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Creation and persistence of ties in cluster knowledge networks

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Abstract

Knowledge networks are important to understand learning in industry clusters but surprisingly little is known about what drives the formation, persistence and dissolution of ties. Applying stochastic actor-oriented models on longitudinal relational data from a mature cluster in a medium-tech industry, we show that triadic closure and geographical proximity increase the probability of tie creation but does not influence tie persistence. Cognitive proximity is positively correlated to tie persistence but firms create ties to cognitively proximate firms only if they are loosely connected through common third partners. We propose a micro perspective to understand how endogenous network effects, cognitive proximity of actors and their interplay influence the evolutionary process of network formation in clusters.

JEL: D85, L14, R11, O31

Keywords: knowledge networks, cluster evolution, network dynamics, stochastic actor-oriented models

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Kapcsolatok kialakulása és fennmaradása klaszterek tudáshálózatában

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Összefoglaló

Az iparági klaszterek mögötti kooperatív tanulás megértéséhez fontos a tudáshálózatok vizsgálata, azonban meglepően keveset tudunk arról, hogy ezen hálózatokban hogyan jönnek létre, maradnak fenn vagy szűnnek meg kapcsolatok. Egy érett feldolgozóipari klaszter idősoros kapcsolati adatai és sztochasztikus aktororientált modellek segítségével bemutatjuk, hogy a triadikus bezáródás és a földrajzi közelség növelik a kapcsolatok létrejöttének esélyeit, de nem befolyásolják azok fennmaradását. A kognitív közelség pozitívan hat a kapcsolatok fennmaradására, de a cégek csak akkor alakítanak ki kapcsolatot technológiai profil tekintetében hasonló vállalkozásokkal, ha nincsenek közös partnereik. Tanulmányunkban a klaszter tudáshálózatok evolúciójának megértéséhez egy olyan micro perspektívát javaslunk, amelyben a kapcsolatok szelekciójának alapját a felmerülő költségek és bizonytalanságok, valamint a nem redundáns vagy az új tudás keresése adják. Az endogén hálózati hatások, a kognitív közelség és ezek interakciójának befolyását vizsgálva jobban megérthetjük a klaszterek mögötti tudáshálózatok formálódásának evolúciós mechanizmusait.

JEL: D85, L14, R11, O31

Tárgyszavak: tudáshálózat, klaszterevolúció, hálózati dinamika, sztochasztikus aktororientált modell

INTRODUCTION

The idea that knowledge is not in the air available for everyone in industry specializations as opposed to what Marshall (1920) suggested has brought social networks into the forefront of cluster research (Breschi and Lissoni, 2009, Cantner and Graf, 2006, Cooke, 2002, Dahl and Pedersen, 2003, Fornahl and Brenner, 2003, Giuliani and Bell, 2005, Gordon and McCann, 2000, Ethridge et al., 2016, Sorensen, 2003). Despite distant ties might provide the region with new knowledge, most of the learning processes occur within certain spatial proximity (Bathelt et al., 2004, Glückler, 2007). Social ties are important for local knowledge flows because personal acquaintance reduces transaction costs between co-located actors and enhances the efficiency of mutual learning (Borgatti et al., 2009, Maskell and Malmberg, 1999). Knowledge networks that link "[...] firms through the transfer of innovation-related knowledge, aimed at the solution of complex technical problems." (Giuliani, 2010, p. 265) have been found very useful empirical tools in providing novel understanding of learning in clusters (Boschma and Ter Wal, 2007, Giuliani, 2007, 2010, Giuliani and Bell, 2005, Morrison and Rabellotti, 2009).

Scholars argue that the evolution of knowledge networks is closely related to the evolution of the cluster itself and therefore we can get new insights into cluster development by analyzing the dynamics of the underlying knowledge networks (Boschma and Fornahl, 2011, Glückler, 2007, Iammarino and McCann, 2006, Menzel and Fornahl, 2010, Martin and Sunley, 2011, Staber, 2011, Li et al., 2012, Ter Wal and Boschma, 2011). Path-dependent trajectories are claimed to characterize knowledge network change in clusters because tie selection, being an evolutionary process, is strongly influenced by the previous structure of the network, which is termed network retention (Glückler, 2007). Technological or cognitive proximity in clusters is thought to further contribute to the establishment of ties and drive the network towards lock-in (Boschma and Frenken, 2010, Ter Wal and Boschma, 2011). Empirical evidence supports these theories by illustrating that endogenous network effects – such as triadic closure, reciprocity and status – influence tie selection and drives cohesive formulation of cluster knowledge networks (Giuliani, 2013) and that technological proximity further increases the probability of ties (Balland et al., 2016).

Notwithstanding the tendency towards cohesive formulation of social and collaboration networks (Powell et al., 2005), Glückler (2007) also emphasizes that variation of local networks is another major evolutionary process that characterizes path destructive development of regions. He claims that novelty not only arrives from extra-regional ties but can be generated by bridging and brokering loosely connected parts of the local network (Burt, 2004, Granovetter, 1973, Rosenkopf and Padula, 2008). However, it is still not clear how forces of retention and variation jointly drive the dynamics of cluster knowledge networks.

In this paper, we aim to enter the above discussion by making two points. First, we claim that tie creation and tie persistence in cluster knowledge networks have to be analyzed separately in order to get a better understanding of the evolutionary process of network change. The distinction is important because the micro-motivations of creating and maintaining ties might involve different costs and constraints (Jackson, 2008), different level of variety and in-depth learning (Rivera et al., 2010), as well as uncertainty (Dahlander and McFarland, 2013). In the next chapter, we argue that the firm commits itself easier to an existing tie with high opportunity costs if the knowledge of the source firm is highly applicable (Cohen and Levinthal, 1990). On the contrary, the firm is more likely to establish a new tie when the search costs and additional uncertainties of the new contact are relatively low (Dahlander and McFarland, 2013). In our second contribution, we posit that the interplay of endogenous network formation and cognitive proximity is necessary to investigate because similar alters usually form cohesive groups in networks (McPherson et al., 2001) and in turn, endogenous network effects can further increase the role of similarity in new tie creation (Kossinets and Watts, 2009, Wimmer and Lewis, 2010). Therefore, the joint effect of proximity and endogenous network effects are important to disentangle their separate role in knowledge network dynamics (Balland et al., 2015, Broekel, 2015).

To certify our arguments, we decompose the hypotheses taken from the previous literature (Balland et al., 2016, Giuliani, 2013) into propositions; and analyze the effect of triadic closure, geographical and cognitive proximities, and also the joint effect of triadic closure and cognitive proximity on tie creation and tie persistence, respectively. Our empirical network data was collected by face-to-face interviews in the printing and paper product cluster in a Hungarian town in years 2012 and 2015. This network fits well to our aims because the cluster is in the mature phase and has a long history in the region; there is a variety of cognitive proximity across firms; and the majority of the local companies apply some kind of specialized technology to create unique paper products.

Applying stochastic actor-oriented models, we find that triadic closure and geographical proximity increase the probability of tie creation but does not influence tie persistence. These findings suggest that proximity in the network and in space lower the costs and uncertainties of the firm when it searches for new connections. Further, cognitive proximity is positively correlated to the probability of tie persistence but firms create ties to cognitively proximate firms only if they do not share partners. This result implies that firms repeat contact and strengthen ties to those partners that have similar technological profile and thus can offer highly applicable knowledge. Further, the last finding also anticipates that variation might counter-act cohesion in cluster knowledge networks.

LITERATURE AND FRAMEWORK

KNOWLEDGE NETWORKS AND CLUSTER EVOLUTION

Social networks that span across company borders facilitate knowledge flows between firms and therefore have become a cornerstone for understanding why firms in clusters outperform firms outside clusters (Giuliani and Bell, 2005, Gordon and McCann, 2000, Sorensen, 2003). Geographical proximity is crucial for such binds between firms because it creates opportunities for face-to-face and frequent interactions, and by increasing the socializing potential facilitates trust-based social relationships (Storper and Venables, 2004). Such processes lead to the emergence of coherent local collectives, shared rules and norms, and consequently, to more effective local learning, while new impulses can be primarily accessed through extra-regional links (Amin, 2000, Asheim, 1996, Bathelt et al., 2004, Malmberg, 1997). Empirical findings support this view by showing that central firms in the knowledge network are more innovative than firms in the periphery (Boschma and Ter Wal, 2007), by illustrating that the extent of extra-regional links are associated with better performance (Fitjar and Rodriguez-Pose, 2011, Morrison and Rabellotti, 2009), and by showing that the density of individual ties between co-located firms fosters productivity growth in the region (Lengyel and Eriksson, 2016).

However, scholars also warn us that too coherent ecosystems and social environments makes renewal difficult (Uzzi, 1997) and can govern regions into locked-in development paths (Grabher, 1993). This is at least partly because social tie formation in clusters itself is path-dependent and depends on the structure of the network itself (Glückler, 2007). Two of the well-documented phenomena of network evolution apply to cluster networks as well: central firms are likely to become more central (Barabasi and Albert, 1999) and alters tend to requite ties or close triangles in the network (Granovetter 1985, Watts and Strogatz, 1998). Another source of path-dependency is driven by similarity-effect between co-located agents. Because similarity increases the likelihood of tie formation, which is often referred to as homophily in social sciences (McPherson et al., 2001), the high level of cognitive and technological proximity between cluster firms breed cohesive tie formation and lock-in (Boschma and Frenken, 2010, Cantner and Graf, 2006).

To explain the changes in the knowledge network over time, Ter Wal and Boschma (2011) propose a macro perspective. They argue that a stable centre-periphery structure emerges over the growth stage of the cluster life cycle and the network becomes dense and cohesive only in the mature phase. An alternative micro perspective was suggested by Glückler (2007) who claimed that partner selection prevail at the firm level and therefore the micro-foundations of tie creation are fundamental for understanding the evolutionary mechanisms of network change. He further argues that besides the retention mechanisms that cause pathdependence in local networks, network variation can destruct these paths by either accessing extra-regional knowledge (Bathelt et al., 2004) or by linking previously unconnected parts of the local network (Glückler, 2007, McDermott et al., 2009).

Due to recent methodological developments, ideas connected to the micro-perspective of social network evolution in clusters became empirically testable (Snijders et al. 2010); however, only very few papers do such analyses. Giuliani (2013) pioneers this field and establishes a framework in which the macro outcomes of social network change are explained by its' micro-foundations. She points out that retention-driven endogenous network effects, such as cohesion and status, together with exogenous effects, such as firm level capability, establish a stable hierarchy in the cluster knowledge network in a way that firms with low absorptive capabilities hold back endogenous network effects from driving the network into absolute cohesion. Balland et al. (2016) contributes by comparing the endogenous network effects and exogenous proximity effects across business networks and technological advice networks and find that proximity effects only prevail in technological networks but network effects drive the dynamics of both technological and business networks.

In the next two sub-sections, we provide a new micro approach for cluster knowledge network evolution. Like previous studies, our framework contains selection and retention; however, we stretch the argument further by including variation as well (Glückler, 2007). In doing this, we separate tie persistence and tie creation and expose that endogenous network effects and proximity effects are not independent from each other. We posit propositions instead of hypotheses, which is a way to stress that the framework remains empirical and the generality of the results requires further investigations (Uzzi, 1997).

TIE CREATION AND TIE PERSISTENCE

To find solution for a technical problem, the firm can either maintain ties by asking advice from existing contacts or can search for and create new ties. Both maintaining ties and searching for new partners demands direct costs – these might include time demand, need for financial resources, cognitive effort, or social constraint –, and the opportunity costs of allocating resources to the specific tie instead of other ties (Glückler, 2007, Hansen, 1999). Asking advice from existing contacts needs shared time and commitment and strengthening the connection thus is thought to involve large opportunity costs (Coleman, 1988, Uzzi, 1997); while asking a new partner demands some but arguably less effort (Burt, 2004, Granovetter, 1973).

There are further qualitative differences between creating a new tie or maintaining an existing one, for which one can apply the exploration versus exploitation dichotomy (Beckman et al. 2004, Levinthal and March, 1993, March 1991, Verspagen and Duysters

2004). On the one hand, exploring a new knowledge source offers opportunities for firms in clusters to find new variety of knowledge (Hansen, 1999, Reagans and McEvily, 2003) but involves uncertainties as well because no prior experience exists about the new partner (Dahlander and McFarland, 2013, Lavie and Rosenkopf, 2006). On the other hand, maintaining and thus strengthening the connection can ease the transfer of complex or tacit knowledge (Aral, 2016, Reagans and McEvily, 2003) and uncertainties are less profound when exploiting the link to an existing partner (Greve et al., 2010, Hanaki et al., 2007). Inter-organizational ties dissolve if the firm finds alternative ties that offer better and still affordable solutions and persist only if the tie represents a valuable connection (Seabright et al., 1992).

It follows from this literature that the firm will select to maintain those existing ties with higher probability that provide access to relatively high value-cost ratio, perhaps because these ties provide more relevant and more applicable knowledge than other existing ties. On the contrary, the firm is more likely to establish a tie when the search costs and additional uncertainties of the new contact are low compared to other possible new contacts. The framework of recent paper is in line with this logic. We argue in the following that endogenous network effects, geographical and cognitive proximities drive network dynamics by influencing the relative costs and uncertainties of creating or maintaining ties and the relative value of knowledge access.

Endogenous network effects – such as cohesion – decrease costs of new tie creation because a shared contact might help to establish the new connection and can also diminish uncertainties by providing information about potential partners (Granovetter, 1986). However, cohesion also increases the likelihood that new connections will give access to redundant knowledge (Hansen, 1999) and therefore too much cohesion harms variation in the network and, after a certain threshold, the performance of firms and the network itself (Aral and van Alstyne, 2011, Uzzi, 1997, Uzzi and Spiro, 2005). On the contrary, it is not clear how cohesion influences the costs of tie persistence. Strong and cohesive ties increase the willingness of the knowledge source to share complex knowledge and therefore decrease the relative costs of repeated communication (Reagans and McEvily, 2003) but cohesive ties also demand more time and commitment (Granovetter, 1973) and thus their maintenance can also extensively increase the opportunity costs of the tie (Glückler, 2007).

We opt for triadic closure as a measure of network cohesion and test how it influences tie creation and tie persistence. Previous results are mixed; Giuliani (2013) found that triadic closure had a positive effect on the probability of tie presence in cluster knowledge networks; while Shipilov et al. (2006) found that triadic closure only influences tie creation positively and has no significant effect on tie persistence. Staber (2011) also finds those ties are less durable that are brokered through a third party. We therefore, propose positive correlation for both mechanisms and test these effects empirically before we further discuss the role of cohesion in cluster knowledge networks.

Proposition 1A: Triadic closure is positively correlated to the probability of tie creation.
Proposition 1B: Triadic closure is positively correlated to the probability of tie persistence.

If Proposition 1A is supported, we can argue that cohesion reduces costs and uncertainties of searching for new partners; whereas support for Proposition 1B would mean that network cohesion facilitates complex knowledge sharing.

Geographical proximity is thought to increase the opportunity to meet and formulate new relationships (Borgatti et al., 2009, Marmaros and Sacerdote, 2006, Rivera et al., 2010, Storper and Venables, 2004) and also to maintain contacts (Lambiotte et al., 2008, Lengyel et al., 2015) primarily through decreasing travel and transportation costs. However, geographical proximity also offers potentials to form weak ties (Wellman, 1996) and scholars argue that other types of proximities are more important to establish strong connections when geographical proximity is given (Boschma, 2005, McPherson et al., 2001). The physical closeness of actors decreases the costs of setting up a new relationship, but it also moderates the costs of repeating interactions. Therefore, we propose positive correlation for both tie creation and tie persistence before we discuss the role of geographical proximity in the evolution of cluster knowledge networks.

Proposition 2A: Geographical proximity is positively correlated to the probability of tie creation.
Proposition 2B: Geographical proximity is positively correlated to the probability of tie persistence.

If Proposition 2A is supported, we can argue that geographical proximity facilitates tie formation by decreasing costs of face-to-face interaction; whereas evidence for Proposition 2B would support the idea that geographical proximity facilitates repetition and therefore eases the persistence of ties.

Cognitive proximity influences the dynamics of cluster knowledge networks (Balland et al., 2016, Boschma and Frenken, 2010) and evidence shows that similarity in knowledge increases the probability of interaction in groups (Carley, 1991, Galaskiewicz and Shatin, 1981). However, it is still not entirely clear how cognitive proximity influences tie creation and tie persistence separately. One might expect that cognitive proximity facilitates tie creation because it decreases the level of uncertainty related to new partners and thus the firm can expect accurate and useful advice from those partners that can understand the technical problem the firm faces (Cohen and Levinthal, 1990, Lane and Lubatkin, 1998, Nelson and Winter, 1982). However, the probability of finding redundant knowledge rises with cognitive proximity because there is an overlap in the knowledge bases of firms (Boschma, 2005). Furthermore, similarity of knowledge bases can lower the rising costs of repeated knowledge transfer and thus it is easier to maintain a tie (Reagans and McEvily, 2003). Nevertheless, the role of cognitive proximity in tie creation and tie persistence needs further understanding and we propose a positive relation for both dynamics and will discuss the influence of cognitive proximity on knowledge network dynamics with the empirical results at hand.

Proposition 3A: Cognitive proximity is positively correlated to the probability of tie creation.
Proposition 3B: Cognitive proximity is positively correlated to the probability of tie persistence.

In case Proposition 3A gets empirical support, we can argue that new ties involve less uncertainty between cognitively proximate partners therefore cognitive proximity is important to establish relationships in clusters. Evidence for Proposition 3B would underlie that strong ties are more likely between firms with similar technological profiles because the ease of knowledge transfer and the high value of knowledge compensate for high opportunity costs.

INTERPLAY BETWEEN NETWORK EFFECTS AND COGNITIVE PROXIMITY

Endogenous network effects and proximity effects are not independent from each other in network evolution because link formation induced by similarity usually establishes cohesive groups of similar individuals, which is commonly referred to as homophily in the sociology literature (McPherson et al., 2001). In turn, studies that focus on the origins of homophily claim that the high levels of homophily observed in social networks are to a large extent due to structural properties of the network, such as triadic closure and reciprocity, which further induce connections between similar individuals (Kossinets and Watts, 2009, Wimmer and Lewis, 2010). This issue tells us that it is difficult to disentangle cohesion effects and effects of technological or cognitive proximities in knowledge network evolution. Admitting that recent paper cannot solve the problem, we aim to make a step towards understanding whether endogenous network effects and cognitive proximity strengthen or weaken each other in driving the dynamics of cluster knowledge networks.

It is difficult to overstate the importance of this effort for economic geography. Because proximity in too many dimensions of knowledge relations harm renewal capacities of regions (Grabher, 1993), "[…] solution to such regional lock-in phenomena clearly lies in trying to re-organize the network relations such that interactions can take place between actors that are less proximate […]" (Boschma and Frenken, 2010, p. 130-131). However, it is still unclear how network variation happens while network retention is clearly in action (Glückler, 2007). We argue that the joint effect of endogenous network effects and cognitive proximity on network dynamics can provide us novel insights into this question. This problem has not been studied in economic geography before and there are hardly any empirical papers to base our expectations upon. An exception is Rosenkopf and Padula (2008) who find that similarity – in their case structural homophily that captures similarity in status instead of knowledge base – predicts tie formation between loosely connected parts of networks, but does not predict tie formation in cohesive sub-networks. Their results imply that network variation is only possible if network endogeneity and homophily weaken each others' effect.

One can look at the joint effect of dyadic network variables by using their interaction (Powell et al. 2005); in this paper, we opt for the interaction between triadic closure and cognitive proximity. We borrow the argument of Rosenkopf and Padula (2008) to formulate our expectation and posit that ties are less likely to form and persist between cognitively proximate potential partners in the cluster if they also share contacts. However, Huber (2012) does not find such clear negative relation between social proximity and cognitive proximity when looking at the importance of knowledge ties in the Cambridge IT cluster; whereas cognitive proximity and social proximity have not been found to co-evolve in the German R&D collaboration network either (Broekel, 2015). Therefore, we choose to keep the empirical nature of our expectation and discuss potential implications for cluster evolution with the research results at hand.

Proposition 4A: The interaction of triadic closure and cognitive proximity is negatively correlated to the probability of tie creation.
Proposition 4B: The interaction of triadic closure and cognitive proximity is negatively correlated to the probability of tie persistence.

In case Propositions 4A and 4B are verified, we could argue that sharing partners simplifies the creation and maintenance of connections to cognitively distant peers by reducing the uncertainty whether it is worth to establish the new knowledge access or not and by reducing the costs of repeated knowledge transfer. Alternatively, such findings could also suggest that the firm is more likely to reach out and keep relation to those partners with similar and easy to apply knowledge if they do not share partners because the likelihood of finding novelty is higher (Boschma, 2005, Granovetter, 1973, Hansen, 1999). In sum, verification of these propositions would provide new evidence that network endogeneity and network variation are simultaneously present in cluster evolution and are driven by the interplay between cohesion and cognitive proximity.

THE STUDY SETTING

PRINTING AND PAPER PRODUCT INDUSTRY IN KECSKEMÉT

Printing and paper product industry has a long tradition in the region of Kecskemét1. The town is about 80 km south from Budapest, the capital of Hungary, and accounts for around 115.000 inhabitants with an economy rooted in agriculture as well as processing and manufacturing industries (heavy machinery and car manufacturing). The first printing-house called Petőfi Press was established in the 1840s and it still works under this name. Since the 1990s, after the planned economy collapsed in Hungary, numerous small and medium enterprises (SMEs) were born and created a strong local base for the industry. International companies have also located their facilities in the town (e.g. Axel-Springer). By now, the location quotient calculated from the number of employees shows significant relative concentration of both the manufacture of articles of paper and paperboard (LQ=4.602) and the printing and service activities related to printing (LQ=1.059).

The relatively high concentration and simultaneous presence of small and big firms resulted in intensive local competition, which requires flexible specialization of SMEs and the local industry as such. Almost all of the present companies apply some kind of specialized technology to create unique paper products (e.g. specifically printed, folded, unique paper products, packaging materials, stickers and labels). Firms typically deal with customized traditional goods or services, do not carry out R&D activities, the cluster is built around mature technological knowledge and smaller, customer-driven process oriented innovations are typical in order to satisfy the customers' unique needs. In sum, the local industry can be characterized as an old social network based cluster (Iammarino and McCann, 2006) and it provides appropriate conditions for analyzing the dynamics of the knowledge network. Firstly, as we discovered along the first round of interviews in 2012, there is a strong local network behind the clusters which is characterized by informal networking processes and based on the interactions of technicians to search for advice on technical problems that cannot be solved in house. For example, they may want advice on how to set a new type of printing machine or ask for experience with a special type of packaging carton. Secondly, the cluster is in a mature life-cycle stage as the number of firms are relatively stable and there are no external effects that might influence networking processes and we should control for.

DATA COLLECTION AND MANAGEMENT

For the selection of the particular firms we used The Company Code Register (2011) by the Hungarian Central Statistical Office, which is a nation wide firm level dataset with seat

[1] For a visual presentation of the location of Kecskemét in Hungary and the location of firms around the town see Section I in the Online Supplementary Information file.

addresses, classification of economic activities and basic firm statistics. We chose all firms that had at least 2 employees, had the company seat in the urban agglomeration of Kecskemét and were classified under the industry code 17 (Manufacture of paper and paper products) or 18 (Printing and reproduction of printed media) in the Statistical Classification of Economic Activities of Eurostat (2008). Based on 2012 data, 38 firms suited the above conditions and we merged those firms that had identical addresses and similar names, which resulted in a final number of 35 firms.

We collected data by face-to-face structured interviews with skilled workers (mostly with co-founders, operational managers or foremen). The relational data was collected through the so called “roster recall” method (Wasserman and Faust, 1994); each firm was asked to report relations to any other cluster firms presented to them in a complete list (roster). The question formulated to collect knowledge network data was exactly the same as used in several studies before (Giuliani and Bell, 2005, Morrison and Rabellotti, 2009). This question is related to the transfer of innovation-related knowledge and only reveals the inter-firm linkages that are internal to the cluster and specifically address problem solving and technical assistance (Giuliani and Bell, 2005). This is meant to capture not only the bare transfer of information, but the transfer of contextualized complex knowledge instead. In our setting, revealed relationships are trust-based, informal connections that are vulnerable to the loss of confidence. We collected additional year-specific firm-level information about main activities, number of employees, type of ownership and external knowledge linkages of firms. We also used an open question to explore other important actors for knowledge sharing not mentioned in the roster.

We managed to get answers from 26 different companies in year 2012 and repeated the interviews in 2015 with the same firms. Compared to previous studies on cluster knowledge network evolution (Giuliani, 2013, Balland et al., 2016) we take a mid-time interval of three years to indicate significant changes in network relations. Burt (2000) suggests that non-repeated contacts vanish after three years. Although two companies were closed down during the years, other two were mentioned by the respondents in the open questions at the end of the roster. Thus, we collected 26 responses in year 2015 too and reached more than 70% of the local firms in the industry at both time points. The data gathering could be judged as a success as only one firm refused to answer our questions in 2012. Most of the non-responding actors were shut down or temporarily stopped their business activities and all of them were domestic small and medium-sized enterprises (SMEs).

The questions related to firms’ knowledge transfers have been used to construct two directed adjacency matrices with n x n cells (where n stands for the number of respondents) for the two time points, in which each cell reports on the existence of knowledge being transferred from firm i in the row to firm j in the column. The cell (i, j) contains the value of 1 if firm i has transferred knowledge to firm j and contains the value of 0 when no transfer of knowledge has been reported between firm i and j.

DESCRIPTIVE ANALYSIS

The main characteristics of the examined firms did not change from 2012 to 2015[2]. Most of them are SMEs, there is only one firm with more than 100 employees and only a minority of them is foreign-owned (less than 20%). Two companies were closed down along the studied period, but two other companies joined to the sample by 2015. As we can clearly see in Table 1, the knowledge network became sparser over time. From the 223 knowledge ties apparent in 2012 only 110 linkages persisted. Interestingly, no firms became isolated by 2015. On average, actors asked for technical advice from 8 firms in 2012 and only from 6 firms in 2015. We used the Jaccard index to measure the stability of the network, which is higher than 0,3 and within appropriate limits for the analysis of network evolution (Ripley et al., 2015). The visual representation of the knowledge networks (Figure 1) suggests that the degree distribution is not proportional. In both cases the network is hierarchical and some actors have remarkably more connections than others. This is in line with previous studies that have shown the uneven and hierarchical nature of knowledge exchange in clusters (Giuliani, 2007).

Table 1

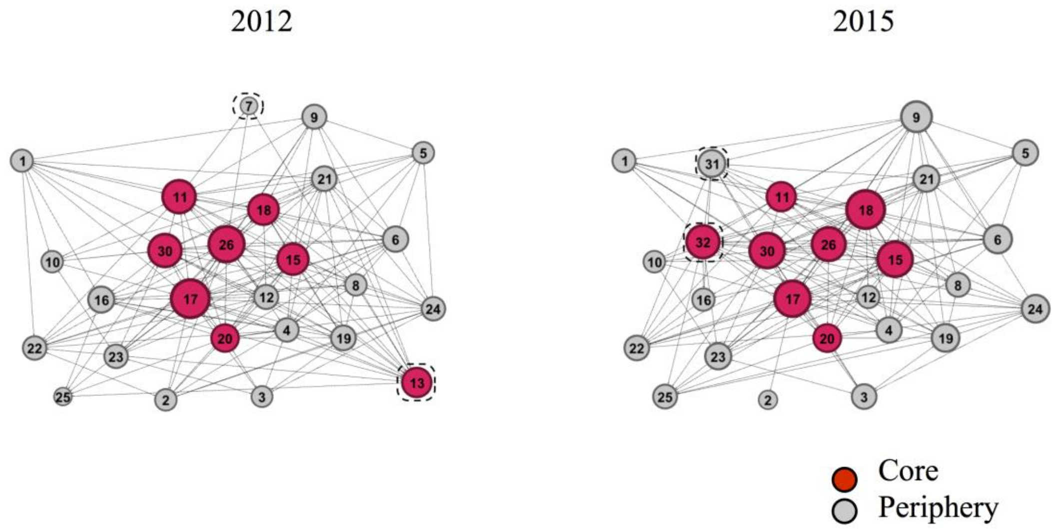
Descriptive statistics of the knowledge network in 2012 and 2015

	2012	2015
Nodes	26	26
Ties	223	181
Density	0,295	0,239
Average degree	7,964	6,464
Ties created	-	71
Ties persisted	-	110
Ties dissolved	-	113
Isolates	0	0
Jaccard index	-	0,374

[2] Detailed descriptive statistics of the sample firms are provided in Section II of the Online Supplementary Information file.

Figure 1

The local knowledge network of the printing and paper product industry in Kecskemét in 2012 and 2015



The high number of tie dissolution and the unstable nature of the core-periphery structure suggest that neither the network nor the cluster is in a growing stage (Ter Wal and Boschma, 2011)3. In line with that, the personal interviews in 2015 confirmed that the local competition had intensified. Some of the central firms in the 2012 knowledge network revealed that they do not share or dare to contact other firms for technical advice because they fear their market share, reputation, and know-how. These descriptive findings imply that the cluster under study is in the phase of its' life-cycle when increasing competition could cause secrecy in clusters as firms keep their technical solutions for themselves and tend to share less knowledge (Menzel and Fornhal, 2010) and not in the phase when competition stimulates firms to innovate as idealized by Porter (1990).

METHODOLOGY AND VARIABLES

Similarly to previous papers on knowledge network evolution (Balland, 2012, Giuliani, 2013, Balland et al., 2013, Ter Wal, 2014, Balland et al., 2016), we apply stochastic actor-oriented models (SAOMs). These models can take account of three classes of effects that influence the evolution of networks (Ripley et al., 2015, Snijders et al., 2010). Firstly, endogenous or structural effects that come from the network structure itself (e.g. degree-related effects, triadic closure, reciprocity). Secondly, dyadic covariate effects e.g. similarity or proximity (commonly referred to as homophily or assortativity) between pair of actors. Thirdly, individual characteristics of actors are also taken into account because the ego-effect expresses the tendency of a given characteristic to influence the network position of the node.

3 As shown in detail in Section III of the Online Supplementary Information file, we find that both the composition and the density of linkages changed in the core of the cluster knowledge network.

Further, SAOM estimations rely on three basic principles (Snijders et al., 2010). First, the evolution of the network structure is modeled as the realization of a Markov process, where the current state of the network determines its further change probabilistically. Second, the underlying time parameter t is continuous, which means that the observed change is the result of an unobserved series of micro steps and actors can only change one tie variable at each step. Third, the model is 'actor-oriented' as actors control and change their outgoing ties on the basis of their positions and their preferences.

In SAOMs, actors drive the change of the network because at stochastically determined moments they change their linkages with other actors by deciding to create, maintain or dissolve ties. Formally, a rate function is used to determine the opportunities of relational change, which is based on a Poisson process with rate λi for each actor i. As actor i has the opportunity to change a linkage, its choice is to change one of the tie variables xij, which will lead to a new state as x,x ∊ C(x0). Choice probabilities (direction of changes) are modeled by a multinomial logistic regression, specified by an objective function fi (Snijders et al., 2010):

$$P\{X(t) \text{ change to } x \mid i \text{ has a change opportunity at time } t, X(t) - x^0\}$$

$$= p_i\left(x^0, x, v, w\right) = \frac{\exp\left(f_i\left(x^0, x, v, w\right)\right)}{\sum_{x' \in C\left(x^0\right)} \exp\left(f_i\left(x^0, x', v, w\right)\right)}$$

When actors have the opportunity to change their relations, they choose their partners by maximizing their objective function fi (Broekel et al., 2014, Balland et al., 2013). This objective function describes preferences and constraints of actors. Choices of collaboration are determined by a linear combination of effects, depending on the current state (x0), the potential new state (x), individual characteristics (v), and attributes at a dyadic level (w) such as proximities. Therefore, changes in network linkages are modeled by a utility function at node level, which is the driving force of network dynamics.

$$f^i\left(x^0, x, v, w\right) = \sum_k \beta_k s_{ki}\left(x^0, x, v, w\right)$$

The estimation of the different parameters βk of the objective function is achieved by the mean of an iterative Markov chain Monte Carlo algorithm based on the method of moments, as proposed by Snijders (2001). This stochastic approximation algorithm estimates the βk parameters that minimize the difference between observed and simulated networks. Along the iteration process, the provisional parameters of the probability model are progressively adjusted in a way that the simulated networks fit the observed networks. The parameter is then held constant to its final value, in order to evaluate the goodness of fit of the model and the standard errors. For a deeper understanding of SAOMs see Snijders et al. (2010) and for an economic geography review see Broekel et al. (2014).

Table 2 demonstrates three different specifications of SAOMs (Ripley et al., 2015). Evaluation models compare the probability of presence to the absence of the tie at time t+1 regardless of tie status at t. Creation models compare the probability of creating a previously not existing tie to not creating a tie; while the endowment model compares the probability of tie persistence to tie termination. These three specifications represent three different dependent variables of network evolution. Previous studies only looked at the evaluation models (Balland et al., 2016, Giuliani, 2013) and had to assume that the odds ratios in the creation and endowment models are identical (Ripley et al., 2015). However, these probability ratios typically differ, which is the case in our empirical sample as well. The differentiation between dependent variables in SAOMs is rarely applied (Cheadle et al., 2013) and empirical studies based on this distinction are completely missing from the economic geography literature.

Table 2

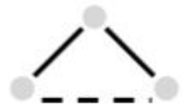
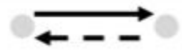
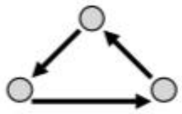
Tie changes considered by the evaluation, creation and endowment functions

	Evaluation		Number of ties	**Creation**		Number of ties	**Endowment**		Number of ties
	t	*t* + 1		*t*	*t* + 1		*t*	*t* + 1	
Creation	*i* *j*	*i* → *j*	71	*i* *j*	*i* → *j*	71			
Persistence	*i* → *j*	*i* → *j*	110				*i* → *j*	*i* → *j*	110
Termination	*i* → *j*	*i* *j*	113				*i* → *j*	*i* *j*	113
No ties	*i* *j*	*i* *j*	462	*i* *j*	*i* *j*	462			
Odds ratio			181/575			71/462			110/113

The effects of structural, dyadic, and individual variables are estimated in order to test the propositions; these variables are described in Table 3. To investigate how structural effects or network cohesion shape the evolution of the knowledge network behind the examined cluster we investigate the role of triadic closure that is often used in SAOM papers and captures the notion when partner of partners become partners so that a triad is created (Giuliani, 2013, Balland et al., 2016). In order to control for other endogenous network effects, like other papers do, we include density (out-degree of actors), reciprocity and directed cycles (3-cycles).

Table 3

Operationalization of structural, dyadic and firm level variables

Structural variables			
	Description	Formula	Visualization
Triadic closure	Tendency toward triadic closure when two knowledge ties existed in the previous period	$T_i = \sum_{j,h} x_{ij} x_{ih} x_{jh}$	
Reciprocity	Tendency of mutual knowledge exchange	$R_i = \sum_{j} x_{ij} x_{ji}$	
Cyclicity	Tendency of knowledge exchange in cycles	$C_i = \sum_{j,h} x_{ij} x_{jh} x_{hi}$	
Density	Overall tendency of actors to ask advices	$D_i = \sum_{j} x_{ij}$	
Dyadic variables			
Geographical proximity	Physical distance of firms subtracted from the maximum distance in the sample		
Cognitive proximity	Number of digits two firms share in common in their NACE 4 codes		
Common partners X cognitive proximity	Number of common third partners multiplied by the number of digits two firms share in common in their NACE 4 codes		
Firm level variables			
External knowledge ties	Number of knowledge linkages outside the region		
Age	Number of years since establishment		
Ownership	Equals *1* if foreign and *0* if domestic		
Employment	Total number of employees		

To capture the importance of dyadic effects on knowledge network tie formation, we focus on geographical proximity, cognitive proximity and the interaction of possible triads and cognitive proximity. Proximities are frequently used as dyadic effects in SAOM based knowledge network studies (Balland, 2012, Balland et al., 2013, Balland et al., 2016, Ter Wal, 2014). Geographical proximity is operationalized as the distance of the selected pair of firms subtracted from the maximum of the physical distance of firms. The variable takes higher value as the distance between firms diminishes. We applied a valued measure for cognitive proximity corresponding to the number of digits the two firms have in common in their NACE 4 codes (Balland et al., 2016)[4]. This measure assumes that two firms have similar technological profiles and therefore are in cognitive proximity if they operate at the same sector category (Frenken et al., 2007). To control for the independence of network structural

[4] More details and descriptive statistics of our cognitive proximity measure can be seen in Section IV of the Online Supplementary Information file.

effects and actor similarity on tie creation and persistence, we also investigate the interaction variable of the number of common third partners and cognitive proximity on dyadic level.

The importance of external relationships has been highlighted in the cluster literature (Bathelt et al., 2004, Glückler, 2007, Morrison, 2008). To measure the effect of extra-regional connections as an individual characteristic, we used the number of external knowledge ties (mean it links to other regions in Hungary or abroad). Additionally, we used actor related control variables as type of ownership, age, and the number of employees.

Since our networks are directed, we can control for the effect of individual characteristics on incoming and outgoing ties (Ripley et al., 2015). Alter variables represent the effect of individual characteristics on the actor's popularity to other actors. A positive parameter will imply the tendency that the in-degrees of actors with higher values on this variable increase more rapidly. Ego variables represent the effect of individual characteristics on the actor's activity. A positive parameter will imply the tendency that actors with higher values on this variable increase their out-degree more rapidly. The differentiation is important in case of cluster knowledge networks as the motives behind knowledge sharing and knowledge exploration could be highly influenced by the characteristics and capabilities of firms.

RESULTS

Table 4 presents the results of two SAOM specifications. Model (1) represents the general model while Model (2) contains the interaction of triadic closure and cognitive proximity as well. In each model, we first run evaluation models, then we also estimate network change in different versions of creation and endowment models. All parameter estimations in all models are based on 2000 simulation runs in 4 sub-phases. Parameter estimates can be interpreted as log-odds ratios, appropriate to how the log-odds of tie formation change with one unit change in the corresponding independent variable (Balland et al., 2016) because they are non-standardized coefficients from a logistic regression analysis (Steglich et al., 2010, Snijders et al., 2010). Since the null hypothesis is that the parameter is 0, statistical significance can be tested by t-statistics assuming normal distribution of the variable. The convergence of the approximation algorithms is sufficient for each model because all t-ratios are smaller than 0.1.

Table 4

Dynamics of the knowledge network

	Model (1)			Model (2)		
	Evaluation	**Creation**	**Endowment**	**Evaluation**	**Creation**	**Endowment**
Triadic closure	0.188***	0.382***	0.016	0.216***	0.440***	0.078
	(0.030)	(0.067)	(0.100)	(0.035)	(0.069)	(0.109)
Geographical proximity	0.029	0.186*	-0.101	0.041	0.257**	-0.086
	(0.039)	(0.101)	(0.076)	(0.043)	(0.123)	(0.080)
Cognitive proximity	0.109**	0.007	0.188**	0.275***	0.287**	0.350**
	(0.048)	(0.093)	(0.079)	(0.076)	(0.145)	(0.146)
Common partners X cognitive proximity				-0.049***	-0.121***	-0.035
				(0.017)	(0.046)	(0.025)
External knowledge ties alter	-0.012	-0.029	-0.012	-0.015	-0.039	-0.014
	(0.016)	(0.031)	(0.031)	(0.017)	(0.032)	(0.029)
External knowledge ties ego	0.070***	0.111**	0.164***	0.081**	0.129*	0.158**
	(0.023)	(0.049)	(0.062)	(0.033)	(0.067)	(0.064)
Age alter	0.009	0.014	0.010	0.017	0.027	0.013
	(0.011)	(0.022)	(0.020)	(0.012)	(0.025)	(0.019)
Age ego	-0.020	-0.044*	0.002	-0.014	-0.024	0.012
	(0.012)	(0.025)	(0.046)	(0.014)	(0.028)	(0.042)
Employment alter	0.001	-0.002	0.002	0.001	-0.001	0.002
	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)
Employment ego	-0.000	-0.001	-0.002	-0.000	-0.000	-0.002
	(0.001)	(0.002)	(0.004)	(0.001)	(0.002)	(0.005)
Ownership similarity	0.058	0.690*	-0.443	0.100	0.758*	-0.342
	(0.182)	(0.397)	(0.322)	(0.200)	(0.428)	(0.349)
Cyclicity	-0.176***	-0.321*	-0.006	-0.177***	-0.348**	-0.037
	(0.060)	(0.171)	(0.151)	(0.065)	(0.173)	(0.161)
Reciprocity	0.746***	1.604**	0.419	0.688***	1.327*	0.312
	(0.225)	(0.795)	(0.399)	(0.241)	(0.778)	(0.529)
Density	-1.594***	-3.928***	-1.464***	-1.763***	-4.299***	-1.665***
	(0.180)	(0.446)	(0.360)	(0.211)	(0.518)	(0.381)
Rate parameter	12.287	15.264	10.347	11.201	13.570	10.441
	(1.341)	(1.827)	(1.003)	(1.126)	(1.459)	(1.019)
Iteration steps	4195	4141	4141	4155	4194	4015
Convergence t-ratios	< 0.089.	<0.09.	< 0.088.	< 0.039.	< 0.052.	< 0.061.

The coefficients of triadic closure are positive and significant in the evaluation models, which is in line with previous findings (Balland et al., 2016, Giuliani, 2013) and has a positive and significant effect in the creation models, but has no significant effect in the endowment models. These findings confirm Proposition 1A, but does not support 1B as triadic closure positively influences the probability of new tie creation, but do not influence the probability of tie persistence in the cluster knowledge network. These results suggest that the structure of the network promotes opportunities to establish connections and shared contacts reduce the costs and uncertainties of the search for new partners. However, our findings do not support the idea that the maintenance of cohesive relationships is a general source of network retention in clusters.

Our second proposition concerns the role of geographical proximity as an influential factor of network dynamics. Unlike in a previous result (Balland et al., 2016), we find that the coefficient of geographical proximity is only significant and positive in creation models but does not influence the dependent variable in the evaluation and endowment models. Therefore, we confirm Proposition 2A and dismiss 2B. This finding underlines the importance of micro-level geography and means that physical proximity provides opportunities for establishing knowledge ties, lowers costs and uncertainties of tie creation, but does not affect the assessment and maintenance of relationships. The results are in line with the literature that questions the sufficiency of geographic proximity for knowledge transfer, learning and innovation and highlights the importance of other proximity dimensions (Boschma, 2005, Boschma and Frenken, 2010).

The third proposition addresses the role of cognitive proximity on tie creation and tie persistence in cluster knowledge networks. Unlike the previous two propositions, results in Model (1) and Model (2) are different. While the coefficients of cognitive proximity are positive and significant in both models for evaluation and endowment, the effect of cognitive proximity on tie creation turns positive and significant only in Model (2). Therefore, we can not accept Proposition 3A but can confirm 3B. These results suggest that firms are more likely to maintain strong ties to partners with similar technological profiles. One can think of various possible implication of this result. Cognitive proximity might help the persistence of ties by reducing the costs of knowledge transfer and therefore enabling the partners to repeat the interaction. In turn, the strong relations that emerge by persisting cognitively proximate ties might be foster the transfer of complex knowledge between firms in the cluster.

Finally, our fourth proposition posit that endogenous network effects and cognitive proximity are not independent and therefore we use a dyadic level variable to see how the interaction of the number of common partners and the extent of cognitive proximity affects tie creation and tie persistence. As we proposed, the interaction variable has a negative effect on both creation and persistence of ties, but the coefficients are only significant in case of the evaluation and creation models. This result only confirms Proposition 4A but do not support 4B. . Results in Model (2) suggest that the creation of a tie between two firms is less likely if they share many common partners and are cognitively proximate at the same time. In this case cognitive proximity in itself supports tie creation, as firms might expect valuable knowledge from firms with similar technological profile, but they can not get any information about the partner via indirect relations. Second, cognitive proximity and therefore the value of expected advice seems to be a major force behind tie persistence, as firms maintain costly strong ties with actors even though they might get the knowledge indirectly. These results lead to the conclusion that cohesive network effects and the effect of cognitive proximity are not independent and by the analysis of their interplay we can get a much better picture about the evolutionary process of knowledge network formation in clusters.

Additionally, we included structural and firm level control variables in both models. The rate parameter indicates the estimated number of opportunities for change per actor, which refers to the stability of the network over time. The positive and relatively high value suggests that there were significant changes in the formation of new ties. Meanwhile, the negative and highly significant coefficients of density indicate that firms tend not to form and maintain knowledge linkages with just any other firm in the cluster (Snijders et al., 2010, Ripley et al., 2015). Similar coefficients were found for density previously (Balland et al., 2016, Giuliani, 2013). The negative and significant effect of cyclicity in the evaluation and creation models indicate that actors create their relationships with their partner's partner in a certain hierarchy, but knowledge does not circulate among them. Instead, a dominant actor is more likely to provide it to the other two partners in the triad. However, cyclicity does not affect the persistence of knowledge ties.

Further, the number of external ties as a control variable suggest that firms that build and maintain linkages with actors outside the region establish and maintain their local ties more likely. These firms only seek for advice and absorb knowledge from cluster firms and do not share their own experiences with others. Findings suggest that the evolution of the knowledge network is influenced more by external stars, those firms that have strong extra-cluster knowledge linkages, but weak local integration (Giuliani and Bell, 2005, Morrison et al., 2013). Age has a barely significant and negative coefficient for tie creation in Model (1) but shows no significant influence on tie formation in any other model versions. Therefore, we can not say that older and more experienced firms create significantly fewer ties than relatively younger ones. The size of firms does not influence their knowledge tie formation, however, the similarity of firms' ownership has a significant effect on tie creation in both Model (1) and Model (2). This indicates that new ties are more easily established within the group of domestic or foreign firms than across these groups. The reason behind this notion could be the barriers of language, the difference in routines and skills or the technological gap between foreign and domestic companies. This finding underlines previous results related to the importance of ownership structure in knowledge spillovers effects (Elekes and Lengyel, 2016).

A variety of robustness checks were carried out in order to confirm the stability of the results[5]. First, we have run both Model (1) and Model (2) stepwise with different combinations of variables. We have also tried to include in-degree or network status as a control variable but it had no significant effect on tie formation and led to large t values of convergence. Every model has been run with only ego and only alter variables of individual characteristics as well. Along the large variety of different simulation runs, the size, sign and significance of the estimates of the main explanatory variables were stable. The incorporation of both ego and alter versions of firm level characteristics further improved both our model convergences and interpretation. Second, in order to ensure our results on the different effects of proximities, we also applied Mann-Whitney tests for the distribution of proximity values in case of tie creation and tie persistence.

[5] The correlation tables of all presented SAOMs can be seen in Section V of the Online Supplementary Information file.

Table 5

Distribution of proximity values in case of tie creation and tie persistence

	Created ties		No ties
Number of ties	71		462
Average geographic proximity	8,676		7,807
Mann-Whitney test (*p*-value)		0,0008	
Average cognitive proximity	1,929		1,894
Mann-Whitney test (*p*-value)		0,7756	
	Persisted ties		**Dissolved ties**
Number of ties	110		113
Average geographic proximity	8,336		8,407
Mann-Whitney test (*p*-value)		0,8812	
Average cognitive proximity	2,209		1,584
Mann-Whitney test (*p*-value)		0,0054	

In Table 5, we compare the distribution of geographical proximity and cognitive proximity between created ties versus lacking ties (as in the creation model), and between persisted ties versus terminated ties (as in the endowment model). The p-values suggest that in case of tie creation the value of geographic proximity is significantly higher for created ties than for lacking ties, while the value of cognitive proximity is higher for persisted ties than for dissolved ties. The distribution tests further strengthen the robustness of our SAOM based results.

CONCLUSIONS AND DISCUSSION

According to the first results of this paper, triadic closure and geographical proximity increase the probability of tie creation, but do not influence tie persistence. These findings mean that firms select those new partners with higher likelihood that they share third partners with or that are in physical proximity. This suggest that being close in the network and in space creates opportunities for face-to-face meetings and speeds up information flow, and thus lower costs and uncertainties of searching new knowledge ties. However, our results do not support the idea that these ties also persist on the long run. Cohesive and geographically proximate ties are equally likely to be terminated than non-cohesive and physically distant relations. A straightforward interpretation of the latter finding is that firms choose to maintain knowledge ties driven by the content of accessible knowledge and once the tie has been established, network structure and spatial location does not play a primer role.

Indeed, we find that cognitive proximity favours the persistence of ties but a positive and significant effect for tie creation has been found only when we introduced the interaction between triadic closure and cognitive proximities to the model. The first result suggest that a firm is more likely to repeat communication and maintain a knowledge tie with cognitively proximate partners than with cognitively distant peers. Our interpretation is that the applicability of knowledge increases with cognitive proximity and therefore these ties are more valuable for firms. An alternative explanation is that cognitive proximity decreases the costs of knowledge transfer and therefore, firms can repeat interaction to have access to complex knowledge even if the opportunity costs of strong relations are increasing.

The negative and significant co-efficient of the interaction between triadic closure and cognitive proximity has far-reaching implications for the evolution of cluster knowledge networks. This finding suggests that the two sources of path-dependency, namely network retention and lock-in driven by cognitive and technological proximities, do not strengthen each other. On the contrary, these forces seem to counter-act each other. A straightforward explanation of why firms ignore those ties that are cohesive in terms of network structure and also in terms of technological profile is that they are looking for new varieties of knowledge in the cluster. Consequently, network retention and network variation are simultaneously present in local knowledge networks.

Notwithstanding the new insights we provide, further research is needed to focus on the interference between retention and variation forces in knowledge networks. Based on our results, we propose that the creation and persistence of ties have to be analysed separately, because the micro level motivations of creating and maintaining ties are different. Further, we posit that the joint effect of endogenous network formation and proximities have to be investigated to get a clearer picture on how ties form in clusters. Such research shall aim not only to understand the patterns of relational change, the selection and retention mechanisms of network evolution, but also to take steps towards the recognition of forces that vary relational structures in clusters in a way that establishes new diversities in clusters. These together will allow us to fine-tune our understanding on how social networks and industry clusters co-evolve.

We have to emphasize the explanatory nature of our study and highlight some of the limitations and related future research opportunities. Based on the literature, other types of proximities, knowledge base or absorptive capacity of firms and the interplay of these with other structural variables are also need to be investigated (Giuliani, 2013, Balland et al., 2016). It must be stressed that the complex mixture of the analyzed factors might lead to different dynamics across regions and industries because specializations differ in terms of thresholds of costs and benefits of cooperation (Gordon and McCann, 2000) and because the level of market uncertainties – e.g. strengthening competition or external shocks – might strongly influence network dynamics (Beckman et al., 2004). Further, our exercise is based on a mature cluster of printing and paper product creation with increasing level of competition. Therefore, the conclusions might be limited to traditional manufacturing clusters, and network dynamics in other stages of cluster lifecycle could be different (Ter Wal and Boschma, 2011). Cohesive forces might have more influence on network change in an earlier life-cycle stage; competition or the fear from technological lock-in could change the willingness of cooperation in a later, mature or declining phase. According to the general thought, cognitive proximity has a dominant role in cluster lock-in (Boschma, 2005, Broekel and Boschma, 2012), which could intensify competition in clusters as well. This is an important point that future research shall address because repeated knowledge sharing increases the similarity of knowledge bases between co-located firms, which might lead competition and consequently thinning cooperation. Therefore, we shall also understand better the differences between tie creation and tie persistence in growing and in shrinking knowledge networks. The task is urgent because our models regarding tie persistence are not conclusive at all. A potential question can be, how does secrecy and free-riding influence knowledge network evolution? Further insights might be get from agent-based simulation models, in which agents punish those partners that are not sharing their knowledge by deleting the ties to them (Rand et al., 2011).

Additional limitation is – similarly to many papers on this topic – that the implications are based on the inter-firm alliance literature; however, advice networks might change more rapidly and the decision behind tie creation and persistence might be less strategic or even less conscious. Moreover, we are unable to control for the pre-existing friendships or other social ties among entrepreneurs, which might result more robust estimates. Moreover, our cognitive proximity measure simplifies the differences in knowledge bases of firms and therefore comparison to Giuliani (2013) is difficult. Further, ties are assumed to be identical in terms of transmitted content. Thus, the volume, depth and diversity of information content of the communications should be looked at (Aral and van Alstyne, 2011). This would allow us to investigate how the value of advice influences the persistence of ties, which we could not do in this paper.

Another key issue for future research is the availability of longitudinal knowledge network data. With longer and more detailed relational datasets on cluster knowledge networks we might get answers to several, still open questions. First, we might get a better picture about how network dynamics change along the cluster life-cycle as we can investigate how the importance of structural and proximity effects change over time. Second, longitudinal data with more than two time points is needed to investigate tie re-creation, which might be driven by different forces than tie creation. Third, by using relational data on individual level rather than firm level we might get much more accurate understanding on the motives of tie creation and persistence.

REFERENCES

Ahuja, G., Soda, G., Zaheer, A., 'The Genesis and Dynamics of Organizational Networks', Organization Science, 23, 2012, pp. 434-448.

Amin, A., 'Industrial districts'. In: Sheppard, E., Barnes T.J. (eds.) A Companion to Economic Geography, Oxford: Blackwell Publishing, 2000, pp. 149-168.

Aral, S., 'The future of weak ties', American Journal of Sociology, 121, 2016, pp. 1931-1939.

Aral, S., Van Alstyne, M., 'The Diversity-Bandwidth Trade-off', American Journal of Sociology, 117, 2011, pp. 90-171.

Asheim, B., 'Industrial districts as learning regions: a condition for prosperity', European Planning Studies, 4, 1996, pp. 379-400.

Balland, P-A., 'Proximity and the Evolution of Collaboration Networks: Evidence from Research and Development Projects within the Global Navigation Satellite System (GNSS) Industry', Regional Studies, 46, 2012, pp. 741-756.

Balland, P-A., Belso-Martínez, J. A., Morrison, A., 'The dynamics of technical and business networks in industrial clusters: embeddedness, status or proximity?', Economic Geography, 92, 2016, pp. 35-60.

Balland, P-A., Boschma, R., Frenken, K., 'Proximity and innovation: from statics to dynamics', Regional Studies, 49, 2015, pp. 907-920.

Balland, P-A., De Vaan, M., Boschma, R., 'The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987-2007', Journal of Economic Geography, 13, 2013, pp. 741-765.

Bathelt, H., Glückler, J., 'Toward a relational economic geography', Journal of Economic Geography, 3, 2003, pp. 117-144.

Bathelt, H., Malmberg, A., Maskell, P., 'Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation', Progress in Human Geography, 28, 2004, pp. 31-56.

Beckman, C.M., Haunschild, P.R., Phillips, D.J., 'Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection', Organization Science, 15, 2004, pp. 259-275.

Borgatti, S. P., Mehra, A., Brass, D. J., Labiance, G., 'Network Analysis in the Social Sciences', Science, 323, 2009, pp. 892-895.

Boschma, R., 'Proximity and Innovation: A Critical Assessment', Regional Studies, 39, 2005, pp. 61–74.

Boschma, R., Fornahl, D., 'Cluster evolution and a roadmap for future research', Regional Studies, 45, 2011, pp. 1295-1298.

Boschma, R., Frenken, K., 'The spatial evolution of innovation networks. A proximity perspective'. In: Boschma, R., Martin, R. (eds) The Handbook of Evolutionary Economic Geography, Cheltenham: Edward Elgar, 2010, pp. 120-135.

Boschma, R., Ter Wal, A. L. J., 'Knowledge networks and innovative performance in an industrial district: the case of a footwear district in the South of Italy', Industry and Innovation, 14, 2007, pp. 177-199.

Breschi, S., Lissoni, F., 'Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows', Journal of Economic Geography, 9, 2009, pp. 439-468.

Broekel, T., 'The co-evolution of proximities – a network level study', Regional Studies, 49, 2015, pp. 921-935.

Broekel, T., Balland, P.-A., Burger, M., Van Oort, F., 'Modeling knowledge networks in economic geography: a discussion of four methods', The Annals of Regional Science, 53, 2014, pp. 423–452.

Broekel, T., Boschma, R., 'Knowledge networks in the Dutch aviation industry: the proximity paradox', Journal of Economic Geography, 12, 2012, pp. 409-433.

Burt, R. S., 'Decay functions', Social Networks, 22, 2000, pp. 1-28.

Burt. R. S., 'Structural holes and good ideas', American Journal of Sociology, 110, 2004, pp. 348-399.

Cantner, U., Graf, H., 'The network of innovators in Jena: an application of social network analysis', Research Policy, 35, 2006, pp. 463-480

Carley, K., 'A theory of group stability', American Sociological Review, 56, 1991, pp. 331-354.

Cheadle, J. E., Stevens, M., Deadric, T. W, Bridget, J. G., 'The differential contributions of teen drinking homophily to new and existing friendships: An empirical assessment of assortative and proximity selection mechanisms', Social Science Research, 42, 2013, pp. 1297-1310.

Cohen, W. M., Levinthal, D. A., 'Absorptive capacity: a new perspective on learning and innovation', Administrative Science Quarterly, 35, 1990, pp. 128-153.

Coleman, J. S., 'Social capital in the creation of human capital', American Journal of Sociology, 94, 1988, pp. S95-S120.

Cooke, P., 'Knowledge Economies. Clusters, Learning and Cooperative Advantage', London: Routledge, 2002.

Cooke, P., De Laurentis, C., Tödtling, F., Trippl, M., 'Regional Knowledge Economies. Markets, Clusters and Innovation', Cheltenham: Edward Elgar, 2007.

Dahl, M. S., Pedersen, C. O. R., 'Knowledge flows through informal contacts in industrial clusters. Myth or reality?', Research Policy, 33, 2003, pp. 1673–1686.

Dahlander, L., McFarland, D.A., 'Ties that last: tie formation and persistence in research collaborations over time', Administrative Science Quarterly, 58, 2013, pp. 69-110.

Elekes, Z., Lengyel, B., 'Related trade linkages, foreign firms and employment growth in less developed regions', Papers in Evolutionary Economic Geography, 2016, Nr. 16. 20.

Ethridge, F., Feldman, M., Kemeny, T., Zoller, T., 'The Economic Value of Local Social Networks', Journal of Economic Geography, 16, 2016, pp. 1101-1122.

Eurostat, 'Nace Rev. 2. Statistical classification of economic activities in the European Community', Luxembourg: European Communities, 2008.

Fitjar, R.D., Rodriguez-Pose, A., 'When local interaction does not suffice: sources of firm innovation in urban Norway', Environment and Planning A, 43, 2011, pp. 1248-1267.

Fornahl, D., Brenner, T., 'Cooperation, networks and institutions in regional innovation systems', Cheltenham: Edward Elgar, 2003.

Frenken, K., Van Oort, F., Verburg, T., 'Related Variety, Unrelated Variety and Regional Economic Growth', Regional Studies, 41, 2007, pp. 685–697.

Galaskiewicz, J., Shatin, D., 'Leadership and networking among neighborhood human service organizations', Administrative Science Quarterly, 26, 1981, pp. 434-448.

Giuliani, E., Bell, M., 'The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster', Research Policy, 34, 2005, pp. 47-68.

Giuliani, E., 'The selective nature of knowledge networks in clusters: evidence from the wine industry', Journal of Economic Geography, 7, 2007, pp. 139-168.

Giuliani, E., 'Clusters, networks and economic development: an evolutionary economics perspective'. In Boschma, R., Martin R. (eds) The Handbook of Evolutionary Economic Geography. Cheltenham: Edward Elgar, 2010.

Giuliani, E., 'Network dynamics in regional clusters: Evidence from Chile', Research Policy, 42, 2013, pp. 1406-1419.

Glückler, J., 'Economic geography and the evolution of networks', Journal of Economic Geography, 7, 2007, pp. 619-634.

Gordon, I. R., McCann, P., 'Industrial Clusters: Complexes, Agglomeration and/or Social Networks?' Urban Studies, 37, 2000, pp. 513-532.

Grabher, G., 'The weakness of strong ties – the lock-in of regional development in the Ruhr area'. In Grabher, G. (ed) The embedded firm, London: Routledge, 1993, pp. 255-277.

Granovetter , M., 'The strength of weak ties', American Journal of Sociology, 78, 1973, pp. 1360-1380.

Granovetter, M., 'Economic Action and Social Structure: The Problem of Embeddedness', American Journal of Sociology, 91, 1986, pp. 481-510.

Greve, H. R., Baum, J. A. C., Mitsuhashi, H., Rowley, T., 'Built to last but falling apart: cohesion, friction, and withdrawal from interfirm alliances', Academy of Management Journal, 53, 2010, pp. 302-322.

Hanaki, N., Peterhansl, A., Dodds, P. S., Watts, D. J., 'Cooperation in evolving social networks', Management Science, 53, 2007, pp. 1036-1050.

Hansen, M. T., 'The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits', Administrative Science Quarterly, 44, 1999, pp. 82-111.

Huber, F., 'On the role of interrelationship of spatial, social and cognitive proximity: personal knowledge relationships of R&D workers in the Cambridge Information Technology Cluster', Regional Studies, 46, 2012, pp. 1169-1182.

Iammarino, S., McCann, P., 'The structure and evolution of industrial clusters: Transitions, technology and knowledge spillovers', Research Policy, 35, 2006, pp. 1018-1036.

Jackson, M. O., 'Social and Economic Networks', Princeton, NJ: Princeton University Press, 2008.

Kossinets, G., Watts, D.J., 'Origins of homophily in an evolving social network', American Journal of Sociology, 115, 2009, pp. 405-450.

Lambiotte, R., Blondel, V. D., de Kerchove, C., Huens, E., Prieur, C., Smoreda, Z., Van Dooren, P., 'Geographical dispersal of mobile communication networks' Physica A: Statistical Mechanics and its Applications, 387, 2008, pp. 5317-5325.

Lane, P. J., Lubatkin, M., 'Relative absorptive capacity and interorganizational learning', Strategic Management Journal, 19, 1998, pp. 461-477.

Lavie, D., Rosenkopf, L., 'Balancing exploration and exploitation in alliance formation', Academy of Management Journal, 49, 2006, pp. 797-818.

Lengyel, B., Eriksson, R., 'Co-worker networks, labour mobility and productivity growth in regions', Journal of Economic Geography, 17, 2016, pp. 635-650.

Lengyel, B., Varga, A., Ságvári, B., Jakobi, A., Kertész, J., 'Geographies of an online social network', PLoS ONE, 10, 2015, e0137248.

Levinthal, D. A., March, J. G., 'The myopia of learning', Strategic Management Journal, 14, 1993, pp. 95-112.

Li, P., Bathelt, H., Wang, J., 'Network dynamics and cluster evolution: changing trajectories of the aluminium extrusion industry in Dali, China', Journal of Economic Geography, 12, 2012, pp. 127-155.

Malmberg, A., 'Industry geography: location and learning', Progress in Human Geography, 21, 1997, pp. 573-582.

March, J. G., 'Exploration and exploitation in organizational learning', Organization Science, 2, 1991, pp. 71-87.

Marmaros, D., Sacerdote, B., 'How do friendships form?' Quarterly Journal of Economics 121, 2006, pp. 79-119.

Marshall, A., 'Principles of Economics – An Introductory Volume', London: MacMillan, 1920.

Martin, R., Sunley, P., 'Conceptualizing cluster evolution: beyond the life cycle model?', Regional Studies, 45, 2011, pp. 1299-1318.

Maskell, P., Malmberg, A., 'Localised learning and industrial competitiveness', Cambridge Journal of Economics, 23, 1999, pp. 167-185.

McPherson, M., Smith-Lovin, L., Cook, J. M., 'Birds of a feather: Homophily in social networks', Annual Review of Sociology, 27, 2001, pp. 415-444.

Menzel, M. P., Fornahl, D., 'Cluster life cycles – dimensions and rationales of cluster evolution', Industrial and Corporate Change, 19, 2010, pp. 205-238.

Morrison, A., 'Gatekeepers of knowledge within industrial districts: who they are, how they interact', Regional Studies, 42, 2008, pp. 817-835.

Morrison, A., Rabellotti, R., 'Knowledge and information networks in an Italian wine cluster', European Planning Studies, 17, 2009, pp. 983-1006.

Morrison, A., Rabellotti, R., Zirulia, L., 'When Do Global Pipelines Enhance the Diffusion of Knowledge in Clusters?', Economic Geography, 89, 2013, pp. 77-96.

Nelson, R. R., Winter, S. G., 'An evolutionary theory of economic change', Cambridge MA: Harvard University Press, 1982.

Porter, M. E. (1990) The Competitive Advantage of Nations. London: Macmillan.

Powell, W.W., White, D.R., Koput, K.W., Owen-Smith, J., 'Network dynamics and field evolution: the growth of interorganizational collaboration in the life sciences', American Journal of Sociology, 110, 2005, pp. 1132-1205.

Rand, D.G., Arbersman, S., Christakis, N.A., 'Dynamic social networks promote cooperation in experiments with humans', PNAS, 109, 2011, pp. 19193-19198.

Rapoport, A., 'Mathematical models of social interaction'. In Luce, R. D., Bush, R. R., Galanter, E. (eds) Handbook of Mathematical Psychology. New York: John Wiley & Sons. 1963.

Reagans, R., McEvily, B., 'Network structure and knowledge transfer: the effects of cohesion and range', Administrative Science Quarterly, 48, 2003, pp. 240-267.

Ripley, R., Snijders, T., Boda, Zs., Vörös, A., Preciado, P., 'Manual for RSiena (Version October 10)', University of Oxford: Department of Statistics, 2015.

Rivera, M.T., Soderstrom, S. B., Uzzi, B., 'Dynamics of dyads in social networks: assortative, relational, and proximity mechanisms', Annual Review of Sociology, 36, 2010, pp. 91-115.

Rosenkopf, L., Padula, G., 'Investigating the microstructure of network evolution: alliance formation in the mobile communications industry', Organization Science, 19, 2008, pp. 669-687.

Seabright, M.A., Levinthal, D,A,, Fichman, M., 'Role of individual attachments int he dissolution of interorganizational relationships', The Academy of Management Journal, 35, 1992, pp. 122-160.

Shipilov, A. V., Rowley, T. J., Aharonson, B. S., 'When Do Networks Matter? A Study of Tie Formation and Decay'. In: Baum, J. A. C., Dobrev, S. D., Van Witteloostuijn, A. (eds) Ecology and Strategy, Advances in Strategic Management, Volume 23. Emerald Group Publishing Limited, 2006.

Snijders, T., 'The statistical evaluation of social network dynamics'. In Sobel, M., Becker, M. (eds) Sociological Methodology, Basil Blackwell, Boston and London, 2001.

Snijders, T. A. B., Van de Bunt, G. G., Steglich, C. E. G., 'Introduction to stochastic actor-based models for network dynamics', Social Networks, 32, 2010, pp. 44-60.

Sorensen, O., 'Social networks and industrial geography', Journal of Evolutionary Economics, 13, 2003, pp. 513-527.

Staber, U., 'Partners forever? An empirical study of relational ties in two small-firm clusters', Urban Studies, 48, 2011, pp. 235-252.

Steglich, C. E. G., Snijders, T. A. B., Pearson, M., 'Dynamic networks and behavior: Separating selection from influence', Sociological Methodology, 40, 2010, pp. 329-393.

Storper, M., Venables, A. J., 'Buzz: face-to-face contact and the urban economy', Journal of Economic Geography, 4, 2004, pp. 351-370.

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

Ter Wal, A. L. J., Boschma, R., 'Applying social network analysis in economic geography: framing some key analytic issues', The Annals of Regional Science, 43, 2009, pp. 739-756.

Ter Wal, A. L. J., Boschma, R., 'Co-evolution of firms, industries and networks in space', Regional Studies, 45, 2011, pp. 919-933.

Uzzi, B., 'Social structure and competition in interfirm networks: The paradox of embeddedness', Administrative Science Quarterly, 42, 1997, pp. 35-67.

Verspagen, B., Duysters, G., 'The small world of strategic technology alliances', Technovation, 24, 2004, pp. 563-571.

Wasserman, S., Faust, K, 'Social Network Analysis: Methods and Applications', Cambridge: Cambridge University Press, 1994.

Wellman, B., 'Are personal communities local? A Dumptarian reconsideration', Social Networks, 18, 1996, pp. 347-354.

Wimmer, A., Lewis, K., 'Beyond and below racial homophily: ERG models of a friendship network documented on Facebook', American Journal of Sociology, 116, 2010, pp. 583-642.