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Tie creation versus tie persistence in cluster knowledge networks

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Abstract

Knowledge networks in industrial clusters are frequently analyzed but we know very little about creation and persistence of ties in these networks. We argue that tie creation primarily depends on opportunities and thus the position of actors in the network and in space; while tie persistence is influenced by the value of the tie. Accordingly, results from a Hungarian printing and paper product cluster suggest that reciprocity, triadic closure, and geographical proximity between firms increase the probability of tie creation. Tie persistence is positively affected by technological proximity between firms and the number of their extra-regional ties.

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1. 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, Cooke, 2002, Dahl and Pedersen, 2003, Fornahl and Brenner, 2003, Gordon and McCann, 2000, Kemeny et al., 2015, Sorensen, 2003). Social ties are important for local knowledge flows because personal acquaintance reduces transaction costs between co-located actors, which enhance the efficiency of mutual learning (Borgatti et al., 2009, Maskell and Malmberg, 1999). It is also well understood that most of the learning processes occur within certain spatial proximity despite distant ties might provide the region with new knowledge (Bathelt et al., 2004, Glückler, 2007).

Knowledge networks provide us with direct understanding of local learning by linking co-located firms through technical advice and the transfer of innovation-related knowledge (Boschma and Ter Wal, 2007, Giuliani, 2007, 2010, Giuliani and Bell, 2005, Morrison and Rabellotti, 2009). More recently, scholars look at the underlying factors behind knowledge network dynamics. Giuliani (2013) demonstrated that general rules of social network evolution apply for knowledge networks in clusters as well; while Balland et al. (2016) showed that various dimensions of proximity across firms matter for dynamics of knowledge networks more than for business networks. These papers argue that the evolution of knowledge networks is very closely related to the evolution of the cluster itself and therefore we can get new insights into the well researched field of cluster development by analyzing the knowledge networks (Boschma and Fornhal, 2011, Boschma and Frenken, 2010, Iammarino amd McCann, 2006, Menzel and Fornhal, 2010, Martin and Sunley, 2011, Staber, 2011, Li et al., 2012).

Unfortunately, tie creation and tie persistence in knowledge networks have not been separated in the previous papers and researchers investigated the probability of tie existence without considering the previous status of the tie (Balland et al., 2016, Giuliani, 2013). This creates a niche because the mechanisms of link creation and link persistence are considered fundamentally different in the inter-connected literatures of social network dynamics and inter-firm alliances (Dahlander and McFarland, 2013). Therefore, the main aim of this paper is to distinguish the dynamics of tie creation and tie persistence in cluster knowledge networks. The distinction is important and might have important implications for cluster evolution theory.

Based on the literature, we argue that the probability of tie creation in the knowledge network depends on the opportunities for establishing the tie, which is dependent on the position of agents in the network and their position in space. For example, agent A is more likely to ask for technical advice from agent B and thus establish a tie if B has already asked advice from A, or if both A and B knows agent C (Granovetter, 1986) and also if A and B are geographically close to each other (Lambiotte et al., 2008, Lengyel et al., 2015). In other words, reciprocity, triadic closure, and geographical proximity lower the costs of tie establishment. However, the persistence of a tie – whether the firm asks advice again from the same firm – depends on how the firm evaluates the quality of the previous suggestion (Greve et al., 2010, Hanaki et al., 2007). The value of knowledge might be a central concern in tie assessment, which brings technological proximity and external ties into the focus of our research. Technological proximity between firms might increase the value of knowledge and therefore the probability of persistence because ties to firms with similar technological profile might transmit better advice regarding specific technical problems (Rivera et al., 2010). Also, new knowledge might be important for firms to have access to and therefore firms might nurse connections to those firms that import new knowledge to the region (Boschma, 2005, Glückler, 2007).

In order to enter the above niche, we map the knowledge network of the printing and paper product cluster of Kecskemét, Hungary in 2012 and 2015 and analyze the major forces behind tie creation and tie maintenance. The cluster is perfect for such analyzes because printing industry has a long history in the region, has a high concentration of employment, includes few international companies but is dominated by small- and medium-sized enterprises (SMEs). The firms are almost equally distributed across printing services, production of paper products, and pre-printing processes, which provides us with a variety of technological proximity across firms. The majority of the local companies apply some kind of specialized technology to create unique paper products but companies do not carry out intensive R&D activities, and therefore external links to other regions are important sources of new knowledge.

Stochastic actor-oriented models are applied to examine the effect of reciprocity, triadic closure, geographical and technological proximity and the number of external knowledge ties of firms on the evolution of cluster knowledge network. As the major contribution of the paper, we investigate the impact of the above factors on tie creation and on tie persistence in separate models.

The paper is structured as follows. The literature of social network and inter-firm alliance dynamics is reviewed in Section 2 where research hypotheses are developed as well. Section 3 introduces the context of the research and the details of data collection. Variables and methodology are described in Section 4, which is followed by a presentation of results in Section 5. The paper closes with a discussion on the consequences of the findings for cluster evolution and proposes an outline for future research.

2. Literature and hypotheses

Industrial clusters have been recognized as major engines of regional competitiveness and growth (Porter, 1990, Krugman, 1991) because geographic concentration of economic activities that operate in the same or interconnected sectors enable businesses to gain from complementarities, collaborations and knowledge spillovers (Cooke et al., 2007, Gordon and McCann, 2000). Particular attention has been paid to the relationship between clustering, localised learning, and innovation (Bathelt et al., 2004) and informal transfer of knowledge and thus social networks across firms are claimed to be important (Bathelt and Glückler, 2003, Ter Wal and Boschma, 2009). 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 in two ways. First, knowledge is not automatically accessible for everyone in clusters, but its transfer is determined by trust-based relationships of actors (Giuliani and Bell, 2005, Giuliani, 2007, Morrison and Rabellotti, 2009). Second, central actors in knowledge networks can get new knowledge easier and earlier and therefore are associated with better innovation performance (Boschma and Ter Wal, 2007).

The dynamics of clusters and their underlying social networks are thought to be interrelated (Iammarino and McCann, 2006, Glückler, 2007, Boschma and Fornahl, 2011) and are also claimed to co-evolve (Ter Wal and Boschma, 2011); however, we know very little how ties in knowledge networks emerge, persist and eventually dissolve. In a pioneering article, Giuliani (2013) proposed that there is a general tendency towards cohesive formulation of knowledge networks primarily driven by endogenous network effects, such as reciprocity and triadic closure (Granovetter, 1986, Rapoport, 1963). Furthermore, the findings of Giuliani (2013) confirm that capability effects also matter in the form of dyadic-level similarities, such as technological proximity, because firms with similar knowledge bases are more likely to establish connections (Boschma and Frenken, 2010), as well as in the form of firm capabilities because firms with weak knowledge bases are less likely to establish new links (Ahuja et al., 2012, Cohen and Levinthal, 1990). In another previous article the recent paper extensively builds upon, Balland et al. (2016) demonstrated that the effect of geographical and technological proximities are much more profound for dynamics in knowledge networks than in business networks. This latter finding supports the idea that besides geographical proximity, additional forms of proximities are needed for learning (Boschma, 2005).

Unfortunately, the collusion of tie creation and tie persistence in these papers (Balland et al., 2016, Giuliani, 2013) left us with major uncertainties regarding the pattern of network dynamics, which might lead us to oversimplified conclusions. A great deal of economics, business, and sociology literatures discusses why and how the motivation behind formulation of social relations differs from maintenance of social relations and micro-foundations usually depart from the costs and the payoffs of ties (for overviews see Jackson, 2008, Dahlander and McFarland, 2013, and Rivera et al., 2010, respectively).

The costs of a tie denote the efforts needed to establish and maintain a connection ranging from travel costs, communication costs, and further opportunity costs (Borgatti et al., 2009), which might depend on the network structure as well. For example, Agneesens and Wittek (2012) proposes that the cost of advice seeking means that the status of the firm decreases in the community. Conversely, reciprocity of advice and trust emerging from social closure might lower the costs of tie creation (Marsden and Campbell, 1984, Uzzi, 1997, Walker et al., 1997). The costs of tie creation in cooperation networks influences the probability of the tie together with the expected benefit of the tie (Ohtsuki et al., 2006). Firm strategies regarding tie creation might vary according to related costs; if tie creation is cheap then firms might risk the uncertain new links but if tie creation is expensive then firms will establish efficient links only (Goyal and Vega-Redondo, 2005).

The benefit of the cooperation can be directly connected to tie persistence, because the firms learn about their partners when working together and are able to better compare the expected benefits of terminating versus maintaining the tie (Greve et al., 2010, Hanaki et al., 2007). Scholars found that inter-organizational ties dissolve if the firm finds alternative ties that offer better and still affordable solutions and persist only if the tie represents valuable connection (Seabright et al., 1992). In line with the previous literature, Dahlander and McFarland (2013) argues that creation of ties is led by opportunities searching for desirable resources at potential partners, which leads the firm towards a short-term broadening of its network. However, the firm reflects on the quality of the partner when sustaining the link, which leads to long-term strategies of inter-firm co-operation.

The cost-benefit approach is very straightforward for understanding cluster knowledge network dynamics better, because costs might be associated with the opportunities of tie creation in the cluster; while the value of advice can be connected to payoffs of firms given certain relations to other firms. The above literature opens up new questions for cluster research and four hypotheses of previous studies might be revisited.

First, one might expect that trust, social capital, and embeddedness in the relational structure of the network reduces uncertainties, and hidden transaction costs and favors tie creation (Granovetter, 1986). In particular, reciprocity of advice seeking and a shared third party increases the probability of establishing a tie. However, as Uzzi (1997) argues, reciprocity and triadic closure may encourage cooperation and increase its payoffs, this is only true on the short run but after a certain threshold embeddedness can isolate firms from external information circulating in other parts of the network. Accordingly, Shipilov et al. (2006) found that triadic closure had a positive influence on tie creation but had no effect on tie persistence in inter-organizational alliance networks. Similarly, triadic closure of co-worker networks across firms was found to hold back industrial growth in regions (Eriksson and Lengyel, 2016). Thus, we think reciprocity and triadic closure lowers the costs of tie creation but do not affect the value of the knowledge the tie provides access to.

H1: Reciprocity and triadic closure positively influence the probability of tie creation but do not influence tie persistence in the cluster knowledge network.

Second, geographical proximity is thought to increase the opportunity to meet and formulate new relationships (Borgatti et al., 2009, Rivera et al., 2010, Storper and Venables, 2004). Findings in telephone-call networks and large scale online social networks support the claim that the probability of ties decreases as distance grows (Lambiotte et al., 2008, Lengyel et al., 2015). Furthermore, the role of geographical proximity cannot be neglected in micro-geographic units, proximity was found to increase the extent of communication even within a small geographical unit as a college dormitory (Marmaros and Sacerdote, 2006). Although geographic proximity is claimed to facilitate face-to-face interactions, communication between agents, and the exchange of knowledge by Boschma (2005), another question remains whether geographic proximity is sufficient for knowledge linkages and innovation too. In a more recent paper, other proximity dimensions are assumed to be important for knowledge ties (Boschma and Frenken, 2010) and therefore we think that geographical proximity only decreases costs of tie creation but does not influence the quality of advice and the assessment of ties in knowledge networks.

H2: Geographical proximity positively influences the probability of tie creation but does not influence tie persistence in the cluster knowledge network.

Third, technological proximity has been found to have a positive influence on knowledge network dynamics in both of the previous papers we follow (Balland et al., 2016, Giuliani, 2013). These findings are in line with the argument that knowledge resides mostly in skills of individual workers and routines of firms (Cohen and Levinthal, 1990, Nelson and Winter, 1982), which makes the transfer of knowledge difficult even in industrial clusters. The similarity of firms' knowledge bases is relevant for the transfer of knowledge and may significantly influence the extent of knowledge transferred through a link (Boschma, 2005, Boschma and Frenken, 2010). Therefore, technological proximity may be very important for the value of advice, because competent firms might provide better suggestion for technical problems, and therefore might positively influence the assessment of tie quality.

H3: Technological proximity positively influences the probability of tie persistence in the cluster knowledge network.

Fourth, the importance of external relationships has been highlighted in the literature (Bathelt et al., 2004, Glückler, 2007, Morrison, 2008). Firms who build and maintain linkages with actors outside the region with the purpose of learning and knowledge sharing are often called technological gatekeepers (Morrison et al., 2013, Giuliani, 2011). These firms can impregnate the cluster with new knowledge and therefore foster local learning processes, increase international competitiveness and avoid lock-in of the cluster. Gatekeepers' knowledge is often associated with central positions in cluster network (Morrison, 2008) and the number of external ties can be associated with high value that might motivate local firms to establish and maintain relations with gatekeepers.

H4: External knowledge ties positively influence the probability of tie creation and persistence in the cluster knowledge network.

Status has been regarded important for social network dynamics (Gould, 2002) because preferential attachment might be at play and new ties are established most likely with actors having the highest number of connections (Barabási and Albert, 1999). This implies for advice networks as well where few actors stand out in terms of number of advice asked from (Lazega et al., 2012, Ter Wal and Boschma, 2011). Although the influence of these central actors is high in the network (Giuliani, 2007, Morrison and Rabellotti, 2009), no significant effect of status was found on network dynamics in cases of cluster knowledge networks (Balland et al., 2016, Giuliani, 2013). Therefore, we only investigate the influence of status in a robustness check.

3. The study setting

3.1. Printing and paper product industry in Kecskemét

Printing and paper product industry has a long tradition in the region of Kecskemét[1]. 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 sector has high employment concentration in the region. The location quotient calculated from the number of employees shows significant 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 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 tipically 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.

[1] Kecskemét is about 80 km south from Budapest, the capital of Hungary, and accounts for around 115.000 inhabitants with an economy routed in agriculture as well as processing and manufacturing industries (heavy machinery and car manufacturing).

In sum, the local industry can be characterized as an old social network based cluster (Iammarino and McCann, 2006) and therefore provide perfect conditions for analyzing the dynamics of the knowledge network.

3.2. Data collection and manipulation

We collected data at the firm level by face-to-face structured interviews with skilled workers (mostly with co-founders, operational managers or foremen) in years 2012 and 2015 from those firms that have at least 2 employees, had a 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.

The relational data was collected through the so called "roster recall" method (Wasserman and Faust, 1994, Ter Wal and Boschma, 2009, Maggioni and Uberti, 2011); 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-firms 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. Additional year-specific firm-level information concerned main activities, number of employees, total revenue, share of export in total sales, type of ownership and external knowledge linkages of the firm.

We managed to get answers from 26 different companies in year 2012 and repeated the interviews in 2015 with the same firms. 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 questions related to firms' knowledge transfers have been used to construct two directed adjacency matrices with $n \times n$ 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.

3.3. Descriptive analysis

Table 1 shows the main characteristics of the examined firms in 2012 and 2015. Most of the firms were founded along the 1990s when self-owned firm foundation became possible in Hungary. Two companies were closed down along the studied period, but two other companies joined to the sample by 2015. The technological profile of the cluster is diverse; however, printing dominates and less firms deal with paper product creation and pre-printing processes. The examined firms are mainly SMEs and only a minority of them is foreign-owned. Interregional relations in terms of export/ net revenue ratio and also in terms of extra-regional knowledge exchanges decreased over time.

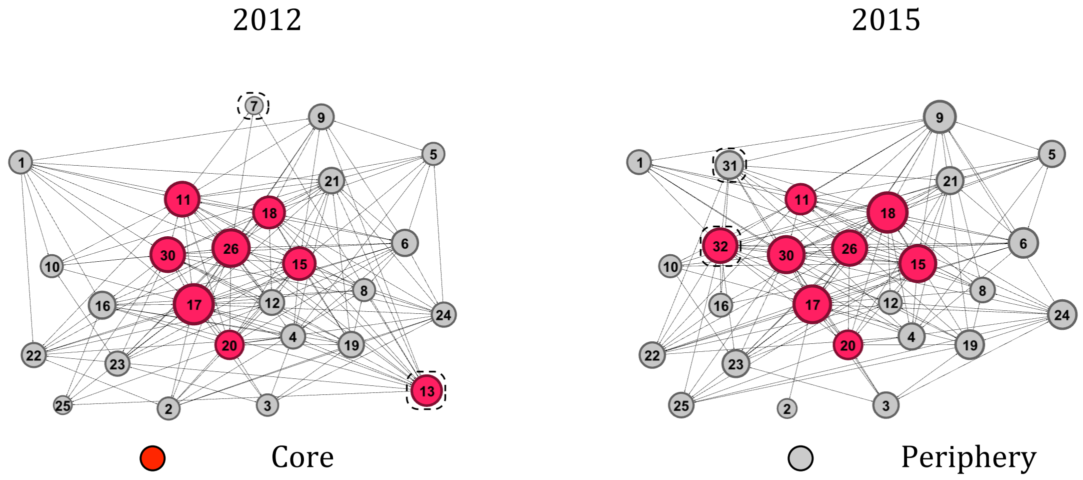
Table 1 Descriptive statistics of the sample in 2012 and 2015

Characteristics	Number of firms		
	2012 (N=26)	Entry/exit	2015 (N=26)
Year of establishment			
Up to 1990	2		2
1990s	14		14
2000s	8		9
2010s	2		1
Entry		2	
Exit		2	
Main activities			
Paper product creation	7		6
Printing	12		11
Pre-printing processes	4		6
Other related activities	3		3
Size (number of employees)			
Small (1-10)	18		18
Medium (11-100)	7		7
Large (101-)	1		1
Average number of employees per firm	27		26
Ownership			
Domestic	21		21
Foreign	5		5
Exporters	13		11
Average number of knowledge linkages outside the region	7		4

Source: Author's own data.

As we can clearly see in Table 2, 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. The visual representation of the knowledge networks (Figure 1) suggests that the degree distribution is not proportional. In both cases the network is hierarchical in a sense, that 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).

Figure 1 The local knowledge network of the printing and paper product industry in Kecskemét in 2012 and 2015



Source: Author's own data.
Note: The size of the nodes is proportional to degree. Firms who left the 2012 sample or entered the 2015 sample are marked by dashed frame.

Table 2 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

Source: Author's own data.

Similarly to previous studies (Giuliani and Bell, 2005), the core/periphery model of Borgatti and Everett (1999) identifies a cohesive group of central firms with high number of connections to each other and a group of peripheral firms loosely connected to the core and to each other at both points in time (Table 3). The fall of density affected every part of the network relatively equally. Both the core and the periphery became less connected by 2015 and the number of knowledge exchanges between the two parts also decreased. Furthermore, the composition of the core transformed as 25% of the core firms changed to periphery and 12.5% of them closed down.

Tabel 3 Core and periphery in 2012 and 2015, density and dynamics

	The density of linkages (knowledge transfer from row to column)		
	Core	Periphery	Final fit
2012			0.837
Core (n_c=8)	0.839	0.486	
Periphery (n_p=18)	0.389	0.163	
2015			0.841
Core (n_c=7)	0.738	0.391	
Periphery (n_p=19)	0.361	0.146	
	Stability of the core-periphery structure (dynamics in rows)		
Persistence	62.5%	88.9%	
Change	25%	5.6%	
Exit	12.5%	5.6%	

Source: UCINET 6 applied to author's own data.

Note: The density of a network is the total number of ties divided by the total number of possible ties. The percentages are calculated on the population of firms present in 2012 (26 firms), therefore, it includes incumbents of 2015 but not new entrants.

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). 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' lif-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). We think that all these ideas call for a better understanding of link dynamics, for which a distinction between tie creation and persistence is necessary because firm strategies might depend on changing costs and benefits.

4. Methodology and variables

We apply stochastic actor-oriented models (SAOMs) for the analysis of the cluster knowledge network dynamics because these models allow simultaneous analysis of different effects on network change (Snijders et al., 2010). This simulation-based methodology has been successfully applied to analyze global and regional knowledge network evolution in different cases (Balland, 2012, Giuliani, 2013, Balland et al., 2013, Ter Wal, 2014, Balland et al., 2016).

SAOMs can take account of three classes of effects that influence the evolution of networks (Ripley et al., 2015). Firstly, endogenous or structural effects that come from the network structure itself (e.g. degree-related effects, triadic closure, reciprocity). Secondly, dyadic covariate effects are based on the existence of similarity or proximity (commonly referred to as homophily or assortativity) between pair of actors in the network. 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. 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 λ_i for each actor i. As actor i has the opportunity to change a linkage, its choice is to change one of the tie variables x_{ij}, which will lead to a new state as $x, x \in C(x^0)$. Choice probabilities (direction of changes) are modeled by a multinomial logistic regression, specified by an objective function f_i (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 f_i (Broekel et al., 2014, Balland et al., 2013). This objective function describes preferences and constraints of actors as choices of collaboration are determined by a linear combination of effects, depending on the current state (x^0), 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 β_k 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 β_k 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 4 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. Our contribution is that we test creation and endowment models as well besides evaluation models. 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.

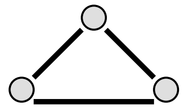
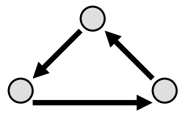
Table 4 Tie changes considered by the evaluation, creation and endowment functions

	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

Source: Author’s own construction based on Ripley et al. (2015).

The effects of structural, dyadic, and individual variables are estimated in order to test the hypotheses; these variables are described in Table 5. To investigate how structural effects or network cohesion shapes the evolution of the knowledge network behind the examined cluster we investigate the role of triadic closure and reciprocity (H1). Triadic closure 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). Reciprocity is examined as the number of mutual ties. In order to control for other endogenous network effects, we include density (out-degree of actors) and directed cycles (3-cycles), all of which are recommended in SAOMs.

Table 5 Operationalization of structural, dyadic and firm level variables

	Structural variables		
	Description	Formula	Visualization
Triadic closure (H1) (Embeddedness)	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 (H1)	Tendency of mutual knowledge exchange	$R_i = \sum_{j} x_{ij} x_{ji}$	
Density	Overall tendency of actors to ask advices	$D_i = \sum_{j} x_{ij}$	
Cyclicity	Tendency of knowledge exchange in cycles	$C_i = \sum_{j,h} x_{ij} x_{jh} x_{hi}$	
	Dyadic variables		
Geographical proximity (H2)	Physical distance of firms subtracted from the maximum distance in the sample		
Technological proximity (H3)	Number of digits two firms share in common in their NACE 4 codes		
	Firm level variables		
External ties (H4)	Number of knowledge linkages outside the region (in 2015)		
Age (experience)	Number of years since establishment (in 2015)		
Ownership	Equals *1* if foreign and *0* if domestic		
Net Revenue	Categorical variable for net revenue (in 2015)		
Employment	Log transformation of the total number of employees (in 2015)		

Source: Author's own construction based on Balland et al. (2016), Giuliani (2013), Snijders et al. (2010)
Note: The plain lines and arrows represent pre-existing ties, while the dashed arrows represent the expected ties that will be created if the corresponding structural effect is positive.

To capture the importance of dyadic effects on knowledge network tie formation, we focus on geographical proximity (H2) and technological proximity (H3). 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 technological proximity corresponding to the number of digits the two firms have in common in their NACE 4 codes (Balland et al., 2016). This assumes that two firms have similar knowledge bases and therefore are in technological proximity if they operate at the same sector category, which is in line with the related variety literature (Frenken et al., 2007).

We suggested above that the extra-regional knowledge linkages of firms influence their connections in the local knowledge network (H4). 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 (or experience), value of net revenue, and the number of employees.

5. Results

Table 6 presents the results of SAOM run in RSiena as described in the previous section. We first run evaluation models, then we also estimated 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 was excellent for all the variables in the different models (as all the t-ratios were smaller than 0.1).

Table 6 Dynamics of the knowledge network

	Evaluation			Creation			Endowment		
	Estimate	(s.e.)	t-value	Estimate	(s.e.)	t-value	Estimate	(s.e.)	t-value
Reciprocity (H1)	0.731***	(0.218)	3.345	1.458**	(0.721)	2.024	0.475	(0.472)	1.006
Triadic closure (H1)	0.192***	(0.032)	6.035	0.402***	(0.065)	6.230	0.026	(0.111)	0.231
Geographical proximity (H2)	0.041	(0.040)	1.030	0.177*	(0.097)	1.835	-0.078	(0.084)	-0.924
Technological proximity (H3)	0.095**	(0.047)	1.996	0.063	(0.092)	0.688	0.161*	(0.090)	1.790
External knowledge ties (H4)	0.086***	(0.029)	2.995	0.148**	(0.067)	2.205	0.185**	(0.092)	2.005
Age	-0.018	(0.014)	-1.265	-0.035	(0.028)	-1.258	0.009	(0.057)	0.163
Ownership	0.099	(0.282)	0.351	-0.736	(0.758)	-0.971	1.718	(1.184)	1.451
Net revenue	-0.559***	(0.212)	-2.641	-0.782*	(0.401)	-1.950	-1.686*	(0.891)	-1.892
Employment	0.391	(0.288)	1.358	0.954	(0.640)	1.491	0.447	(1.165)	0.383
Cyclicity	-0.203***	(0.062)	-3.258	-0.414**	(0.166)	-2.495	-0.045	(0.189)	-0.235
Density	-1.552***	(0.154)	-10.070	-3.329***	(0.376)	-8.859	-1.973***	(0.331)	-5.964
Rate parameter	11.732	(1.225)		13.985	(1.572)		10.190	(0.987)	
Convergence t-ratios	All convergence t-ratios < 0.065			All convergence t-ratios < 0.099			All convergence t-ratios < 0.09		

Source: Author's own data.

Note: Results of the stochastic approximation. The estimated parameters based on 4007 iteration steps in the evaluation model, 3881 iteration steps in the creation model and 3810 iteration steps in the endowment model. The convergence of the models was good, as all t-ratios were smaller than <0.1. The coefficients are significant at the * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$ level.

Our first hypothesis refers to triadic closure and reciprocity as influential effects of knowledge tie creation. The coefficients of triadic closure and reciprocity are positive and significant in the evaluation model, which is in line with previous findings (Balland et al., 2016, Giuliani, 2013). However, when separating the models according to the previous status of ties, we find that these variables had a positive and significant effect in the creation model, but had no significant effect in the endowment model. These results confirm that reciprocity and triadic closure positively influence the probability of new tie creation, but do not influence the probability of tie persistence in the cluster knowledge network. Therefore, H1 is verified.

Our second hypothesis 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 the creation model but does not influence the dependent variable in the evaluation and endowment models. This finding underlines the importance of micro-level geography and means that physical proximity provides opportunities for establishing knowledge ties but do not affect assessment of relationships. Therefore, H2 is verified. 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 and Frenken, 2010).

The third hypothesis about the effect of technological proximity on ties persistence in cluster knowledge networks is also verified as its coefficients are positive and significant in the evaluation model and in the endowment model but not in the creation model. This suggests that the odds-ratio of tie persistence drives the positive effect of the evaluation model. The results imply that despite the possibility of tough competition between the actors in the same field, technological proximity might positively influence the assessment of tie quality because competent firms might provide better suggestion for technical problems.

Finally, the fourth hypothesis addresses the role of external knowledge linkages in the dynamics of local knowledge networks. We find positive and significant coefficients of external knowledge ties in all three models. This result confirms that external knowledge ties are important for tie creation and tie persistence as well; we can verify H4. The finding means that those firms that have access to more external actors form more local knowledge ties over time; and their local ties are likely to persist as well. Because firms do not carry out intensive R&D activity in the case of our cluster, gatekeepers have decisive role in importing new knowledge to the region. Those co-located firms that cannot renew or strengthen their knowledge base by incorporation of more new knowledge directly from outside the region, try to increase cooperation with gatekeepers and attribute great value to the link with them.

A variety of further structural variables were used to control for additional endogenous network effects. Rate parameter and density are automatically reported in this type of estimation. 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 co-efficients 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. However, cyclicity does not affect the persistence of knowledge ties at all.

We also included control variables for firms' ownership, age, employment and net revenue. The only significant control variable related to firm performance is net revenue that has a negative effect on the number of present knowledge ties over time. This finding means that the firms who are economically more successful will have less knowledge linkages over time, which is also confirmed by our interviews where firms unfold that they became less opened for knowledge sharing and tend to ask less advice from local competitors because of intensifying local competition.

A variety of robustness checks were carried out in order to confirm the stability of the results. The size, sign and significance of the estimates of the main explanatory variables did not change in these checks, and therefore, the tests of the hypotheses are valid and reliable. First, we included in-degree as a control variable, which led to large convergence t values. This is due to a very strong negative correlation between Density (out-degree) and in-degree square root (–0.870) Second, we excluded the net revenue from the control variables, which resulted in a negative and significant effect of the age variable and all other effects remain stable.

6. Discussion

In this study we separately examined tie creation and tie persistence in a cluster knowledge network for the first time in economic geography literature. The exercise is very important because we can see the underlying effects of network dynamics clearer. We argue that the findings have further important implications for understanding cluster evolution better.

In a previous study Giuliani (2013) argued that the effect of triadic closure and reciprocity result in a more cohesively knit knowledge network, which drive cluster evolution towards convergence. We find that triadic closure and reciprocity – supplemented by the given geographical proximity in clusters – only support the creation of knowledge linkages between firms, but do not favor the persistence of cooperative knowledge sharing. These results suggest that the structure of the knowledge networks might provide co-located firms with opportunities to establish new ties by reducing the costs and uncertainties of tie establishment but do not influence the value of these ties. Therefore, knowledge network cohesion might be very influential on the short run but cannot be generalized to dominate cluster evolution on the long run.

Based on the literature of inter-firm alliances we can argue that co-located firms evaluate their existing relations by comparing the maintenance costs to the expected benefits of knowledge sharing. While costs of tie persistence may rise in a cluster with increasing competition and also due to decreasing prestige among the cluster firms, among other transaction costs, only those ties are maintained that provide greater benefits than costs. In this paper we show that the maintenance of ties is positively influenced by technological proximity between firms. This finding suggests that the value of technical advice increases as overlap in technological profile of firms grows. Regarding cluster evolution, this means that long term cohesion might be driven by technological proximity among co-located firms, which is in line with central ideas in the literature. According to the general thought, technological proximity has a dominant role in cluster lock-in and could intensify competition in clusters as well because repeated knowledge sharing increases the similarity of knowledge bases between co-located firms, which might lead competition and consequently thinning cooperation.

Last, but not least, we find that external knowledge ties of firms are important for both creating and maintaining local ties, meaning that access to external knowledge attracts local firms and provides substantial value for the link. This finding can be directly implemented in the cluster evolution argument, because external knowledge ties can help to avoid the lock-in process driven by the long-term and continuous learning between technologically similar firms by providing new knowledge to the cluster.

Certainly, the characteristics of networks and network dynamics can be different along the cluster lifecycle (Ter Wal and Boschma, 2011). Our exercise is based on a rarefying knowledge network where dynamics might be different from a growing knowledge network. Therefore, further research shall compare the dynamics of tie creation and tie persistence over the full life-cycle of industrial clusters. Furthermore, this paper focused on one cluster only, which makes generalization difficult. Further empirical investigations are needed for comparing the network dynamics in different cluster types. Additional limitation of our paper is that the examined knowledge ties are assumed to be equal because we could not incorporate the value of the transferred knowledge into the model. Last, dynamically changing individual characteristics could be used to develop better models for understanding the role of structural and individual effects as well in knowledge network evolution.

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