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Driving Forces Behind Relational Knowledge Sourcing in Clusters: Single- and Multilevel Approaches

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Abstract
The critical importance of knowledge sourcing as learning relationships and its impact on innovation have been widely discussed in the cluster literature. The aim of this paper is twofold. First, inspired by the relational turn in economic geography, this paper reviews the driving forces of relational knowledge sourcing in clusters. Particularly, it discusses the critical factors of inter-organizational knowledge sourcing embedded at node (agency), dyadic (proximity), and structural (network micro-determinants) levels. In doing so, it goes beyond the cluster literature and builds on concepts and evidence in multiple related fields ranging from network science to behavioral studies, to relational inequality theory and evolutionary economic geography. Second, it synthesizes and extends the scholarly debate on knowledge sourcing in clusters by addressing a multilevel perspective. This article raises multiple theoretically informed research questions for future empirical cluster studies and underlines potential implications for cluster and place-based innovation policies.

Keywords Agency · Proximity · Network micro-determinants · Multilevel approach · Cluster

Introduction

The production and exchange of knowledge are the driving forces of technological change and long-term economic development (Lucas, 1988). Knowledge sourcing is a process of seeking required knowledge and expertise, whereby organizations and individuals can potentially innovate, overcome bottlenecks, and possibly improve their

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economic performance. Several contributions suggest that such a process plays a fundamental role in collective learning and the spread of knowledge across co-located actors, especially within clusters and other local productive systems (Pyke et al., 1990; Porter, 1998; Bathelt et al., 2004; Brenner et al., 2011; Capello 1999; Basile et al., 2012); Lazzeretti et al., 2019). In fact, many scholars point towards the critical role of the Marshallian industrial atmosphere in knowledge sourcing within clusters, where "mysteries of the trade become no mysteries; but are as it were in the air, and children learn many of them, unconsciously" (Marshall, 1890, p. 225). In this regard, geographical proximity, among other factors, paves the way for creating social ties and bridging cognitive gaps (Balland et al., 2015a; Boschma, 2005).

Conversely, a few recent contributions challenge this view, arguing that the diffusion of knowledge in a cluster or other types of local productive systems is not always and solely diffused "in the air" (Fitjar & Rodríguez-Pose, 2017). On this line, knowledge does not spread uniformly across local actors, but it spreads within a core group of agents and selectively and unevenly (Balland & Rigby, 2016; Boschma & Ter Wal, 2007; Giuliani & Bell, 2005; Maghssudipour et al., 2021; Molina-Morales & Martínez-Fernández, 2009).

Against this decoupled backdrop, the relational turn in economic geography aims to understand this dynamic interplay between spatial and aspatial factors and account for how organizations make decisions (Bathelt & Glückler, 2003, 2011). For example, Glückler et al. (2016, pp. 6–7) claim that: "despite the potential of combining the relational and the geographical perspectives there has been long unintended silence between the two fields [...] the mutual conditionality between space and networks is thus a fascinating and still unexplored area of research." This approach has motivated an upsurge of cluster studies that empirically investigate the effect of a vast number of factors on knowledge sourcing, considering individual, spatial, and relational factors (for an extensive review, see Hermans, 2020).

From the theoretical viewpoint, Ahuja et al. (2012) posit nodes, ties, and structure as network primitives and propose several dimensions as centrality and constraint (for ego networks) and as degree distribution, connectivity, clustering, density, and degree assortativity (for the whole network) as relevant architecture dimensions to be investigated. Moreover, they also add that the contents of interconnections and distinct flows (multiplexity) are relevant factors in explaining network structures. When moving to a dynamic perspective, network micro-foundations such as agency, opportunity, and inertia, as well as network micro-dynamics like homophily, heterophily, prominence attraction, brokerage, and closure, seem to be critical elements in driving the evolution of sets of relationships.

Reviewing the empirical studies shows that the interplay of several concepts emerging from different theoretical backgrounds played a critical role in forming a conceptual framework for the structure and dynamics of localized knowledge sourcing. For example, scholars in sociology mostly elaborate on the concepts of norms, status and homophily (e.g., Lazega et al., 2012), social relations (Burt, 1992; Granovetter, 1973), and social contexts (Feld, 1981). Management and transition studies argue that collaboration patterns differ due to fundamental differences across "technological regimes" and sectoral specificities (Breschi et al., 2000; Kogut, 2000; Malerba, 2002; Malerba

& Adams, 2013; Pavitt, 1984; Sedita et al. (2021); Simensen & Abbasiharofteh, 2022). Organization and management theorists unravel relational complexity by adopting a multilevel perspective, i.e., node, dyadic, and structural levels (Ahuja et al., 2012). Although one can observe similarities in different disciplines (e.g., proximity in economic geography and homophily in sociology), there still seems to be a need for studies that go beyond the boundaries of a given strand of literature and investigate the joint effects of the various factors identified in different disciplines.

The aim of this paper is twofold. First, while we acknowledge the fruitfulness of the relational turn in cluster studies in understanding the process of knowledge sourcing, we aim to underline several research gaps and unanswered pressing questions regarding knowledge sourcing forces embedded at the node (organizational), dyadic (proximity), and structural (network) levels. We argue that answering such questions improves our understanding of the universality of knowledge sourcing in clusters and reconciling conflicting empirical results. In doing so, we build on recent empirical studies in the cluster literature inspired by the relational turn (Abbasiharofteh & Broekel, 2020; Balland et al., 2015b; Belso-Martinez, 2016; Boschma & Ter Wal, 2007; Capone & Lazzeretti, 2018; Giuliani, 2011; Giuliani & Bell, 2005; Juhász & Lengyel, 2018; Lazzeretti & Capone, 2016; Maghssudipour et al., 2020) as well as on concepts and evidence in multiple related fields ranging from network analysis inspired by behavioral studies (Burt et al., 2013) to relational inequality theory (Tilly, 1999; Tomaskovic-Devey & Avent-Holt, 2019) and to evolutionary economic geography (Boschma & Martin, 2010).

Second, we discuss that moving beyond a single-level network perspective is one of the most challenging aspects that economic geographers and regional scientists addressed (Glückler & Doreian, 2016). We review recent efforts in this respect that include studies mostly focusing on factors at one level and include factors at the other levels to ensure the robustness of empirical investigations. Alternatively, we suggest how future cluster studies could go beyond the investigations of separated factors embedded at different levels, and address theoretically informed research questions that underline cross-level interdependencies. This is particularly interesting within clusters where multiple socio-economic relations and place specificities substantially influence knowledge sourcing processes.

This work offers at least two main contributions. On the one hand, it advances the cluster literature discussing critical factors of inter-organizational knowledge sourcing by interacting with different streams of research such as network science, behavioral studies, relational inequality theory, and evolutionary economic geography. On the other hand, it extends this debate by addressing a multilevel perspective and providing multiple theoretically informed research questions for future empirical research.

This paper is structured as follows. "Node Level: the Problem of Agency" section focuses on the node (organization) level and investigates the agency problem in knowledge sourcing. "Dyad Level: Complementarity and Substitutability Between Proximity Dimensions" section builds on the proximity framework and discusses research challenges regarding complementarity and substitutability between proximity dimensions. "Structural Level: Relational Inequality" section moves on to the structural level; it elaborates on an upsurge of network studies in the cluster literature and discusses research directions in relation to the drivers of inequal clusters' performance. "Adopting a Multilevel Approach" section underlines the research gaps regarding the interplay between different levels (node, dyad, structural levels). "Conclusions" section concludes the paper.

Node Level: the Problem of Agency

An individual or organizational level decision is the micro-foundation of tie creation and a fundamental force affecting the structure and dynamics of knowledge sourcing networks in clusters (Giuliani & Bell, 2005). Glückler (2007) claims that firm-level decisions might be driven by retention and variation mechanisms. Retention is concerned with the path-dependent behavior of organizations in creating knowledge ties associated with their routines and previous knowledge sourcing patterns. Variation, however, introduces novelty and path-breaking patterns in collaboration networks. While an upsurge of empirical studies analyzing the concept of retention in cluster studies (e.g., proximity dimensions and network micro-forces), the driving forces behind variation have attracted less attention.

Variation might occur because of organizations' decisions in an uncertain environment with bounded rationality. In cluster studies, however, scholars usually include individual characteristics such as age and size of organizations (e.g., Balland et al., 2013; Juhász & Lengyel, 2018; Molina-Morales et al., 2015). These mostly binary or categorical variables serve as controls in almost all cases, but they do not entirely capture the effect of the agency. This research gap calls for studies that integrate a behavioral dimension into current frameworks in cluster studies, which can substantially contribute to our understanding of why and how organizations share knowledge (in other words, why and how they create knowledge ties). While evolutionary economic geography emphasizes the critical role of the micro-behavior of agents and its collective impact on uneven geographical patterns of innovative performance (Boschma & Frenken, 2018; Giuliani & Bell, 2005), surprisingly, there has not been much cross-fertilization between cluster studies and behavioral economics (Thaler, 1980; Thaler & Sunstein, 2009; Tversky & Kahneman, 1974, 1981).[1]

Clark (2018) underlines the relevance of context for framing behavior. He reviews the behavioral turn in economics and geography, and argues that the embeddedness of a given actor influences decision-making in time and space as well as the nature of decisions. Building on Clark's work, we argue that the problem of agency can be addressed by incorporating the role of cognitive capacity and certainty in a decision environment in cluster studies.

[1] Several studies in political science include behavioural dimensions using the stochastic actor-oriented models (SAOM) that can be used as a point of departure for integrating behavioural dimensions into knowledge sourcing studies. See Manger et al. (2012), Rhue and Sundararajan (2014), Berardo and Scholz (2010), and Liang (2013).

Cognitive Capacity

Knowledge exchange is related to preference and individual choices (Howells, 2012). Organizations make decisions on knowledge sourcing with limited cognitive capacity (Trippl et al., 2014); thus, organizations tend to interact with others that are perceived as actors capable of sharing novel knowledge (Crespo et al., 2013). However, having an objective judgment of the potential benefits of interacting with other actors may be difficult or impossible. Consequently, organizations decide to relate to others, taking into account more self-evident and visible characteristics that are assumed to be associated with possessing useful and novel knowledge. The accuracy and effectiveness of such decisions reflect the ability of organizations to detect and extract innovative ideas from their environment (Emre Yildiz et al., 2020). In the early twentieth century, Schumpeter (1911) already argued that larger firms are more likely to innovate because they are capable of allocating more resources and labor to research and exploring new ideas, which might lead to larger firms having a higher degree of absorptive capacity (Cohen & Levinthal, 1990). This influences the level and sophistication of learning and innovation of organizations (particularly firms). Thus, one can argue that larger or more experienced organizations build on their accumulated knowledge and developed routines. In contrast, new entrants must rely on their judgment-related reasoning and decision heuristics. The latter is subject to biases associated with heuristics such as the “herding effect” (as one of few studies, see Suire & Vicente, 2009). Considering evolutionary processes, one should distinguish between two spin-offs of the same size and experience if they inherited routines from parent organizations with different cognitive capacities (Buenstorf & Klepper, 2009).

Certainty in a Decision Environment

There is an interplay between knowledge sourcing decisions taken by individual organizations and the context in which they are embedded (Clark, 2018). Organizations are embedded in various institutional settings and socio-cultural contexts. Actors’ embeddedness within specific economic and social environments plays a key role in understanding how they take decisions (Becattini, 1990). Still, only a few attempts exist to measure to what extent some agents have different degrees of embeddedness and stronger or weaker relations within a cluster (Molina-Morales et al., 2013). Hassink et al. (2016) highlight the potentialities of place-based analysis to avoid investigations exploring space-neutral cases where space is interpreted as a container and to guard against the risk of investigating place-blinded relational spaces. For instance, different knowledge bases in the dominating industry of a cluster can explain relevant features of knowledge networking (Plum & Hassink, 2011).

Moreover, clusters are associated with different regulatory systems, the quality of government, and collaboration culture (Cortinovis et al., 2017; Karo & Kattel, 2014; Rodriguez-Pose & Di Cataldo, 2015). Furthermore, local culture (Carayannis & Campbell, 2009) and even the natural environments of society (Carayannis &

Campbell, 2011) impact knowledge sharing and innovation. Differences in such factors bring about a rich (poor) institutional setting and a high (low) degree of certainty in decision environments. Also, the position of clusters along their lifecycle might affect the level of certainty in knowledge sourcing because emerging and growing clusters are associated with a great degree of uncertainty (Abbasiharofteh, 2020; Menzel & Fornahl, 2010; Ter Wal & Boschma, 2011).

Cognitive capacity and certainty in a decision environment can be addressed as a complementing "selection mechanism" (Glückler, 2007) that enables cluster literature to shift away from a much criticized deterministic and linear approach (Martin & Sunley, 2011). While a large body of literature focuses on how organizations involve in knowledge sourcing under circumstances that at least either a high level of certainty in cluster or required cognitive capacity is given (for a review, see Abbasiharofteh, 2020). What is less studied, however, is the situation in which a lack of required cognitive capacity and uncertainty call for judgment-related reasoning and decision heuristics. Table 1 presents a stylized description of different knowledge sourcing behavior patterns under certain circumstances.

Even if the empirical knowledge of how agency interacts with knowledge sourcing patterns in clusters is addressed by a few qualitative studies (Dayasindhu, 2002; Dyba et al., 2020; Lorentzen, 2007; Trippl et al., 2009), it is primarily under-investigated from a quantitative point of view. First, case studies need to study factors that associate with the cognitive capacity of organizations. Second, a new array of studies should investigate what decision biases and under what circumstances affect knowledge sourcing decisions. As a point of departure, behavioral economics identifies and analyzes a set of decision biases and anomalies (Kahneman et al., 1982, 1991; Nagel, 1995; Thaler, 1980; Tversky & Kahneman, 1974, 1981). While most biases are identified at the individual and interpersonal levels, empirical studies will show to what extent these biases are at work at the organizational level. Third, comparative and longitudinal studies should shed light on the varying effect of context and time on how organizations make knowledge sourcing decisions. This suggests future research investigating comparable organizations embedded in clusters with different contextual attributes. In this framework, several different agents and their interactions can play a relevant role in influencing the structures and evolution of clusters and networks operating within them. For example, relations between governments, universities,

Table 1 Knowledge sourcing is influenced by cognitive capacity and certainty in a decision environment

		Certainty in a decision environment	
		Low	High
Cognitive capacity	Low	Path-breaking: using judgment-related reasoning and decision heuristics	
	High		Path-dependent: using developed routines and accumulated knowledge

and main industries can be key driving forces of cluster development, as well as the civic society, and even the natural environment of society can play a relevant role in knowledge production and innovation (Carayannis & Campbell, 2011, Leydesdorff, 2012). The cluster lifecycle model (Menzel & Fornahl, 2010; Ter Wal & Boschma, 2011) and regional innovation system (Cooke, 1992; Cooke et al., 2011) seem to provide required frameworks to distinguish clusters based on their contextual attributes and the level of certainty for taking knowledge sourcing decisions.

A better knowledge of the interplay between agency and knowledge sourcing patterns sets a new goal for cluster policy. Cluster policy should be equipped with a set of tools to identify what circumstances bring about a high level of uncertainty, what organizations merely rely on decision heuristics, and what potential biases are associated with such heuristics. To decrease the level of uncertainty and facilitate knowledge sourcing decisions, cluster policy can in such situations aim at identifying knowledge sources within and outside a cluster and promoting knowledge collaborative tie formation (e.g., promoting knowledge exchange at the local level or establishing science and technology parks). Also, it seems critical that cluster policy supports risk-taking strategies to encourage smaller organizations to explore potential solutions that could lead to a new development path (path-creating) in the cluster.

Dyad Level: Complementarity and Substitutability Between Proximity Dimensions

Various proximity dimensions and their interplay influence the likelihood of forming, maintaining, changing, or dissolving different kinds of relations and consequently, they influence the structure and evolution of knowledge networks. As territorial systems of proximate agents par excellence, the relationship between proximity and knowledge networks is particularly and historically debated by scholars investigating clusters' architecture, functioning, and performance.

Inspired by Marshall (1890), one stream of literature investigates the role played by spatial proximity among economic actors as organizations and firms, proving that it is strictly linked to the tacit component of knowledge (Malmberg & Maskell, 2002). Knowledge can spread tacitly among actors that are neighbors through channels embedded in social interactions (e.g., face-to-face encounters). For this reason, knowledge diffusion can be spatially bounded within the area where those economic actors are based (Anselin et al., 1997; Feldman & Audretsch, 1999). Consequently, the degree of geographical proximity characterizing an agglomeration may be considered a primary source for knowledge exchange (Audretsch & Feldman, 1996).

However, starting from Rallet and Torre's (1999) decoupling between the geographical and non-geographical dimensions of proximity, scholars argued that geographical proximity is neither a sufficient nor a necessary condition for learning and innovation (Boschma, 2005). Boschma (2005) identifies five proximity dimensions that increase the odds of two organizations establishing a knowledge tie.

- Geographical proximity—the extent to which two organizations are spatially close or co-exist in the same geographical area. Geographical proximity fosters formal interactions, physical meetings, and informal and random encounters.
- Social proximity—the extent to which two given organizations are embedded in the same social networks and have common past experiences. Social proximity facilitates the creation of trust and synergy effects, and lowers transaction costs (Coleman, 1988; Granovetter, 1985; Uzzi, 1997).
- Organizational proximity—the level of similarity in control and autonomy in organizational arrangements (Boschma, 2005). Organizational proximity can be defined based on the extent to which organizations follow similar routines and procedures (Broekel & Boschma, 2012).
- Cognitive proximity—the degree of overlap in technological and cognitive domains of organizations, whereby they are able to exploit and absorb the exchanged knowledge (Cohen & Levinthal, 1990; Nooteboom, 1999).
- Institutional proximity—the level of similarity in informal constraints and formal rules under which organizations interact (North, 1990).

Recently, Balland et al. (2020) reviewed empirical studies on proximity dimensions and discussed the main empirical findings. First, the positive effect of geographical proximity on the formation of knowledge ties is not that high when one considers the impact of other dimensions, because geographical proximity is positively correlated with other proximity dimensions in most cases. Second, one proximity dimension can arguably compensate for the lack of the other. For instance, interdisciplinary collaborations are more likely to succeed when they are locally organized (Singh, 2005). This implies that geographical proximity facilitates interaction and mutual learning also between cognitively distant collaborators. Third, an optimal degree of proximity maximizes the benefits of knowledge exchange. For example, Fornahl et al. (2011) suggest that an optimal cognitive distance can exist between collaborating actors since they need to have a certain degree of proximity to understand each other and also a certain degree of distance to learn something new. Fourth, the proximity framework contributes to the knowledge base literature (for a review, see Boschma, 2018). The rationale behind this approach is that an innovative product or service shifts through several phases with various attributes. Thus, the relevance and the magnitude of the effects of proximity dimensions vary across these phases (Davids & Frenken, 2017).

As mentioned above, proximity dimensions interact with one another to overcome the problem of coordination and uncertainty and to prevent adverse outcomes (Boschma, 2005). The five proximity dimensions are interrelated and can substitute for the other forms of proximity, or they may reinforce them (Broekel, 2015). This relational structure may lead to the so-called proximity paradox (Broekel & Boschma, 2012). On the one hand, a certain degree of cognitive proximity and its related absorptive capacity are the tools for effective interacting learning and innovation, and the other four dimensions of proximity may solve the problems of coordination and control since they facilitate knowledge transfer among actors (Boschma, 2005); on the other hand, too much proximity may have a negative impact on innovation in terms of low level of openness and flexibility (lock-in problem) and too little proximity may be dangerous for interactive learning and network creation. While this is a straightforward conceptual argument, we know little about what provides the most optimal proximity in practice and what composition of various proximities guarantees that clusters benefit the most.

Right now, we know little about what causes these variances across domains of technologies and geographies or how policy measures might affect them. Thus, future studies need to go beyond the mere exploration of the relevance of various proximity dimensions in knowledge sourcing and aim at understanding why a specific dimension facilitates knowledge sourcing in the context of one technology and geographical area, and does not in other cases (Boschma, 2018). Moreover, in what way place specificities affect possibilities of interactions between agents and between proximities is largely under-investigated, particularly from the empirical point of view. Only by answering such questions policymakers can take full advantage of the proximity framework.

The extant literature on complexity in economic geography can provide the first insight into the dynamic interplay between proximity dimensions. Balland and Rigby (2016) and Balland, Jara-Figueroa et al. (2020) empirically show that complex activities tend to agglomerate in large cities. Perhaps because complex activities have become increasingly interdisciplinary and require more interaction among experts from different fields. It is plausible that geographical proximity compensates for the lack of cognitive proximity. Yet, empirical studies have focused on geographical and cognitive proximities (Balland & Rigby, 2016), and little is known about the joint effects of other proximity dimensions. Building on the complexity framework (Broekel, 2019; Hidalgo & Hausmann, 2009), future studies could further investigate the dynamic interplay between proximity dimensions and the complexity of a given technology (Juhász et al., 2020).

Also, while most empirical studies focus on investigating five proximity dimensions identified by Boschma (2005), one can argue that the specificity of places (e.g., clusters) can give rise to other complementary proximity dimensions. Against this backdrop, a few scholars introduce other proximity dimensions, such as cultural proximity (Gill & Butler, 2003), technological proximity (Greunz, 2003), virtual proximity (Morgan, 2004), and proximity on the move (Bernela et al., 2019). For instance, Abbasiharofteh and Broekel (2020) investigate place-specificities in explaining the evolution of the inter-organizational collaboration network of the biotech cluster in Berlin. They empirically show that firms' location in East and West Berlin accounts for how new knowledge ties are formed, with East–West ties being less likely to be formed than East-East and West-West ones. Identification and studying such proximity dimensions and their joint effects in different technological contexts may provide a new array of opportunities to complement or compensate for the lack of five main proximity dimensions.

While there are numerous empirical studies investigating the changing effect of proximity dimensions and structural properties on clusters' knowledge sourcing networks (Abbasiharofteh & Broekel, 2020; Balland et al., 2015b; Capone & Lazzeretti, 2018; Ferriani et al., 2013; Giuliani, 2011; Lazzeretti & Capone, 2016), a comparison of results with various empirical settings is a challenging task. Thus, systematic comparative studies must be done to test the validity of the models mentioned above in multiple contexts (Hermans, 2020). In other terms, comparative studies across several cases should help to overcome generalizability bonds through an avenue of research that studies similarities and differences between heterogeneous contexts and historical contingencies rather than static pictures that hardly work for all. Systematic comparative studies might pave the way for creating a taxonomy of clusters based on their knowledge sourcing attributes and add another relational dimension to the current cluster models based on clusters' temporal dimension (Menzel & Fornahl, 2010; Ter Wal & Boschma, 2011).

Proximity literature has significantly contributed to cluster policy because it underlines that regions in a lock-in situation can potentially build on various proximity dimensions to tap into other regions' novelty sources. More advanced knowledge of the interplay between proximity dimensions can increase the efficiency and effectiveness of cluster policies. Promoting clusters with the dominance of various technologies requires a better understanding of how proximity dimensions interact, given the attributes of the domain of each technology. In the smart specialization strategy context, Boschma and Balland (2020) study how inter-regional ties can contribute to European regions' diversification capability. They found that inter-regional ties are beneficial when connected regions provide complementary capabilities. This might imply that "optimal" cognitive proximity compensates for the lack of geographical proximity. A better understanding of complementarity and substitutability between proximity dimensions could ideally assist policymakers in replacing or reinforcing the effect of proximity dimensions to increase the likelihood of creating knowledge ties that transfer needed capability to peripheral regions.

Although the proximity framework has proved its conceptual power, it is not free of limitation. Rutten (2017) points out limitations associated with the proximity approach. The proximities approach tends to oversimplify physical place by reducing it to near-far dichotomies. This oversimplification overlooks the nuanced relationship between social context and physical location. In other words, this approach conflates social context and physical place in explaining knowledge creation. This conflation neglects the influence of factors beyond geographical proximity, such as norms, values, trust, and social capital, which can also impact knowledge creation. Thus, the proximity framework lacks a satisfactory way of connecting knowledge creation's social and spatial contexts and reconciling mixed empirical results. We return to these limitations in the section on adopting a multilevel approach and discuss how taking a multilevel approach can alleviate the proximity framework problems.

Structural Level: Relational Inequality

Knowledge is sourced in social networks in which organizations and individuals are embedded (Granovetter, 1985; Uzzi, 1997). Thus, one could go beyond the individual and dyadic levels and argue that the forces derived from the structure of a given knowledge network might impact how new knowledge ties are created. The notion of endogenous structural effects is given by the path-dependent nature of network evolution and is immanent in the fact that organizations and individuals mostly establish their subsequent ties based on the attributes of ties that are already established (Glückler, 2007). While scholars discuss various structural effects (also known as network micro-determinants) such as multi-connectivity (Powell et al., 2005), threshold effect (Giuliani, 2013), cyclicity (Balland & Rigby, 2016; Juhász & Lengyel, 2018), and density (Balland et al., 2013; Giuliani et al., 2018), we focus on the three effects that have attracted most attention in cluster studies (i.e., cohesion effect, status effect, and assortative mixing). It is important to note that we focus on the structural properties of networks as the driving forces of network evolution (i.e., status effect, cohesion effect, and assortative mixing) and not on a network structure realized because of such forces.

The status effect (or preferential attachment) represents the attractiveness of some actors compared to others within a network. Barabasi and Albert's (1999) study on complex networks empirically demonstrates that networks grow by new nodes being added to the network in a "self-organizing" fashion, resulting in a scale-free degree distribution in the network. More precisely, a new node is more likely to form a tie to nodes with a higher degree centrality, i.e., nodes with a relatively higher number of ties than others. However, empirical studies in economic geography provide limited evidence for preferential attachment being one of the main drivers of knowledge exchange (Balland et al., 2015b; DeStefano & Zaccarin, 2013; Menzel et al., 2017).

The cohesion effect concerns reciprocity and transitivity (or triadic closure). Reciprocity means that actors receiving a knowledge transfer from others are likely to reciprocate the link and this mechanism may incentivize them to reiterate relationships over time. Thus, it indicates a knowledge exchange of type $i \rightarrow j$; then $j \rightarrow i$. On this line, a few investigations empirically proved the role of reciprocity as a critical mechanism explaining knowledge network structures and dynamics within clusters and other local productive systems (for example, Balland & Rigby, 2016; Giuliani, 2013; Giuliani et al., 2018). Transitivity is given when two actors are more likely to interconnect once they have a previous common actor. Thus, it indicates a knowledge exchange of type $i \rightarrow j$; $i \rightarrow h$; then $j \rightarrow h$. This mechanism is often related to trust because the common actor may increase the confidence of the other two in creating and maintaining a relationship (Balland et al., 2015b; DeStefano & Zaccarin, 2013; Giuliani, 2011, 2013). Recently, de Vaan and Wang (2020) have shown that transitivity might be the main driving force of network inequality. However, this does not challenge the importance of the status effect, indicating that more central actors also have more possibilities to bridge structural holes.

Assortative mixing (or homophily) is at work when actors are more likely to create a tie with others with a similar number of already established ties. Several empirical contributions explore the effect of homophily, finding mixed results. For example, Ebbers and Wijnberg (2010) and Abbasiharofteh and Broekel (2020) found a positive effect of homophily on knowledge exchange, while Balland et al. (2013) discovered a negative impact. Moreover, Castro et al. (2014) and Nicotra et al. (2013) proved a positive effect of heterophily, while Molina-Morales et al. (2015) discovered a negative impact.

While above mentioned empirical studies provide information on the structural properties of knowledge networks, more attempts should be made to account for why various structural properties might trigger a lock-in situation in some clusters and economic diversification and cluster rejuvenation in others. For example, within

Table 2 Driving forces of relational inequality and dominant network micro-determinants across cluster lifecycle

	Cluster lifecycle		
	Emerging	Growing	Sustaining
Forces of relational inequality	Exploitation	Exploitation, social closure	Social closure
Dominant network micro-determinants	Status effects	Status effect, cohesion effect	Assortativity

this debate, very recent attempts investigated the role played by the variety of the local industrial structure, the architecture of knowledge networks, and their interplay for regional innovation (van der Wouden & Rigby, 2019), but cluster literature is still far from providing a full-fledged theoretical framework that conceptualizes the drivers of inequality within and among clusters partly emerging from their structural properties. This is perhaps because scholars have borrowed analytical methods from network studies, and there has not been much cross-fertilization between the cluster literature and inequality literature.

Against this backdrop, the literature on relational inequality theory can be used as a point of departure to make sense of empirical results and discuss future research directions. Tilly (1999) in his work "durable inequality" goes beyond the common approach of most works in sociology and economics which mainly focus on individualistic attributes, and argues that inequality is created and reinforced through the twin social mechanisms of "exploitation" and "social closure" both embedded in intra- and inter-organizational relations. Exploitation occurs when more powerful organizations take advantage of their position and take a relatively higher share of resources at the expense of less powerful ones. Similarly, social closure concerns organizational behaviors that reserve benefits for in-group organizations and exclude out-group members from opportunities (for a detailed review, see Tomaskovic-Devey & Avent-Holt, 2019). These two mechanisms complement each other and reinforce inequality unless exogenous factors (e.g., policies or changes in the market structure) disrupt this pattern. This conceptual argument is in line with empirical evidence in cluster studies because exploitation resonates with an organization occupying central positions (status effects), and social closure is related to the effects of triadic closure (cohesion effects) and homophily (assortativity). Thus, this framework resonates with tie formation patterns in clusters along their evolutionary path. Ter Wal and Boschma (2011) and Abbasiharofteh (2020) underline preferential attachment as a driving force of tie formation in the early phase of a cluster lifecycle. In contrast, triadic closure and assortativity replace this effect in later phases.

Factors listed in Table 2 account for inequality in access to knowledge in clusters. Social closure, mainly driven by assortativity, is especially problematic for the innovative performance of a cluster in the sustaining phase. Vicente (2017) argues that as only a limited number of firms and organizations can benefit from public funding at the expense of their peers, their previous experience paves the way for getting further grants. Over time, these fortunate agents collaborate more often with one another, whereby others take peripheral positions or become isolated "islands." This might explain why knowledge sourcing networks tend to show increasing assortativity over time. This implies that assortative mixing can increasingly hamper the diffusion of novel knowledge among organizations. Crespo et al. (2013) investigate the impact of assortativity and disassortativity in clusters from a wide perspective. They argue that the degree of assortativity may be interpreted as an explanation of knowledge flows in core-periphery structures (Borgatti & Everett, 2000), where highly connected actors are tied in the core. In contrast, poorly connected actors are in a relational system in the periphery. The authors argue that assortativity may be related to a lock-in effect since it reduces the opportunities to acquire new ideas. Future studies must investigate whether the relational mechanisms of exploitation and social closure influence how organizations create knowledge ties within and across clusters. Also, empirical investigations can underline attributes of organizations that enable them to occupy a critical position in knowledge networks and, as a result, obtain a greater "claim-making" power (Tomaskovic-Devey & Avent-Holt, 2019).

This subsection has discussed conceptual arguments backed by several empirical studies that geographical areas tend to be subject to relational inequality, leading to an assortative network structure in which highly connected nodes exchange knowledge at the expense of poorly connected ones. This hampers knowledge sourcing and increases the odds of being trapped in a lock-in situation (Vicente, 2017). Thus, policymakers can benefit from a deeper understanding of relational mechanisms to improve the efficiency of place-based innovation policies. This requires that policies shift from only using social network analysis methods to visualize networks in each innovation system towards taking a network perspective and analyzing the needs of a given cluster based on its structural properties (Graf & Broekel, 2020).

The inequality issue has relevant impacts also for policies across clusters. As suggested by Iammarino et al. (2017), space-blind and place-based policies that exclusively follow efficiency may lead to inequality. Thus, they introduce the idea of place-sensitive policies. With this idea, they suggest "a different way of thinking based on maximizing distributed development capabilities" for each region type (p. 27). Thus, a network observatory program is required to collect data on the region- and cluster-specific knowledge sourcing patterns over time to inform policymakers about the extent to which there is a need for the restructuring of the knowledge sourcing network (Frenken et al., 2012). This approach has been partly implemented in the case of the German Leading-Edge Cluster Competition, which enables the effect of a policy measure to be studied over an extended period. For instance, Cantner et al. (2013) investigated three cohorts of this project (in 2008, 2010, and 2012) and evaluated the efficiency and the knowledge sourcing patterns of the involved public and private actors.

So far, cluster policies (excluding a few exceptions) have mainly focused on facilitating the establishment of knowledge ties in a given geographical area (Fornahl & Hassink, 2017). However, the relational and dynamic approaches suggest that innovation policies have to strategically underline innovation-related issues by identifying and satisfying firms' needs based on the position of a given cluster along the cluster lifecycle and its relational properties. Yet, the importance of the properties of knowledge sourcing networks has still not been adequately acknowledged in innovation policies. For instance, the OECD (2017) suggests "boost[ing] labour productivity by fostering innovation and continuing to intensify the links between domestic firms and public research to global innovation networks and value chains…" (p. 1).

Recently, scholars argue that increasing the density of collaboration networks does not necessarily facilitate the knowledge sourcing process and that policymakers first need further information on the main actors in each innovation system, place and sector-related factors, relevant proximity dimensions, and the structural properties of a given network (Abbasiharofteh, 2020; Graf & Broekel, 2020; Vicente, 2017). Such information becomes essential to minimize infrastructural and interaction policy failures because the former is associated with a lack of knowledge infrastructures and the latter with too dense or too fragmented knowledge sourcing relations (Wanzenböck & Frenken, 2020). Thus, this calls for better collaboration of regional scientists, economic geographers, and policymakers to develop specific methods of longitudinal data collection and make them available for innovation policy. The relevance of structural properties is emphasized here because this factor has been overlooked in most policy decisions. However, it should be noted that network-related factors do not rule out non-relational factors' importance. The structural property of a knowledge network is one critical dimension, and it should be analyzed along with other influential factors at the node, dyad, and sectoral levels, as well as considering the temporal, sectoral, and spatial attributes of clusters.

Adopting a Multilevel Approach

While this paper has discussed the drivers of knowledge sourcing at different levels separately, one should not overlook the interdependencies of the already discussed factors nested in various levels (node, dyad, and structural). Although taking a multilevel approach has become common practice in several scientific fields, this approach has only recently attracted attention in cluster studies. In management studies, the multilevel approach has been acknowledged as a promising field of research to investigate inter- and intra-organizational relations. Aguinis et al. (2010) argue that while social network methods have been used to model and comprehend relations between organizations, groups, and individuals, organizations are multilevel in nature and researchers should also examine how structural properties at one level are related to the ones of the other levels.

In cluster studies, economic geographers have started acknowledging the multiplexity of the drivers of knowledge sourcing nested in different levels. In contrast, only a few conceptual and empirical works address the interdependencies of such factors. Several studies focus on the effect of one or multiple specific factors at the dyad or structural levels. In contrast, attributes at the node level (organizational level) serve as controls in most empirical settings (see Hermans, 2020). For example, Balland et al. (2015b) investigate the relevance of the status and embeddedness effects along several proximity dimensions in business and technical networks in Spain. Similarly, Belso-Martínez et al. (2017) and Molina-Morales et al. (2015) take a similar approach and investigate the effect of proximity dimensions and structural properties on the evolution of a knowledge network.

While such studies are the first steps towards adopting a multilevel approach, they say nothing about the combined effects of factors from different levels on the evolution of knowledge sourcing networks. One reason for the lack of evidence might be the dominant firm-centered epistemology in evolutionary economic geography. This perspective may lead to ignoring the interplay between context and firm-level factors (Baumgartinger-Seiringer et al., 2021). To advance this, we build on a few scholarly works that aim at going beyond this single-level perspective.

Yeung (2005) discusses the emergence of a relational approach in economic geography, emphasizing the interconnectedness between socio-spatial relations and economic transformations. The article raises the question of whether this shift signifies progress. The author asserts that contemporary relational economic geography often focuses on thematic aspects, failing to adequately theorize relationality, power dynamics, and the unique practices of actors involved in economic processes. Yeung (2005) points out that "… relational geometries are neither actors (e.g., individuals and firms) nor structures (e.g., class, patriarchy and the state), but configurations of relations between and among them – connecting actors and structures through horizontal and vertical power relations" (p. 38). Similarly, but in a different context, Grabher (2004) highlights the shift from a sectoral understanding of the economy to knowledge-intensive service sectors. His work identifies projects as temporary organizational arenas where knowledge is combined from various sources to achieve specific tasks. Scott (2006) contends that attaining urban creativity necessitates attention to economic factors alongside citizenship, democracy, and incorporating diverse social groups within the urban community. The article emphasizes the importance of organically cultivating creativity by interweaving production, work, and social life in specific urban contexts rather than merely relying on importing creative individuals or groups.

Agency and Network Micro-determinants

The interaction of node- and structural-levels is a fundamental layer in clustered knowledge networks' structure and evolution when one aims to adopt a multilevel perspective. In fact, on the one hand, nodes as individuals or organizations have the final word in the knowledge sourcing decision-making process; on the other hand, individual decisions are potentially biased by the structural properties of knowledge networks and how information follows. While empirical studies in the cluster literature have paid less attention to the interplay between agency and network micro-determinants in knowledge sourcing, network studies have built on behavioral studies and provided evidence for the impact of individual attributes on tie creation as "an alternative to a strict structural perspective" (Totterdell et al., 2008, p. 283).

We take the pioneering work of Ahuja et al. (2012) as a point of departure to develop a conceptual multilevel framework. Ahuja et al. discuss the need for a multilevel approach to network dynamics in organizational and inter-organizational networks. Their work identifies key micro-foundations and micro-dynamics of network evolution. The former includes agency, opportunity, inertia, and exogenous forces, and the latter consists of homophily and prominence attractions. The joint effect between agency and network structure refers to the combined influence of individual agency (motivations, actions, and decisions of network actors) and the underlying structure of the network (the pattern of connections between organizations) on network dynamics. It suggests that the behavior and actions of network actors, driven by their motivations and opportunities, interact with the existing network structure to shape the evolution and changes within the network. This joint effect highlights the reciprocal relationship between agency and network structure, where changes in one can impact the other and vice versa. By understanding this joint effect, researchers can better analyze the interplay between individual agencies and network structure driving network dynamics.

Burt et al. (2013) list network studies investigating how agency and cognition bring about various tie formation behaviors under similar circumstances. The authors argue that the success of brokers varies with their attributes. In another study, Burt et al. (2000) show that French and American managers follow different tie formation patterns, which cultural differences might drive. Network studies include numerous empirical investigations that provide evidence on how the position of individuals in a social network influences their beliefs and behaviors (see, Jackson, 2019). On the interplay between agency and network structure, Podolny (2001) claims that the already established ties are not only “pipes” through which various resources and information flow but also “prisms” through which individuals evaluate others and impact how they form their future relations. Similarly, Smith et al. (2012) empirically show that individuals with low status are more likely to look for information in a smaller subsection of their social network compared to the ones with high status, and individuals with a higher number of structural holes in their social network can more easily create ties to bridge parts of the network with more structural holes.

Although these studies provide a first insight into the relevance of the interplay between agency and knowledge network structure in knowledge tie formation and network evolution, they mostly focus on individuals. This is still an open question whether the same rationale applies to organizations (Balland et al., 2020b).

In a hypothetical sense, the joint effects of agency and network micro-determinants can lead to various forms of change and outcomes within the network. These joint effects may include complex patterns and interdependencies that are not immediately apparent, encompassing many possibilities. Understanding these joint effects requires empirical studies on the interplay between agency and network micro-determinants and their cumulative impact on the network’s evolution. As Ahuja et al. (2012) suggest, it is essential to note that despite micro-dynamics, a network can maintain its structural stability over time, exhibiting little change in density, clustering, or small-world properties. This outcome is due to the potential compensatory nature of micro-dynamics, wherein the dissolution of particular ties is counterbalanced by forming new relations with similar structural characteristics. Consequently, while the overall network may appear stable from a macro perspective, it is important to recognize the underlying dynamism occurring at the level of individual ties and nodes. Thus, the network can exhibit simultaneous stability and dynamism across different levels of analysis.

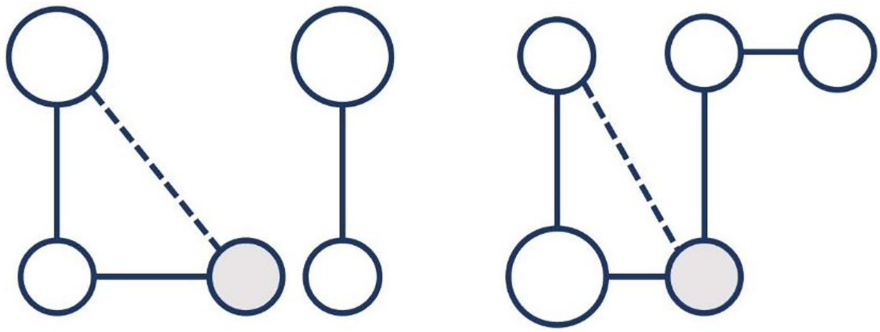

Fig. 1 The interplay between agency and network micro-determinants. Note: Nodes represent organizations and (dotted) lines represent (future) knowledge ties. A larger node size demonstrates a higher status. Left: the likelihood of establishing a knowledge tie with a connected organization of higher status (larger nodes) is enhanced by the effect of triadic closure. Right: the status effect enhances the probability of forming a knowledge tie with another organization of similar status to strengthen the relationship with the one possessing higher status

Thus, future studies need to shed light on the interplay between agency and inter-organizational tie formation. Among a few cluster studies, Giuliani (2013) argues that actors with higher status levels may be more likely to be involved in knowledge sourcing networks than actors with lower levels (Giuliani, 2013). However, status is perceived in relations, and organizations do not have perfect information on the capabilities of other organizations (deVaan & Wang, 2020). This may lead to two knowledge tie formation patterns. First, the effect of triadic closure increases the likelihood of creating a knowledge tie with an affiliated organization with higher status (Fig. 1 [left]). Second, the status effect increases the likelihood of knowledge tie formation with another organization with a similar status in order to strengthen the relation with the one with a higher status (Fig. 1 [right]).

Proximity Dimensions and Network Micro-determinants

While a knowledge tie is formed at the dyad level, one cannot ignore the influence of knowledge network structure on forming a new tie. Balland et al. (2020b) discuss the importance of a "portfolio perspective" in the context of the proximity framework. The authors argue that organizations might have several relations at the same time, and thus to understand the effect of proximity dimensions between organization-pairs, one should investigate all knowledge ties that two given organizations have with others. Similarly, one can more precisely define and measure the concept of "optimal proximity" (Boschma & Frenken, 2010) by considering the knowledge sourcing portfolios of organizations. This implies that organizations perhaps exchange knowledge with others cognitively or geographically proximate or directly connected to their current partners if they aim to exploit existing knowledge (Fig. 2 [left]).

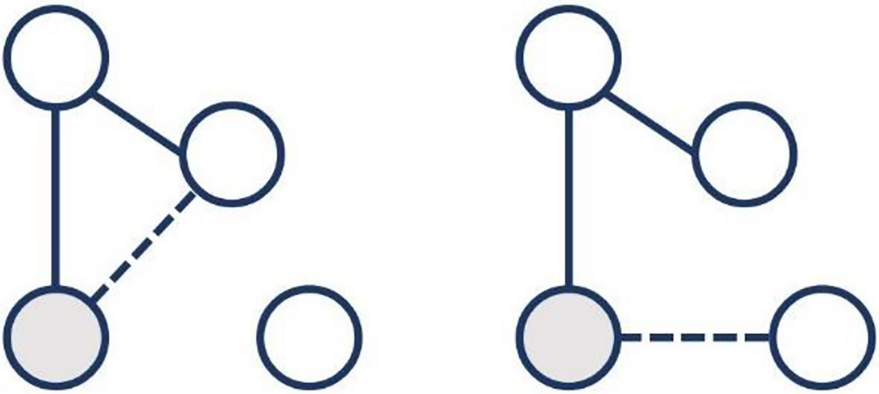

Fig. 2 The joint effects of proximity dimensions and network micro-determinants on knowledge sourcing. Note: Nodes represent organizations, (dotted) lines represent (future) knowledge ties, and the position of nodes reflects their relative proximity in one or several dimensions. Left: to exploit existing knowledge, organizations engage in knowledge exchange with either cognitively or geographically proximate partners or directly connected to their current partners. Right: organizations establish a knowledge tie with an organization that is neither cognitively nor geographically proximate nor directly connected to their current partners if they seek to diverge from the current path and explore new knowledge

Conversely, organizations might form a knowledge tie with an organization not cognitively or geographically proximate or directly connected to their current partners if they want to break out from the current path and explore new knowledge (Fig. 2 [right]). Ignoring the existing knowledge network structure and only focusing on the dyad level does not account for why organizations exchange knowledge with different partners with which they might have the same cognitive or geographical proximity. This conceptual argument is one of few attempts pointing to the interdependency between the dyad (proximities) and structural levels.

On the empirical front, Juhász and Lengyel (2018) investigate the joint effects of cognitive proximity and transitivity on knowledge sourcing. The authors show that this joint effect is positively associated with knowledge tie formation in a cluster in Hungary. Maghssudipour et al. (2020) study the simultaneous functions of social and economic relations on a knowledge sourcing network. Similarly, Hjertvikrem and Fitjar (2020) investigate the effect of monitoring and recruitment networks on a collaboration network. The findings of Abbasiharofteh et al. (2021) indicate that inter-firm relations with a common third partner, which connect cognitively distant firms, and relations without a common third partner that links geographically distant firms, strongly correlate with firms' innovation capabilities. These results correspond to the stylized description of the joint effects of dyad- and structural-level factors on exploitative knowledge sourcing patterns. In contrast, evidence of the joint effects of such factors on explorative knowledge sourcing patterns is still lacking.

The above arguments provide propositions and can be used as a point of departure for building hypotheses in empirical studies to answer two sets of questions. The first set of questions concerns how one or several factors create or remove factors at another level. For instance, do clusters with socially (or cognitively) proximate organizations

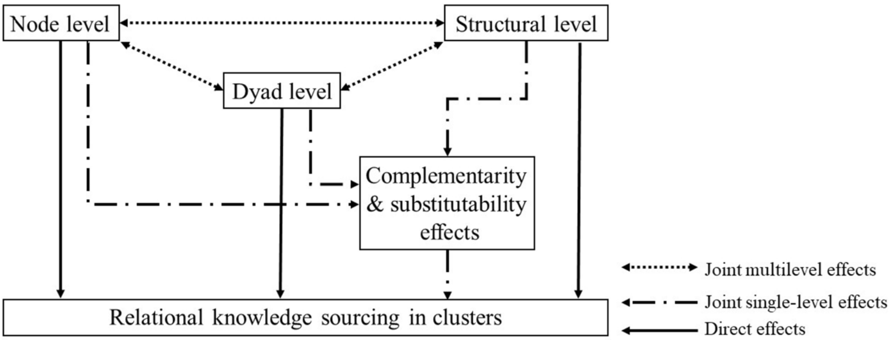

Fig. 3 The nomological network of the driving forces of knowledge sourcing

have relatively dense knowledge networks? Do proximity dimensions and the position of organizations in a knowledge network create a decision-making environment that systematically influences how organizations create future knowledge ties? The second set of questions should address how knowledge sourcing forces at different levels amplify or attenuate the effects of one another. For instance, under what circumstances social proximity and triadic closure may complement or substitute each other? To what extent can node level characteristics (e.g., individual status) affect ties' triadic attributes? What structural properties incentivize organizations to create knowledge ties with cognitively distant partners? Having discussed several propositions and unanswered research questions, researchers should identify empirical regularities on inter-level dependencies. Only then can the cluster literature enjoy a full-fledged conceptual framework that considers the interplay between forces emerging from multiple levels.

The multilevel perspective has relevant policy implications. Once we consider and better understand the interdependency of knowledge sourcing forces at different levels, cluster policy can design tailor-made measures for each cluster by using resources available at one level to compensate for deficiencies at another level.

Conclusions

This article has aimed to provide an overview of conceptual frameworks and empirical findings on relational knowledge sourcing in cluster studies and to point towards major research gaps and potential empirical questions for future research. For clarity, we discuss the driving forces of knowledge sourcing at the node, dyad, and structural levels separately. Subsequently, we have aimed at depicting a coherent picture by accentuating the multilevel aspects of relational knowledge sourcing. Figure 3 provides a nomological network that maps four critical driving forces of knowledge sourcing and their interdependencies.

At the node level (i.e., organizational level), this paper discusses the problem of agency and how different levels of uncertainty in a decision-making environment as well as cognitive capacity could bring about a path-breaking change in the patterns of knowledge tie formation. While this issue can be conceptually addressed within the evolutionary economic geography framework, empirical investigations within cluster contexts are still under-investigated. Thus, future research in cluster studies can underline how the node level and contextual attributes of clusters influence the knowledge sourcing behaviors of organizations.

At the dyad level, this article builds on the proximity framework (Boschma, 2005). It claims that although an upsurge of studies gives evidence on how proximity dimensions individually and jointly trigger knowledge tie formation within and across clusters, the proximity framework cannot adequately explain why a specific proximity dimension is a critical factor in knowledge sourcing in one cluster and not relevant in the other. Also, scholars need to integrate place-specific proximity dimensions into five main dimensions to pave the way for investigating complementarity and substitutability effects among proximity dimensions and for identifying empirical regularities across case studies.

At the structural level, this article reviews multiple cluster studies that investigate network micro-determinants and their effects on knowledge sourcing networks. This part of the paper aims at going beyond using the network science literature as a source of methodological tools and calls for new conceptual bridges with the literature on relational inequality. This approach might help make sense of empirical findings and account for how knowledge networks' structural properties lead to the uneven distribution of innovative performance within and across clusters.

To this end, future empirical research can benefit from recent developments in network science. More specifically, topics such as multiplex networks, multilayer networks, interdependent networks, and networks of networks provide valuable tools whereby cluster studies scholars can aim at answering empirical questions (Cozzo et al., 2018; Kivela et al., 2014). Moreover, recent advancements in machine learning and, consequently, access to new data sources such as trademark data, product launches, and firms' web text and inter-firm hyperlink data provide researchers with more possibilities to map and analyze clusters (Abbasiharofteh et al., 2022, 2023; Nathan & Rosso, 2015).

Finally, we claim that cluster studies can learn from the transition literature, network, and management studies to adopt a multilevel approach and empirically investigate the interplay between factors emerging from different levels (dotted lines in Fig. 3) as well as their potential joint effects on knowledge networks (dashed-dotted lines in Fig. 3). This approach opens a new scholarly debate and brings about a broad range of empirical questions, whereby cluster studies might reach an interdisciplinary conceptual framework of knowledge sourcing.

In sum, we have witnessed that multiple research fields, such as industrial marketing, economic sociology, and organization and network studies started building on relational economic geography principles (Bathelt & Glückler, 2018). In a similar vein, while the present paper has focused on clusters, we suggest that several lines of argument may also contribute to enlarging the debate on other local productive systems where the spread of knowledge through inter-organizational interactions and collaborations plays a key role (e.g., industrial districts). Particularly, the present work offers some insights from both the theoretical and policy-related points of view for the research grounded in contexts in which innovation is a crucial point of local economic performance.

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