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Endogenous effects and cluster transition: a conceptual framework for cluster policy

Milad Abbasiharofteh 

Department Structural Change, Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Halle (Saale), Germany

ABSTRACT

The clustering of firms in related fields has a positive impact on economic performance and innovative behaviour. The cluster lifecycle model provides a framework in order to add a temporal dimension to this ongoing debate. This model conjectures that clusters undergo various phases, in each of which they exhibit distinct characteristics in terms of size, economic performance and knowledge sourcing pattern. While there is strong evidence of a dynamic interplay between knowledge networks and clusters, we know little about how the structural configurations of a knowledge network engender cluster transition, and how these dynamics can be captured and integrated into policies. First, this paper contributes to this debate by providing a conceptual framework that accounts for cluster evolution based on endogenous micro-forces that are immanent in a knowledge sourcing structure. Secondly, this article underlines the failures of recent network-related cluster policies and discusses how the developed framework alleviates these issues.

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1. Introduction

The clustering of firms and supportive institutions facilitates knowledge spillovers, input and output linkages, and skilled labour pooling (Marshall, 1920), and increases firms' competitiveness (Porter, 1998), spinoff activities (Klepper, 2010), and entrepreneurship and the survival chances of start-up firms (Delgado, Porter, & Stern, 2010). Scholars argue that there is a rather strong interplay between the evolution of clusters and that of knowledge networks (Glückler, 2007; Menzel & Fornahl, 2010; Ter Wal & Boschma, 2011). This implies that improving our understanding of the dominant drivers of knowledge network evolution contributes to the knowledge of how clusters evolve over time.

Despite numerous studies, the cluster literature is rather weak when it comes to demonstrating why a cluster emerges and declines as a result of the configuration of its knowledge network. By the same token, the driving forces of cluster diversification are not yet well

CONTACT Milad Abbasiharofteh  abbasiharofteh@iamo.de  Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Theodor-Lieser-Straße 2, Halle (Saale) 06120, Germany  @MABbasiharofteh

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articulated (Lorenzen, 2005). Also, the literature does not clearly delineate the dynamic interplay between space and networks over time (Glückler, Lazega, & Hammer, 2018). To address such issues, two cluster lifecycle models have been developed to provide a better understanding of the process of cluster evolution.

The first model was developed by Menzel and Fornahl (2010), who scrutinize cluster change by taking the temporal dimension into account. This model defines benchmarks for cluster lifecycles based on the age and rate of firm entries and exits as well as the capability of cluster actors to establish local and extra-local collaborative ties. This model is criticized because 'aging' and 'life-course' are not properly defined and it bears the danger of articulating cluster cycles as a deterministic historical sequence (Martin & Sunley, 2011). Also, while this model includes networks as one of the main components of clusters and acknowledges various network structures across four cluster cycles, the dynamic interaction of clusters and networks is not well defined. This implies that the cluster lifecycle model does not integrate the impact of network properties in its framework in order to account for cluster evolution based on both endogenous and exogenous forces (Trippel, Grillitsch, Isaksen, & Sinozic, 2014).

The second model was developed by Ter Wal and Boschma (2011), who integrate the notion of industry lifecycle, networks and the heterogeneities of firms regarding their capabilities. They argue that the cluster is not limited to its geographical boundaries and it has a dynamic interplay with both extra-regional knowledge sources and changes in underlying industries. They argue that clusters reveal various structural properties as they mature, ranging from an unstable (fragmented) structure in the early phase, to a core-periphery and a dissolving network in the growing and decline phases. While this model points towards the relevance of network structure and partly integrates the principles of network theory into the framework of how firms, networks and clustering co-evolve, it says nothing about the variety of micro-forces and their impacts identified in empirical studies in economic geography (see [Appendix](#) for a list of empirical studies). Similar to the model developed by Menzel and Fornahl (2010), the conceptual framework does not add to our understanding of how this could potentially contribute to the design of reality-tailored cluster policy interventions.

The new lifecycle approach thus conceptualizes cluster evolution based on micro forces that emerge from interactions between main cluster components, namely actors, networks and institutions (Fornahl, Hassink, & Menzel, 2014). In line with this new approach, this paper bridges two gaps in the literature. First, it builds on network theory and modifies the cluster lifecycle model by integrating the concept of endogenous effects into the two above-mentioned models, whereby these effects and clusters interact and their dynamic interplay determines the consequent properties of evolving elements. The developed framework rests on six endogenous effects: proximity dimensions, transitivity, assortativity, preferential attachment, exclusion and multi-connectivity. These effects are contextualized in the cluster studies and are then applied to the cluster lifecycle model. This article thus seeks to create a conceptual framework to answer the following questions. (1) How do endogenous effects reshape the structural configurations of a knowledge network and the knowledge sourcing patterns of cluster actors over time? (2) How do endogenous effects in a cluster account for the transition of clusters into a new phase?

Second, this paper underlines the so-called interventionist network-related cluster policies and discusses the failures of such policies. Accordingly, this framework suggests a

new approach to cluster policy and identifies a set of required inputs for policymakers. This approach implies that policymakers can take full advantage of the functionality of endogenous forces to design timely strategies to facilitate knowledge sourcing within and across clusters as well as avoid and overcome lock-in situations.

This paper is organized as follows. Section 2 presents a review of the cluster literature and the relevance of dynamic and network perspectives. Section 3 applies the concept of endogenous effects to the cluster lifecycle model and determines how these effects and clusters co-evolve. Section 4 discusses how cluster policy benefits from this framework and how it minimizes the failure of network-related cluster policies. Section 5 concludes the paper and underlines a number of issues for future research.

2. On clusters and network dynamics

2.1. *Clusters: the unit of analysis I*

Marshall (1920) and Porter (1998) argue that an industrial cluster is a geographic colocation of firms and associated organizations (e.g. universities) in one or several related industries, connected through input-output relations, informal interactions, cooperative local networks and labour mobility. Yet, Martin and Sunley (2003) underline several delineations and approaches on the cluster research and assert that there is not a clear-cut definition of cluster.

To tackle this problem, Delgado, Porter, and Stern (2016) aim at developing a method of identifying clusters. They combine the already developed measures of identifying clusters such as the industries coagglomeration index, input-output links and labour occupation links to maximize the reliability of their new model because each measure has weaknesses and strengths. While this model provides a quantitative solution to define clusters, it suffers from at least two shortcomings. First, their model is limited to specific administration boundaries (e.g. U.S. states), and it is, therefore, biased by the so-called modifiable areal unit problem (Scholl & Brenner, 2014). Second, although Delgado et al. (2016) acknowledge the relevance of knowledge networks, they do not include this factor (due to lack of data) in their algorithm.

While this paper follows Delgado et al. (2016) to identify the main elements of a cluster, this conceptual model underlines regional context (and not administrative boundaries) as the container of one or several clusters which its boundaries do not necessarily correspond to jurisdictions. Regional context concerns the social context, soft and hard infrastructures, and local and national institutions, which accounts for the creation of shared values and common interpretive frameworks (Bathelt & Glückler, 2011, p. 131). Also, while acknowledging the relevance of all types of linkages in clusters underlined by Delgado et al. (2016), this paper specifically focuses on knowledge relations and their impact on the creation and evolution of clusters. Figure 1 provides a stylized illustration of clusters demonstrating the above-mentioned components.

2.2 . *Endogenous effects: the unit of analysis II*

The proximity framework underlines dyad level effects and conjectures that belonging to the same spatial unit ('geographical proximity') or social network ('social proximity'),

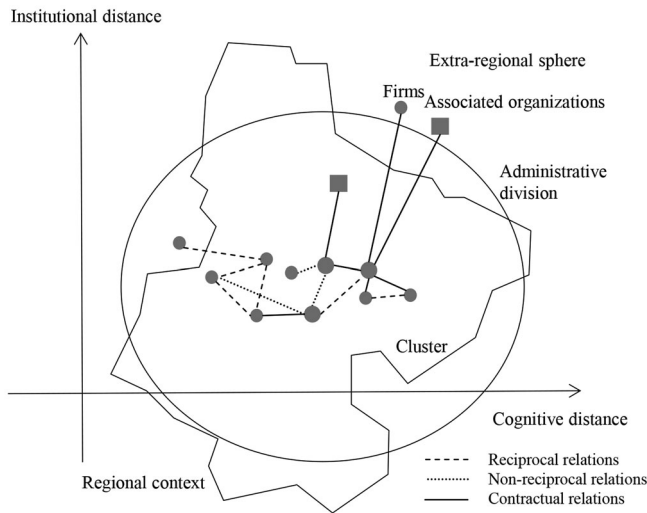


Figure 1. Stylized illustration of a cluster. Source: own illustration.

similarity in interpretation schemes ('cognitive proximity'), rules and laws ('institutional proximity'), and routines and the degree of coordination ('organizational proximity') increase the likelihood of a knowledge tie being established between two given economic agents (Boschma, 2005; Torre & Rallet, 2005). Proximity dimensions evolve over time and they transform, reinforce and substitute one another (Balland, Boschma, & Frenken, 2015; Broekel, 2015). For example, senior managers of different firms accidentally meet due to geographical proximity and, therefore, a social relation could potentially be formed. Over time, social relations decrease cognitive distance and might lead to formal collaborations.

Going beyond the dyadic nature of proximity dimensions, network-level effects also influence the way future ties are formed. 'Transitivity' is one of the most researched network properties. It implies that individuals are more likely to establish a tie with someone with whom they are already connected through a third person, reflecting the effect of social processes such as embeddedness and social capital (Coleman, 1988; Granovetter, 1973).

'Preferential attachment' indicates that the evolution of a network is a direct function of its structure, where the odds of having new ties is determined by the number of ties that each node has already established (Barabási & Albert, 1999). This implies that central nodes attract a higher share of new ties at the expense of peripheral ones.

Contrary to the preferential attachment model, 'assortativity' holds when actors establish ties with alters who have identical structural position, namely a similar number of already established ties.¹ While preferential attachment is reflected by the shape of the degree distribution of nodes, assortativity is presented by the positive (and disassortativity by the negative) degree correlation of connected nodes (Ahuja, Soda, & Zaheer, 2012).

'Exclusion' merits attention when there is a competitive situation, because in such situations a tie is created by excluding another node from a knowledge network (Borgatti, Mehra, Brass, & Labianca, 2009). For instance, firms only cooperate with a limited number of partners because having and maintaining a knowledge relation (e.g. a joint research project) is costly (Boschma & Frenken, 2010).

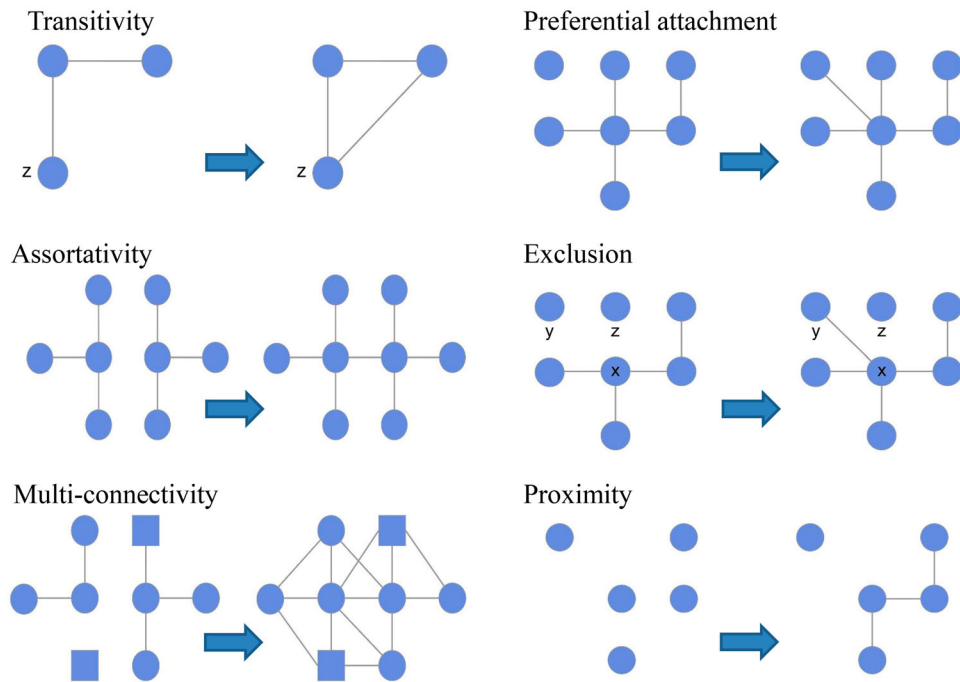


Figure 2. Stylized illustration of endogenous effects and network transition. Source: own illustration.

‘Multi-connectivity’ contrasts preferential attachment and provides an alternative explanation for network evolution. Multi-connectivity holds when a network evolves in a manner whereby it includes multiple direct and indirect links between diverse nodes (Pallotti, Lomi, & Mascia, 2013; Powell, White, Koput, & Owen-Smith, 2005). This implies that multi-connectivity enables nodes to bridge structural holes (Burt, 1992). The following figure is a stylized representation of endogenous effects (Figure 2).

3. Cluster transition and endogenous effects

3.1 . Emerging phase

In the ‘emerging phase’, mostly small firms with diverse knowledge bases operate in one geographical area (Menzel & Fornahl, 2010). It is not a straightforward task to identify an emerging cluster because regions do not exhibit distinct signs in this phase. The dominance of Marshall’s and Porter’s externalities in the literature has caused confusion between cluster externalities and triggering factors. Brenner and Mühlig (2013) distinguish three promoting factors in emerging clusters: prerequisites, self-augmenting events and triggering events. Similarly, Elola, Valdaliso, López, and Aranguren (2012) discuss several local and global critical factors which vary in nature and relevance over time. Their findings underline the importance of historical preconditions, entrepreneurship and factor endowment in the early phase of a cluster. This implies that the factors, which were introduced by Marshall and Porter, are not of relevance for the emerging phase because such externalities are immanent in cases that have reached a critical mass.

The triggering role of spinoffs has become more obvious and some scholars call the emerging phase the reinforcing process of spinoffs (e.g. Shohet, 1998), viz '[a] new work [being] added to older work' (Jacobs, 1970). In this context, the existence of one or several firms along a specific technological path might have momentous consequences for the future of a region (Menzel & Fornahl, 2010). These firms create a cognitive basis for a region and help the region to create its own economic landscape in the long run. Klepper (2007, 2010) challenges Marshall's original idea and argue that spinoff activities are the main trigger of clustering. This implies that new entrants could also emerge from a parent firm and inherit pre-existing practical knowledge and routines. Yet, Klepper (2007) could not empirically rule out all Marshallian externalities that might be tightly linked with spinoff activities (Boschma, 2015).

Generally, innovation policies could play a role in increasing the odds of cluster emergence (Martin & Coenen, 2014). Thus, some scholars believe that institutional requirements precede (rather than follow) the emergence of a cluster (Fornahl et al., 2014). Considering the well-articulated case of Silicon Valley as an example, besides the spinoff activities, cluster prosperity is indebted to Stanford University and its Research Park (Saxenian, 1994).

The radical behaviours of firms in knowledge sourcing engender a constant variation in density, structure and the degree distribution of the knowledge network (Ter Wal and Boschma, 2011), which brings about a fragmented knowledge network consisting of cliques and structural holes. The lack of a cohesive structure impedes the functioning of endogenous effects at the network level. However, social and geographical proximities are the key drivers of cluster transition from an embryonic stage to a critical mass. In this context, uncertainty is high and the dominant mode of knowledge is tacit (Ter Wal and Boschma, 2011). While the minimum level of cognitive proximity is an essential pre-requisite for learning (Nooteboom, 1999), firms encounter difficulties in knowledge sourcing (Ter Wal and Boschma, 2011). As a result, firms shape relations to institutionally

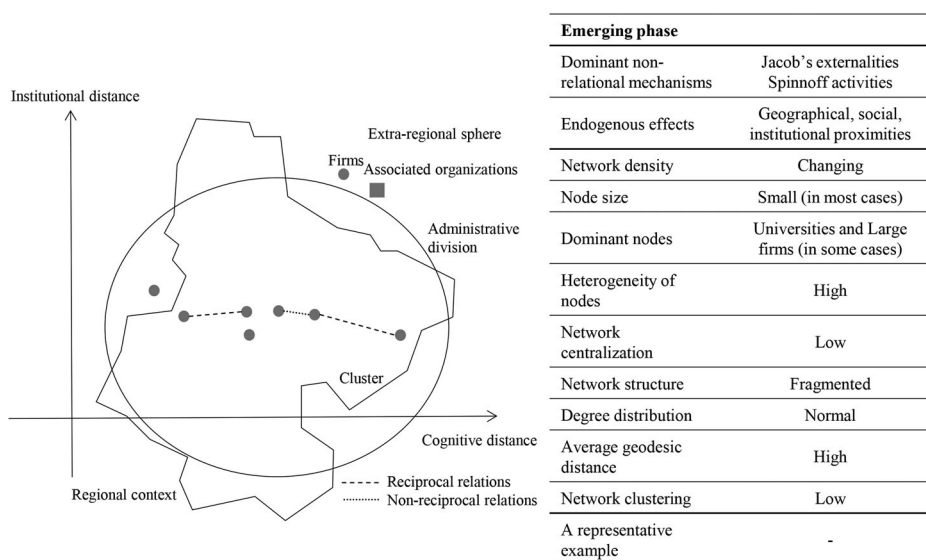


Figure 3. Stylized illustration of a cluster in the emerging phase. Source: own illustration.

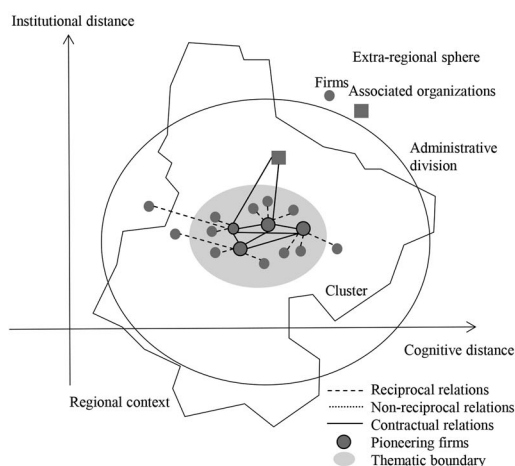
similar partners mostly based on their social contacts and random coincidences derived from geographical proximity (Lazzeretti & Capone, 2016) (Figure 3).

3.2. Growing phase

In the ‘growing phase’, one or several firms find a niche in the market. As a result, firms grow in size and the number of entries and spinoffs increases substantially. The pioneering firms set dominant standards (Ter Wal and Boschma, 2011). As the size of clusters increases, knowledge spillover eases the learning process and pioneering firms crystallize the thematic boundary of core activities (Menzel & Fornahl, 2010). Accordingly, firms adapt themselves to the new environment in order to survive and have a higher market share. This accounts for why new entrants with unrelated knowledge bases might be outperformed (Giuliani & Bell, 2005). Over time, co-location and social networks facilitate the learning process, and firms bridge the cognitive gap more easily and locate themselves closer to one another along the cognitive dimension. As the number of actors and the density of social networks increase, Marshall’s externalities emerge. Newly established associated organizations play a significant role in the codification of tacit knowledge, as well as increasing the knowledge spillovers. In addition, the growing cluster is coupled with a higher degree of customer–supplier contacts and specialization. This condition gives rise to the Porter’s externalities and, consequently, to a higher degree of dispersion of firms along the institutional dimension.

At this point, in order to overcome the problem of uncertainty, firms follow their routines in knowledge sourcing, which is mostly immanent in the emerging phase of a cluster. This implies that firms are likely to collaborate with actors with whom they share a common past. Accordingly, informal social networks play a crucial role in transferring knowledge among firms due to their common past (Agrawal, Cockburn, & McHale, 2006). Thus, transitivity closes open triads and social embeddedness gains importance over pure geographical co-location (Giuliani, Balland, & Matta, 2018; Stefano & Zaccarin, 2013; Ter Wal, 2014). At the core of technological boundaries, pioneering firms with a higher degree of centrality in a knowledge network attract more ties because they are the sources of knowledge and know-how (Giuliani & Bell, 2005). Therefore, preferential attachment is the dominant driving force in a growing cluster (Orsenigo, Pammolli, Riccaboni, Bonaccorsi, & Turchetti, 1997). In reality, however, the degree distribution does not perfectly coincide with the Barabasi–Albert model² because most firms have limited resources to establish a large number of relationships. As a result, firms at the core initiate collaborations that are beneficial to them. This excludes other potential partners from the core of the knowledge network and changes the network based on its actual structural properties. Belso-Martinez (2016) shows that well-known firms have less inclination to build a connection with recently established firms.

Local knowledge networks gradually increase in density due to two main factors. First, there is a temporal dimension to endogenous effects, which implies that these forces could substitute or complement one another (Balland, Boschma, et al., 2015; Broekel, 2015; Juhász & Lengyel, 2017). Secondly, the rich-get-richer effect derived from preferential attachment forces new entrants to occupy peripheral positions. This unfavourable position in a knowledge sourcing network increases the odds of



Growing phase	
Dominant non-relational mechanisms	Marshall's and Porter's externalities Spinnoff activities
Endogenous effects	Geographical, social, and cognitive proximities Preferential Attachment Exclusion Transitivity
Network density	Increasing
Node size	Core: large Periphery: small
Dominant nodes	Pioneering firms
Heterogeneity of nodes	Decreasing
Network centralization	Growing
Network structure	Core-periphery
Degree distribution	Right-skewed
Average geodesic distance	Decreasing
Network clustering	Increasing
A representative example	Silicon Valley in the 1990s

Figure 4. Stylized illustration of a cluster in the growing phase. Source: own illustration.

exiting a cluster. These two forces coupled with the ever-increasing growth of the underlying industry pave the way for the transition of a given cluster to the sustaining phase (Figure 4).

3.3. Sustaining phase

In the 'sustaining phase', employment growth and the rate of entries into and exits from clusters stagnate, and surviving firms inside clusters enjoy the advent of supportive institutions (Menzel & Fornahl, 2010). The strong overlap of knowledge bases among leading firms lowers the chance of radical innovation in a region due to the lack of an optimum degree of cognitive distance for knowledge transfer (Molina-Morales, Belso-Martínez, Más-Verdú, & Martínez-Cháfer, 2015; Nooteboom, 2000). In the sustaining phase, clusters comprise 'rich' institutional environments in which firms are highly embedded as a result of developing a common language, common norms and values, and intense interactions (Staber, 2010). The process of institutionalization could remove the hurdles of knowledge sourcing and play a positive role in the formation of new ties in a mature industry (Iammarino & McCann, 2006).

Since firms at the periphery of the knowledge network already left the cluster, the remaining firms at the cognitive core of the knowledge network run the risk of being trapped in a cognitive lock-in situation (Ter Wal & Boschma, 2011) in which cluster actors rarely exchange novel knowledge and innovation processes encounter difficulties. The dense network of a cluster calls for building ties with actors in the extra-regional sphere in order to tap into the sources of novelty through contractual 'pipelines' (Owen-Smith & Powell, 2004). In doing so, a number of cluster actors need to act as

technological gatekeeper and bridge the structural hole by creating a tie with the outsiders. This allows not only a specific firm but also other local firms to benefit from novel knowledge through already established local ties and the mobilization effect. In practice, however, empirical evidence shows that firms with global ties do not always pass novel knowledge on to the other local firms and function as ‘external stars’ (Giuliani et al., 2018).

Reaching out for novelty also has an impact on a local thematic boundary. Publicly funded organizations and some large firms integrate other standards and values into the thematic boundary (Menzel & Fornahl, 2010). At this point, large firms increasingly rely on R&D projects and non-local cooperative networks in order to acquire new knowledge (Powell, Koput, & Smith-Doerr, 1996). In this context, firms might even leave the agglomeration in order to increase their absorptive capacity and reposition themselves in the knowledge network, and benefit from the lower costs in cheaper areas. Wal and Anne (2014) empirically show that social embeddedness gains importance over geographical proximity over time. Conversely, Balland, de Vaan, and Boschma (2013) show that cognitive and geographical proximity gain in importance as the main channels of knowledge sourcing.³

The interplay between network endogenous effects brings about complexity. Giuliani (2011) demonstrates that geographical proximity triggers reciprocity and transitivity. Over time, these two effects account for the informal hierarchical structure within the cluster. Similarly, Belso-Martínez, Expósito-Langa, Mas-Verdú, and Molina-Morales (2017) show the relevance of several endogenous network forces together with proximity dimensions. Their findings show that transitivity, reciprocity and organizational, social and geographical proximities are relevant driving forces of tie formation in the advanced stage of the cluster. Similar to the growing phase, this phase is also featured by the functioning of several positively correlated effects including social proximity, multi-

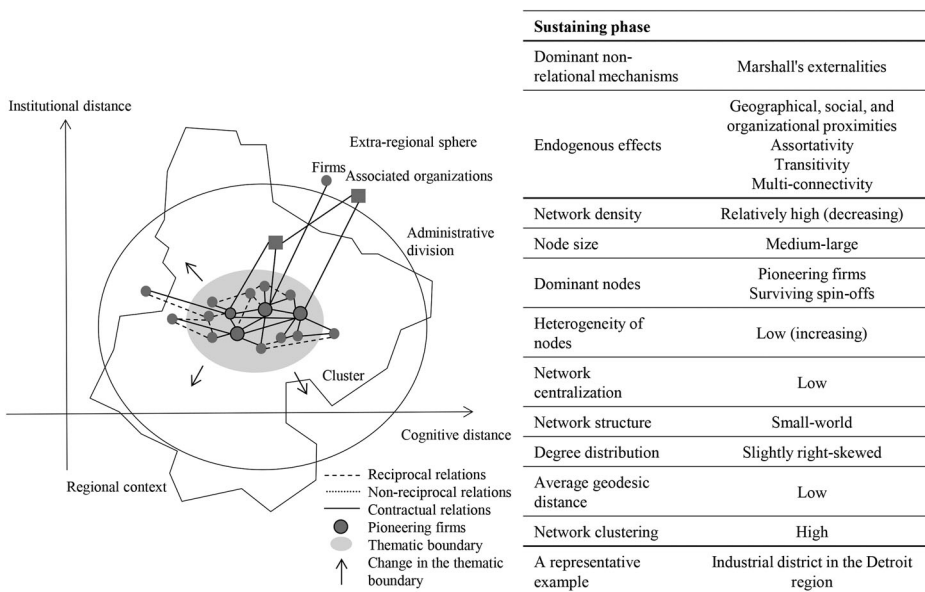


Figure 5. Stylized illustration of a cluster in the sustaining phase. Source: own illustration.

connectivity, transitivity and assortativity (Balland, Belso-Martínez, & Morrison, 2015; Giuliani, 2013; Giuliani et al., 2018; Winship, 2011; Powell et al., 2005) and the lack of optimum cognitive distance to promote beneficial knowledge sourcing (Molina-Morales et al., 2015). This structure is an influential factor for triggering the decline of clusters (Crespo, Suire, & Vicente, 2016). Only a limited number of fortunate clusters can counter-balance the complementary endogenous effects by creating knowledge ties with peripheral local actors or partners in the extra-regional sphere (Figure 5).

3.4. Declining phase

In the ‘declining phase’, firms start to exit a cluster or move to other fields of activities rather than related ones in the cluster. Also, the number of entries into a cluster follows the national rate (Trippel et al., 2014). Start-ups rarely emerge and the employment rate decreases. Moreover, a cluster is not able to grow due to exhausted endogenous technological competences (Menzel & Fornahl, 2010). Clusters encounter neither diversification nor radical exogenous change (e.g. a scientific breakthrough). Thus, firms suffer severely from their strong embeddedness and lack of novelty (Menzel & Fornahl, 2010). For instance, Grabher (1993) studied the Ruhr area and showed that there were optimal Marshall’s externalities in the coal and steel industrial district in terms of infrastructure, skilled labour force and learning processes. The Ruhr area could not, however, revitalize its growth potential due to a strong ‘functional lock-in’ which was mainly the result of specialization and the lack of diversity in the industrial district. In this phase, the dominance of a common language, norms and trust create a strong atmosphere for reciprocal learning and trade, collective actions and lobbying for government support (Iammarino & McCann, 2006). There is, however, a flip side to this because a dense embeddedness and cognitive lock-in in a cluster hampers the transmission of novel knowledge to a cluster. This fact explains the rare rate of radical innovation in old industrial districts.

In the declining phase, the local knowledge network is rather dense (Fornahl et al., 2014) and suffers from a high degree of assortativity (Crespo et al., 2016), where knowledge cannot be exchanged between actors at the core and the periphery. Also, under surviving circumstances, while the knowledge network is neither fragmented nor dysfunctional, fortunate organizations with extra-regional ties are likely to act as ‘external stars’ rather than technological gatekeepers (Giuliani et al., 2018). This leads to an even higher degree of assortativity whereby clusters are doomed to remain in a lock-in situation (Crespo et al., 2016) unless exogenous factors (e.g. policy measures) change these unfortunate structural properties (Figures 6 and 7).

4. Policy implications

The preceding sections of this paper have provided a conceptual framework to articulate how endogenous effects and clusters co-evolve. Scholars have embraced the concept of clustering and its relevance for policies (Brenner & Schlump, 2011; Hassink & Shin, 2005). The European Cluster Observatory⁴ is a prime example of this shift, whereby comprehensive cluster related data on 2000 cluster initiatives at the NUTS-2 level are collected. Using such data, Ketels (2015) and Ketels et al. (2013) argue how a better knowledge of clusters contributes the competitiveness of European regions and provides inputs for

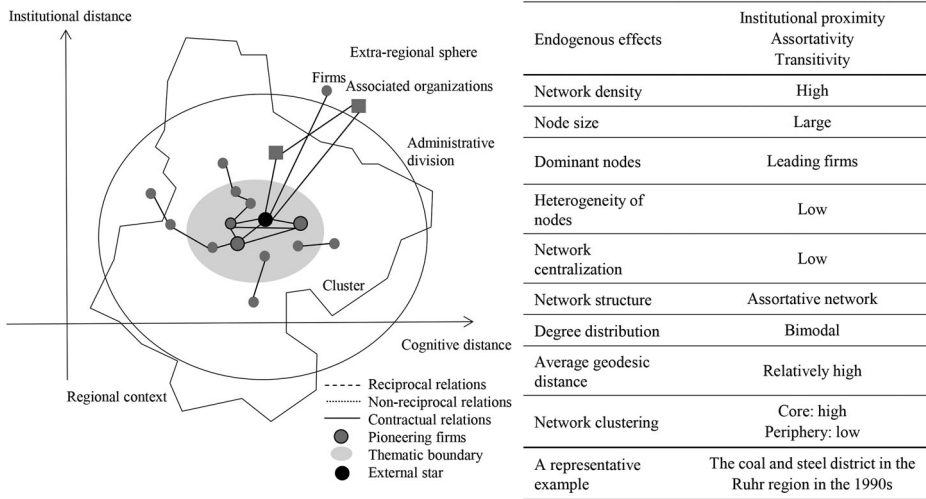


Figure 6. Stylized illustration of a cluster in the declining phase. Source: own illustration.

developing smart specialization strategies. These studies have acknowledged that policies need be designed based the development stage of a given cluster as well as regional specificities and lessons from best practices (Elola, Valdaliso, Franco, & López, 2016; Fornahl & Hassink, 2017; Ketels et al., 2013). Also, scholars emphasize the advantages of knowledge networks in generating social capital (Etxabe & Valdaliso, 2016; Li, Bathelt, & Wang, 2011; Lucena-Piquero & Vicente, 2019; Vicente, 2017). However, the dynamic interplay between

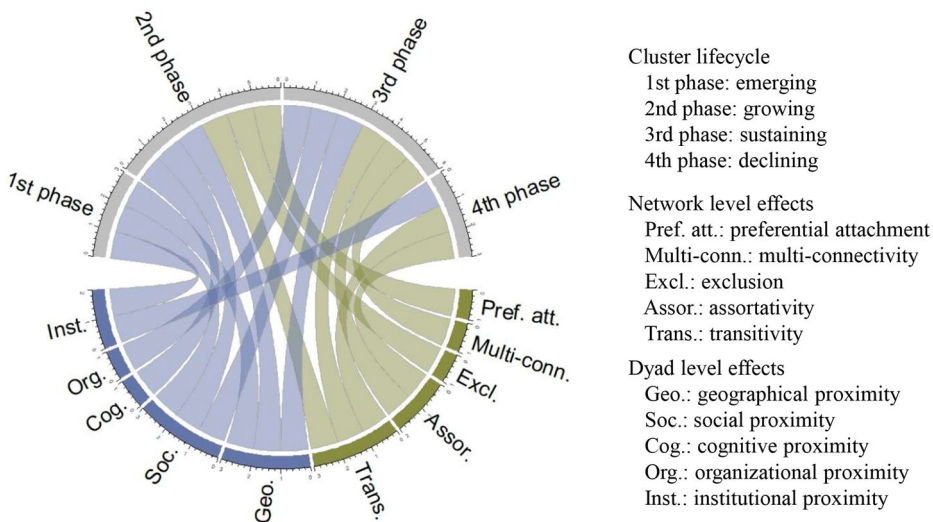


Figure 7. Overview of dominant endogenous effects along the cluster lifecycle. Source: own illustration using the circlize package in R (Gu, Gu, Eils, Schlesner, & Brors, 2014).

endogenous effects (dyad and network levels) and cluster lifecycle has not yet been broadly integrated in cluster policy. For instance, an OECD (2017, p. 1) policy brief suggests to 'boost labour productivity by fostering innovation and continuing to intensify the links between domestic firms and public research to global innovation networks and value chains ...'. However, this section discusses that the intensification of relations could be damaging in some cases and should be considered based on a given development stage and its structural properties. This section, therefore, builds on the developed framework to improve network-related cluster policies.

We take Borrás and Tsagdis (2009) argument as a point of departure. They distinguish two cluster interventionist approaches, namely 'cluster policy' and 'policies for clusters'. While the former has a narrow focus and concentrates on the role of local authorities, the latter rests on a broader focus by defining clusters as complex systems with actors embedded in various networks. In this light, a substantial reason for the failure of network-related policies might be the narrow approach of cluster policies, which focuses only on creating incentives for firms to agglomerate and increase network density, and ignores the relevance of the structural configurations of knowledge networks (Lucena-Piquero & Vicente, 2019; Vicente, 2017). To tackle this issue, current observatory programmes (e.g. the European cluster observatory) need to use relational data collection methods (Ter Wal & Boschma, 2009) to provide information on main actors in the knowledge networks of clusters and their attributes (e.g. publicly or privately funded) as well as the ones of knowledge ties. Cantner, Graf, and Rothgang (2018) argue how overlooking such specificities might lead to a simplistic cluster policy evaluation that is not capable of addressing cluster differences and their transition phases. This issue has been partly addressed in a cluster policy in Germany, called the German leading-edge cluster competition. Rothgang et al. (2017) show in their empirical study that this policy has increased firm-level R&D expenditure and engendered the establishment of a higher number of knowledge relations at the cluster level. Of course, clusters do not follow the same deterministic path over time, and exogenous and endogenous factors induce deviations from the typical cluster lifecycle model. Cluster policy can, however, use the attributes of the stylized phases as benchmarks to identify the position of a given cluster along its evolutionary path.

Apart from the importance of a cluster network observatory programme, the developed framework calls for two complementary strategies for cluster policy. Firstly, building on Cantner and Vannuccini's (2018) argument, cluster policy should distinguish between two interventionist network-related approaches: intensifying (an exploitative approach) and restructuring (an explorative approach) knowledge networks. Interventionist policies intensify knowledge networks when the knowledge network is highly fragmented or when the cluster is diversifying into an emerging or growing industry (early cluster phases). Conversely, policies have to promote the forces of restructuring the network structure when clusters reach a certain degree of maturity and 'innovation slowdown' in order to increase the degree of disassortativity and the odds of path creation, namely overcoming lock-in (late cluster phases).

Secondly, cluster policy should acknowledge and underline dominant endogenous effects in each phase of cluster evolution as the driving forces of network change. It is worth noting that, so far, the application of network theory has been ex-post by using network visualization and quantitative analysis in order to evaluate the impact of policies

(Rothgang et al., 2017; Schmiedeberg, 2010), whereas the current framework takes an ex-ante approach to trigger required changes for cluster prosperity.

In the early phases of a cluster, the mere co-location of firms and organizations does not necessarily translate into knowledge sourcing at the local level (Davis, 2011; Giuliani, 2011). Thus, the main aim of policy should centre on the identification of most connected firms and associated organizations (knowledge gatekeepers) and the intensification of the knowledge network by facilitating knowledge transfer, where local actors can easily build on their geographical proximity and social contacts for knowledge sourcing. This requires 'soft' policy measures (intermediation and coordination) that promote trust building and reciprocity (Cantner & Vannuccini, 2018) in order to strengthen the local knowledge network (Calignano, Fitjar, & Kogler, 2018). In the case of the Basque country, Etxabe and Valdaliso (2016) and Elola et al. (2016) empirically show that cluster associations trigger tie formation and strengthen regional social capital. The findings provided by Etxabe and Valdaliso (2016) suggest that main actors (e.g. large firms and research centres) may have a dual role because they act as gatekeepers of knowledge and connect fragmented cliques to one another (bridging social capital). As it will be discussed shortly, this is obviously a matter of concern to emerging (and to a lesser extent to growing) clusters because reinforcing the position of central actors in a well-established cluster may lead to a lock-in situation (Etxabe & Valdaliso, 2016). Also, it is essential that authorities seek and underline networks that associate with the relevant knowledge bases and the strengths of the local economy for 'smart specialization' (Foray, David, & Hall, 2011; Glückler, 2007).

Also, policymakers also need to attempt to support knowledge-based start-ups and promote risk taking and the entrepreneurial discovery process (Hausmann & Rodrik, 2003; Mieszkowski & Kardas, 2015) because these forces play a crucial role in the establishment of knowledge ties and ease knowledge diffusion (Audretsch & Keilbach, 2004). While beneficial cluster initiatives trigger the emergence of a cluster, these measures should be reduced as soon as the number of firm entries into a cluster increases exponentially, implying a transition to the growing phase and the formation of a cohesive knowledge network. The knowledge network in this phase is characterized by a strong core-periphery structure. Thus, the main aim of cluster policy should focus on avoiding lock-out. Firstly, cluster initiatives should include actors with peripheral positions in the knowledge network to maximize innovative performances. For instance, Lucena-Piquero and Vicente (2019) suggest that policymakers should design a selection mechanism, whereby the participation of young small and medium-sized firms in joint projects is given. Secondly, cluster policy should seek to facilitate and build on the codification of dominant knowledge bases (e.g. patents and scientific publications) in order to attract more actors to the cluster and stabilize the position of the cluster in the extra-regional sphere. For instance, in the context of European clusters, Autant-Bernard, Fadaïro, and Massard (2013) posit that advisory activities should encourage local firms to participate in European collaborative programmes.

The late phases of clusters are characterized by a strong embeddedness and cognitive lock-in. In such situations, the common practice is to build on actual social capital and establish supportive associations and direct interventionist policy. While such efforts have a positive impact on surviving cluster actors, the fruitfulness of these actions for cluster growth is not empirically supported (Elola et al., 2016; Giuliani et al., 2018).

Thus, the main aim of the cluster policy should be to restructure the intra- and inter-cluster knowledge networks in order to maximize the likelihood of novelty diffusion and new path creation (Boschma & Frenken, 2010). In doing so, cluster policies need to combine two strategies. First, the importance of structural disassortativity (core-periphery) of the knowledge network should be taken into consideration because the knowledge capital of actors with peripheral positions is not efficiently diffused in the cluster given the dominance of core players due to the high degree of assortativity in mature clusters (Vicente, 2017). Moreover, peripheral actors need such relations with dominant actors as a basis for radical innovation (Hervás-Oliver, Albors-Garrigos, Estelles-Miguel, & Boronat-Moll, 2017). Second, it is essential to promote the capability (fitness) of influential actors in order to overcome their strong embeddedness and establish new collaborative ties with cognitively distant actors (Broekel, Fornahl, & Morrison, 2015).

Policy should also create incentives for 'external stars' to act as technological gatekeepers (Giuliani et al., 2018). Rosenkopf and Padula (2008) argue that the hierarchical structure of knowledge sourcing networks can only be achieved if proximity dimensions (homophily, in their language) weaken other effects. This implies that policy should promote proximity dimensions other than geographical and social ones because these two dimensions are strongly correlated with other effects. Trippel and Otto (2009) show that Styria (Austria) managed to recover by using its research institutes as the bridging measures for bringing novel knowledge to the cluster. Contrary to Styria, this decisive component was lacking in the metal cluster in Saarland (Germany), which partly accounts for the failure to revitalize the latter cluster. In a similar vein, Owen-Smith and Powell (2004) show the importance of knowledge ties between universities and firms in the Boston biotech community. Thus, this type of relation best suits mature clusters as a means of forming a new growth path and triggering a new transition phase (Lucena-Piquero & Vicente, 2019).

Moreover, the focus should be placed on complementarity issues, namely issues whereby either actors are cognitively distant and cannot learn from one another, or the combinatorial outcome of their skills and know-how do not lead to a new path (Cantner & Vannuccini, 2018). Thus, education, public research, human capital and infrastructure investments, the promotion of universities–firms collaboration, and temporary proximity have to be the main outlines of a given renewal agenda (Brenner & Schlump, 2011; Davids & Frenken, 2017; Elola et al., 2016; Moodysson, 2008) in order to increase the absorptive capacity of local firms (Autant-Bernard et al., 2013; Cohen & Levinthal, 1990). More importantly, increasing and building on diversity plays a crucial role in the lock-in phase because dominant knowledge bases in the cluster are based on mature industries, and therefore, network endogenous effects are among the key drivers of change to overcome a lock-in situation (Santner, 2017). Taken together, this section has laid out a toolkit for grappling with the issues associated with designing interventionist network-related cluster policies (see Table 1 for an overview).

5. Conclusion

The paper has discussed that a better understanding of a dynamic interplay between endogenous forces and clusters contributes to the conceptual power of the cluster lifecycle model. This article has thus thrown light on the impact of the micro dynamics of

Table 1. Overview of relevant interventionist network-related policy approaches and measures.

	Emerging phase	Growing phase	Sustaining phase	Declining phase
Interventionist approach	Intensifying	Intensifying	Restructuring	Restructuring
Cluster policy	Identifying knowledge gatekeepers and increasing the number of actors (nodes) and the odds of tie formation <ul style="list-style-type: none"> • Science and technology parks • Supporting knowledge-based start-ups and risk-taking strategies • Promoting entrepreneurial culture and entrepreneurial discovery process • Increasing multi-connectivity • Promoting social interaction at the local level 	Minimizing exclusion (avoiding lock-out) <ul style="list-style-type: none"> • Intra-cluster joint research projects • Facilitating knowledge codification (e.g. patents) 	Increasing structural disassortativity (avoiding lock-in) <ul style="list-style-type: none"> • Non-local research projects • Disciplinary temporary proximity (e.g. technical fairs) • Increasing the fitness of the actors (nodes) • Education and human capital investment • National and international exchange programmes 	Increasing the structural hierarchy (overcoming lock-in) <ul style="list-style-type: none"> • Non-local research projects • Interdisciplinary temporary proximity (e.g. technical fairs) • Increasing the number and diversity of actors (nodes) • Supporting start-ups in unrelated knowledge bases • Attracting skilled labour force and star scientists • Promoting experimentation and technological search • Promoting entrepreneurial discovery process

knowledge networks and integrated these dynamics into the two cluster lifecycle models developed by Menzel and Fornahl (2010) and Ter Wal and Boschma (2011). By drawing on six endogenous effects (proximity dimensions, transitivity, assortativity, preferential attachment, exclusion and multi-connectivity), this article has added to our understanding of how clusters and knowledge networks co-evolve. This provides a timely framework for further empirical works by pronouncing the relevance of the structural properties in terms of knowledge sourcing.

Acknowledging the relevance of exogenous factors, the notion of endogenous effects at the dyad and structural levels plays a complementary role in order to provide a better understanding of the drivers of change in clusters. The implication of this framework for cluster policy has been discussed in the previous section. This discussion has indicated that cluster policy needs to make a distinction between strategies in the early and late phases and focus on intensifying knowledge ties in the former phases and restructuring knowledge networks in the latter ones. This calls for a change in the approach of cluster policy because traditional approaches ignore the varying needs of clusters over time in different contexts (Fornahl & Hassink, 2017, pp. 1–9) and mostly focus on increasing the density of a given knowledge network (Vicente, 2017). The proposed framework, however, suggests that development policies need to build on the dominant driving forces within a given cluster that emerge from its micro dynamics. Having mentioned the main contributions, it is worth mentioning that this framework represents an ideal model and is deterministic in nature (Martin & Sunley, 2011). Yet, the main goal of this framework is to build on the functionality of endogenous effects to define benchmarks for clusters along their evolutionary paths. Of course, policymakers need to take context and sector specificities into consideration when designing interventionist policies.

There is still much to be done. While there are several empirical studies on clusters and their evolution from a network perspective, there are still significant gaps that need to be filled:

- This framework was developed based on the assumption of reciprocity and the equal value of collaborative ties. However, this is not always the case in real world networks. This raises a number of questions concerning how the quality of ties and the degree of reciprocity interact with endogenous effects (Giuliani, 2011, p. 2013).
- The developed framework remains agnostic about the nature of knowledge that is exchanged through knowledge networks. For instance, endogenous effects might have various magnitude of effects in co-patenting compared to the ones in co-publishing (Lata, von Proff, & Brenner, 2017). This calls for empirical investigations of clusters using various data sources.
- Proximity dimensions are multiplicative in nature, meaning the joint effect of two or more dimensions may greatly exceed their individual effects. Yet, knowledge on the dynamic interplay between proximity dimensions is limited (Broekel, 2015). Future research needs to focus on such joint effects and their relevance for knowledge network and cluster evolution.
- Avoiding the ‘pitfalls of case studies’, a new line of research should be devoted to cases in developing countries. Several empirical findings demonstrate that the dominant driving forces of cluster evolution in such cases diverge from what is dominant in the literature on clusters in developed countries (Abbasiharofteh & Dyba, 2018; Gancarczyk, 2014; Giuliani et al., 2018). The same also applies to low-tech clusters, as the literature mostly focuses on high-tech prospering clusters and overlooks the diversity and dynamics of sectoral systems (Malerba & Vonortas, 2009).
- Network evolution entails processes of tie formation, tie dissolution and tie persistence. Most empirical works, as well as this conceptual practice, focus on endogenous effects as the driver of network change in clusters. Yet, much less is known about the processes behind tie dissolution and persistence in clusters (Juhász & Lengyel, 2017) and their contribution to cluster evolution. Future research should address endogenous effects and their interactions in order to provide a fully-fledged theory of cluster change. Statistically speaking, the advent of advanced analytical tools (e.g. TERGM and SIENA) enables researchers to raise such questions (for a review, see Broekel, Balland, Burger, & van Oort, 2014).
- Clusters are embedded in a larger socioeconomic context (regional and national innovation systems), including other clusters and actors. This issue has been overlooked by the cluster lifecycle argument (Trippel et al., 2014). Thus, another line of research should be devoted to understanding how endogenous effects co-evolve across clusters in a wider context by adopting a multiscalar perspective.

Notes

1. It is worth noting that assortativity could also imply the similarity of nodes in terms of their attributes, which we define under proximity dimensions in this framework.
2. The Barabasi–Albert model conjectures that the probability of tie formation is a function of the number of ties that a node has already established.

3. Such differences might be the result of sector specificity because the former study was based on science-based fields of activity with a relatively high degree of codification (biotech), whereas the latter case was based on creative fields of activity (the video game industry) with a high degree of tacitness.
4. See <http://www.clusterobservatory.eu/>.

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ORCID

Milad Abbasiharofteh  <http://orcid.org/0000-0001-9694-4193>

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Appendix

	Case study	Method	Approach	Measure	Result
Giuliani (2011)	The wine cluster in Chile	Quantitative (SAOM ^a)	Dynamic	Transitivity reciprocity	The mechanisms of transitivity and reciprocity account for the informal hierarchical structure within the cluster.
Stefano and Zaccarin (2013)	Co-authorship and co-invention in the Trieste area (multiplex approach)	Quantitative (ERGM ^b)	Static	Transitivity (triangle AAB and K-triangle ABA) and 3-Star	Transitivity plays a crucial role in tie formation, whereas preferential attachment is found to be insignificant.
Ferriani, Fonti, and Corrado (2013)	Italian multimedia cluster in Bologna	Quantitative (SAOM ^a)	Dynamic	Social interaction and economic interactions	Social interactions have a relatively stronger impact on the formation of multiplex ties.
Giuliani (2013)	A wine cluster in Chile	Quantitative (SAOM ^a)	Dynamic	Cohesion effects (reciprocity and transitivity)	Reciprocity and transitivity contribute to the core-periphery structure of cluster networks, where actors with a higher degree of fitness (accumulated resources) take central positions.
Balland, Belso-Martínez, and Morrison (2015)	The Toy Valley cluster in Spain	Quantitative (SAOM ^a)	Dynamic	Embeddedness status proximity ^c	Status is a driving force for the formation of inter-firm links in business knowledge networks, and proximity plays a decisive role in the formation of technical knowledge networks. Embeddedness has a similar impact on both networks.

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	Case study	Method	Approach	Measure	Result
James, Vissers, Larsson, and Dahlström (2015)	Automotive sector in Västra Götaland, Sweden	Qualitative	Dynamic	Network size Composition pace of change	Over time, knowledge anchoring benefits from the self-enforcing local knowledge networks and actors at the peripheral position.
Molina-Morales et al. (2015)	A foodstuffs cluster in the Valencia region, Spain	Quantitative (ERGM ^b)	Static	Transitivity Node degree (out- and in-degree) Proximity dimensions ^c	The study proves the negative impact of cognitive and institutional proximities on tie formations, whereas social and geographical proximities facilitate the formation of collaborative ties.
Crespo et al. (2016)	Clusters in the European mobile phone industry	Quantitative	Dynamic	Hierarchy assortativity	Hierarchy and assortativity account for different performances of clusters. Clusters can prevent lock-in as long as they sustain a minimum degree of disassortativity.
Lazzeretti and Capone (2016)	The cluster of high technology applied to cultural goods in Tuscany, Italy	Quantitative (SAOM ^a)	Dynamic	Proximity dimensions ^c	Social and institutional proximity are the main drivers of network change in the early stages. Geographical and cognitive proximities become the most influential factors in forming innovation network over time.
Belso-Martínez et al. (2017)	The foodstuff cluster in Valencia, Spain	Quantitative (ERGM ^c)	Static	Transitivity, reciprocity, and proximity dimensions ^c	Transitivity, reciprocity, organizational, social and geographical proximity are relevant driving forces of network formation at the advanced stage of the cluster.
Menzel, Feldman, and Broekel (2017)	The Research Triangle region of North Carolina, USA	Quantitative (SAOM ^a)	Dynamic	Transitivity, preferential attachment, and assortative mixing	No fundamental change was observed during and after dot-com bubble in terms of explorative or exploitative tie formations.
Juhász and Lengyel (2017)	The printing and paper product cluster in Kecskemét, Hungary.	Quantitative (SAOM ^a)	Dynamic	Geographical proximity, cognitive proximity, transitivity, reciprocity, and cyclicity.	Transitivity, geographical proximity, and cognitive proximity joined with having a common third contribute to tie formation whereas cognitive proximity is essential for tie preservation.

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	Case study	Method	Approach	Measure	Result
Capone and Lazzeretti (2018)	The cluster of high technology applied to cultural goods in Tuscany, Italy	Quantitative (ERGM ^b)	Static	Proximity dimensions ^c	The findings show that proximity dimensions have various impacts on different modes of ties. Also, social ties have a strong impact on innovative performances.
Giuliani et al. (2018)	The Cordoba cluster in Argentina	Quantitative (SAOM ^a)	Dynamic	Social drivers (e.g. transitivity), institutional drivers (e.g. cluster policy), agentic drivers (e.g. gatekeeper/external star)	The underperforming cluster shows a local core-periphery (not fragmented) structure, implying that the cluster has a functioning network where dominant actors turn to external stars instead of diffusing knowledge at the local level.
Tanner (2018)	Danish wind power clusters	Qualitative (innovation biography approach)	Dynamic	Geographical proximity	Geographical proximity is essential for exchange knowledge and idea. Yet, its configuration changes over time.

^aStochastic actor-oriented models.^bExponential random graph models.^cProximity dimensions: cognitive proximity, institutional proximity, social proximity, geographical proximity and organizational proximity.