberda, H. W. (2014). Top management team shared leadership and organizational ambidexterity: A moderated mediation framework. *Strategic Entrepreneurship Journal*, *8*(2), 128–148. doi:10.1002/sej.1168

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

Milliken, F. J., Bartel, C. A., & Kurtzberg, T. R. (2010). Diversity and creativity in work groups: A dynamic perspective on the affective and cognitive processes that link diversity and performance. In P. Paulus & B. Nijstad (Eds.), *Group creativity: Innovation through collaboration* (pp. 32–62). Oxford, UK: Oxford University Press.

Mol, M. J., & Birkinshaw, J. (2009). The sources of management innovation: When firms introduce new management practices. *Journal of Business Research*, *62*(12), 1269–1280. doi:10.1016/j.jbusres.2009.01.001

Molina-Morales, F. X., Belso-Martinez, J. A., & Mas-Verdú, F. (2016). Interactive effects of internal brokerage activities in clusters: The case of the Spanish Toy Valley. *Journal of Business Research*, *69*(5), 1785–1790. doi:10.1016/j.jbusres.2015.10.056

Molina-Morales, F. X., Belso-Martinez, J. A., Mas-Verdu, F., & Martinez-Chafer, L. (2015). Formation and dissolution of inter-firm linkages in lengthy and stable networks in clusters. *Journal of Business Research*, *68*(7), 1557–1562. doi:10.1016/j.jbusres.2015.01.051

Molina-Morales, F. X., & Expósito-Langa, M. (2013). Overcoming undesirable knowledge redundancy in territorial clusters. *Industry & Innovation*, *20*(8), 739–758. doi:10.1080/13662716.2013.856622

Morgan, K. J. (2004). The exaggerated death of geography: learning, proximity and territorial innovation systems. *Journal of Economic Geography*, *4*(1), 3–21. doi:10.1093/jeg/4.1.3

Mota, J. Q., & de Castro, L. M. (2004). Industrial agglomerations as localised networks: The case of the Portuguese injection mould industry. *Environment and Planning A*, *36*(2), 263–278. doi:10.1068/a3684

Mowery, D. C., Oxley, J. E., & Silverman, B. S. (1996). Strategic alliances and interfirm knowledge transfer. *Strategic Management Journal*, *17*(S2), 77–91. doi:10.1002/smj.4250171108

Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *Academy of Management Review*, *23*(2), 242–266. doi:10.5465/amr.1998.533225

O´Connor, G. C. (2008). Major innovation as a dynamic capability: A systems approach. *Journal of Product Innovation Management*, *25*(4), 313–330. doi:10.1111/j.1540-5885.2008.00304.x

O'Connor, G. C., Paulson, A. S., & DeMartino, R. (2008). Organisational approaches to building a radical innovation dynamic capability. *International Journal of Technology Management*, *44*(1/2), 179. doi:10.1504/IJTM.2008.020704

Obstfeld, D. (2005). Social networks, the tertius iungens orientation, and involvement in innovation. *Administrative Science Quarterly*, *50*(1), 100–130. doi:10.2189/asqu.2005.50.1.100

OECD & Eurostat. (2007). *Oslo Manual: Guía para la recogida e interpretación de datos sobre innovación*. OECD, Eurostat.

Østergaard, C. R., & Park, E. (2015). What makes clusters decline? A study on disruption and evolution of a high-tech cluster in Denmark. *Regional Studies*, *49*(5), 1–16. doi:10.1080/00343404.2015.1015975

Owen-Smith, J., & Powell, W. W. (2004). Knowledge networks as channels and conduits: The effects of spillovers in the boston biotechnology community. *Organization Science*, *15*(1), 5–21. doi:10.1287/orsc.1030.0054

Ozman, M. (2009). Inter-firm networks and innovation: a survey of literature. *Economics of Innovation and New Technology*, *18*(1), 39–67. doi:10.1080/10438590701660095

Ozman, M. (2015). Networks of knowledge : an appraisal of research themes, findings and implications. In C. Antonelli & A. N. Link (Eds.), *Routledge handbook of the economics of knowledge* (pp. 53–78). London, UK: Routledge.

Patanakul, P., Chen, J., & Lynn, G. S. (2012). Autonomous teams and new product development. *Journal of Product Innovation Management*, *29*(5), 734–750. doi:10.1111/jpim.2012.29.issue-5

Podolny, J. M., & Baron, J. N. (1997). Resources and relationships Social networks and mobility in the workplace.pdf. *American Sociological Review*, *62*(5), 673. doi:10.2307/2657354

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. doi:10.1037/0021-9010.88.5.879

Pouder, R., & St. John, C. H. (1996). Hot spots and blind spots: Geographical clusters of firms and innovation. *Academy of Management Review*, *21*(4), 1192–1225. doi:10.5465/amr.1996.9704071867

Powell, W. W., Koput, K. W., & Smith-doerr, L. (1996). Interorganizational and the collaboration locus of innovation: Networks of learning in Biotechnology. *Administrative Science Quarterly*, *41*(1), 116–145. doi:10.2307/2393988

Presutti, M., Boari, C., & Majocchi, A. (2011). The importance of proximity for the Start-Ups' knowledge acquisition and exploitation. *Journal of Small Business Management*, *49*(3), 361–389. doi:10.1111/jsbm.2011.49.issue-3

Reagans, R., Zuckerman, E., & McEvily, B. (2004). How to make the team: Social networks vs. demography as criteria for designing effective teams. *Administrative Science Quarterly*, *49*(1), 101–133.

Rowley, T., Behrens, D., & Krackhardt, D. (2000). Reundant governance structures: An analysis of structural and relational embeddness in the steel and semicondutor industries. *Strategic Management Journal*, *21*, 369–386. doi:10.1002/(SICI)1097-0266-(200003)21:3<369::AID-SMJ93>3.0.CO;2-M

Ruef, M. (2002). Strong ties, weak ties and islands: structural and cultural predictors of organizational innovation. *Industrial and Corporate Change*, *11*(3), 427–449. doi:10.1093/icc/11.3.427

Simoni, M., & Caiazza, R. (2012a). How does learning intent affect interlocking directorates dynamic? *The Learning Organization*, *19*(5), 388–399. doi:10.1108/09696471211239695

Simoni, M., & Caiazza, R. (2012b). Interlocks network structure as driving force of coopetition among Italian firms. *Corporate Governance*, *12*(3), 319–336. doi:10.1108/14720701211234582

Simoni, M., & Caiazza, R. (2013). Interlocking directorates' effects on economic system's competitiveness. *Business Strategy Series*, *14*(1), 30–35. doi:10.1108/17515631311295695

Singh, J., & Fleming, L. (2010). Lone inventors as sources of breakthroughs: Myth or reality? *Management Science*, *56*(1), 41–56. doi:10.1287/mnsc.1090.1072

Sivasubramaniam, N., Liebowitz, S. J., & Lackman, C. L. (2012). Determinants of new product development team performance: Ameta-analytic review. *Journal of Product Innovation Management*, *29*(5), 803–820. doi:10.1111/jpim.2012.29.issue-5

Smart, P., Bessant, J., & Gupta, A. (2007). Towards technological rules for designing innovation networks: A dynamic capabilities view. *International Journal of Operations and Production Management*, *27*(10), 1069–1092. doi:10.1108/01443570710820639

Smith, K. G., Collins, C. J., & Clark, K. D. (2005). Existing knowledge, knowledge creation capability, and the rate of new product introduction in high-technology firms. *Academy of Management Journal*, *48*(2), 346–357. doi:10.5465/amj.2005.16928421

Smith, M., Busi, M., Ball, P., & Vander, M. R. (2008). Factors influencing an organization's ability to manage innovation: A structured literature review and conceptual model. *International Journal of Innovation Management*, *12*(4), 655–676. doi:10.1142/S1363919608002138

Somech, A. (2006). The effects of leadership style and team process on performance and innovation in functionally heterogeneous teams. *Journal of Management*, *32*(1), 132–157. doi:10.1177/0149206305277799

Somech, A., & Drach-Zahavy, A. (2013). Translating team creativity to innovation implementation: The role of team composition and climate for innovation. *Journal of Management*, *39*(3), 684–708. doi:10.1177/0149206310394187

Somech, A., & Khalaili, A. (2014). Team boundary activity: Its mediating role in the relationship between structural conditions and team innovation. *Group and Organization Management*, *39*(3), 274–299. doi:10.1177/1059601114525437

Sorenson, O. (2003). Social networks and industrial geography. *Journal of Evolutionary Economics*, *13*(5), 513–527. doi:10.1007/s00191-003-0165-9

Stewart, G. L. (2006). A meta-analytic review of relationships between team design features and team performance. *Journal of Management*, *32*(1), 29–55. doi:10.1177/0149206305277792

Stock, R. M. (2014). How should customers be integrated for effective interorganizational NPD teams? An input-process-output perspective. *Journal of Product Innovation Management*, *31*(3), 535–551. doi:10.1111/jpim.12112

Tallman, S., Jenkins, M., Henry, N., & Pinch, S. (2004). Knowledge, clusters, and competitive advantage. *Academy of Management Review*, *29*(2), 258–271. doi:10.5465/amr.2004.12736089

Taylor, A., & Greve, H. R. (2006). Superman or the fantastic four? Knowledge combination and experience in innovative teams. *Academy of Management Journal*, *49*(4), 723–740. doi:10.5465/amj.2006.22083029

Ter Wal, A. L. J. (2014). The dynamics of the inventor network in German biotechnology: geographic proximity versus triadic closure. *Journal of Economic Geography*, *14*(3), 589–620. doi:10.1093/jeg/lbs063

Ter Wal, A. L. J., & Boschma, R. (2011). Co-evolution of Firms, Industries and Networks in Space. *Regional Studies*, *45*, 919–933. doi:10.1080/00343400802662658

Ter Wal, A. L. J., & Boschma, R. A. (2009). Applying social network analysis in economic geography: framing some key analytic issues. *The Annals of Regional Science*, *43*, 739–756. doi:10.1007/s00168-008-0258-3

Tidd, J., & Bessant, J. (2013). *Managing innovation: Integrating technological, market and organizational change* (5th ed.). Hoboken, NJ: Wiley.

Tröster, C., Mehra, A., & van Knippenberg, D. (2014). Structuring for team success: The interactive effects of network structure and cultural diversity on team potency and performance. *Organizational Behavior and Human Decision Processes*, *124*(2), 245–255. doi:10.1016/j.obhdp.2014.04.003

Tushman, M., & Nadler, D. (1986). Organizing for innovation. *California Management Review*, *28*(3), 74–92. doi:10.2307/41165203

Uzzi, B., & Spiro, J. (2005). Collaboration and creativity: The small world problem. *American Journal of Sociology*, *111*(2), 447–504. doi:10.1086/432782

van der Vegt, G. S., Bunderson, S., & Kuipers, B. (2010). Why turnover matters in self-managing work teams: Learning, social integration, and task flexibility. *Journal of Management*, *36*(5), 1168–1191. doi:10.1177/0149206309344117

Vissa, B., & Chacar, A. S. (2009). Leveraging ties: The contingent value of entrepreneurial teams' external advice networks on Indian software venture performance. *Strategic Management Journal*, *30*(11), 1179–1191. doi:10.1002/smj.v30:11

West, M. A., & Anderson, N. R. (1996). Innovation in top management teams. *Journal of Applied Psychology*, *81*(6), 680–693. doi:10.1037/0021-9010.81.6.680

Whittington, K. B., Owen-Smith, J., & Powell, W. W. (2009). Networks, propinquity, and innovation in knowledge-intensive industries. *Administrative Science Quarterly*, *54*(1), 90–122. doi:10.2189/asqu.2009.54.1.90

Wong, S. S. (2008). Task knowledge overlap and knowledge variety: The role of advice network structures and impact on group effectiveness. *Journal of Organizational Behavior*. doi:10.1002/job.490

Yeung, A. C. L., Lai, K. H., & Yee, R. W. Y. (2007). Organizational learning, innovativeness, and organizational performance: A qualitative investigation. *International Journal of Production Research*, *45*(11), 2459–2477. doi:10.1080/00207540601020460

Yu, D., & Hang, C. C. (2010). A reflective review of disruptive innovation theory. *International Journal of Management Reviews*, *12*(4), 435–452. doi:10.1111/ijmr.2010.12.issue-4

Zhou, J. (1998). Feedback valence, feedback style, task autonomy, and achievement orientation: Interactive effects on creative performance. *Journal of Applied Psychology*, *83*(2), 261–276. doi:10.1037/0021-9010.83.2.261

Zhou, Y., Hong, Y., & Liu, J. (2013). Internal commitment or external collaboration? The impact of human resource management systems on firm innovation and performance. *Human Resource Management*, *52*(2), 263–288. doi:10.1002/hrm.v52.2