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1. What if a cluster is declining? – The dynamics behind a local knowledge network

Sándor Juhász – Balázs Lengyel

Knowledge networks are important tools for analyzing the local flows of innovation-related knowledge and consequently on the success of regional clusters. An increasing number of studies focused on the forces that shape and form these networks but the role of these factors in shrinking networks is not well understood. Do firm characteristics or the network structure explain the emergence and decline of knowledge ties in a cluster? In order to address the above question, we map the knowledge network from micro-level relational data collected by a roster recall method questionnaire in the printing and paper product industry of the urban agglomeration of Kecskemét, Hungary in years 2012 and in 2015. The investigated knowledge network became smaller over the period, which is mainly due to increasing competition across the co-located firms. Results of stochastic actor-oriented models suggest that embeddedness, network status, cognitive proximity and the external knowledge ties of firms play an important role in the dynamics of knowledge networks, even in case of a declining cluster in a transition economic setting.

Keywords: knowledge networks, network dynamics, cluster life-cycle

1. Introduction

The relevance of regional clusters in firms' competitiveness and innovation performance is generally acknowledged by now. Along the past ten years the interest of researchers turned to the patterns of how firms gain and exchange knowledge in a cluster context. The flow of knowledge has been a central subject of research on regional clusters (Cooke 2002, Fornahl – Brenner 2003). In accordance to that, knowledge networks have been used as central concept in the literature dealing with local social networks behind clusters (Giuliani – Bell 2005, Morrison – Rabellotti 2009). Knowledge network is defined as a network that links firms through the transfer of innovation-related knowledge (Giuliani 2010). The analysis of this type of networks helps to capture industrial atmosphere or innovative milieu in a region, knowledge spillovers and social, economical embeddedness of firms. Along the examination of the above phenomena and in order to deeper understand clusters, local knowledge network analysis became a widely used tool (Giuliani – Bell 2005, Giuliani 2007, Boschma – Ter Wal 2006, Morrison – Rabellotti 2009). Interestingly, only a few studies have applied an evolutionary perspective and tried to capture the driving forces behind the change of local knowledge networks in time, however, it is very much in line with a new strand of research that investigates cluster evolution processes more generally (Iammarino –

McCann 2006, Glückler 2007, Menzel – Fornhal 2010, Boschma – Fornhal 2011, Martin – Sunley 2011, Staber 2011, Li et al. 2012, Giuliani 2013).

In this research – similarly to other empirical papers concerning network evolution behind clusters (Giuliani 2013, Balland et al. 2016) – we search for the driving forces of knowledge networks, but with two special settings. Firstly, there is still no empirical evidence about how knowledge networks evolve behind clusters in transition economies like Hungary. We argue that despite the special characteristics of transition economies, embeddedness of firms and their status in the knowledge network influence new tie formation. Secondly, we will test our hypothesis on a small scale cluster network that shrinks over time. Cognitive proximity of actors help to share tacit knowledge more easily and therefore facilitate new knowledge linkages, even if a network diminishes. Additionally, we argue about the importance of external linkages and their influence to new knowledge tie creation between local firms.

We test our hypotheses in the context of the printing and paper product cluster of Kecskemét, Hungary. There are no formal contracts behind the cluster, but it has long history in its region, the critical amount of SMEs, high concentration of employment and most of the local companies apply some kind of specialized technology to create unique paper products. We collected the necessary micro-level relational data by face-to-face semi-structured interviews in 2013 and 2016 from 28 firms. We investigated the dynamics of knowledge network formation with the help of Stochastic Actor Oriented Model (SAOM) developed by Snijders (2010). The empirical results show that embeddedness and network status are two main effects guiding the network evolution even in a diminishing network context. While cognitive proximity plays an important role in knowledge tie creation, micro-level geography has no significant effect on new knowledge tie establishment. Another interesting finding is that firms with more external knowledge relationships form more local linkages than firms with fewer ties to other regions.

Our article is structured as follows. The theoretical framework and research hypotheses are developed in Section 2. Section 3 presents the context of the research and the details of data collection. In Section 4 and 5 details the used methodology and the empirical results, followed by the concluding remarks and discussion in Section 6.

2. Literature and hypotheses

The basic idea of clusters – understood here as the geographic concentration of economic activities that operate in the same or interconnected sectors (Gordon – McCann 2000) – has earned high attention in the last thirty years as they have been recognized as drivers of regional competitiveness and growth (Porter 1990, Krugman 1991). This is mainly due to that they enable businesses to gain from complementarities, collaborations and knowledge spillovers (Cooke et al. 2007). Among the many research directions related to the field, particular attention was paid to the relationship between clustering, localised learning and innovation (Bathelt et al. 2004). According to a central claim, the share of knowledge basis enable cluster firms to continuously combine and re-combine similar or non-similar resources to produce new knowledge and innovations. Therefore, successful clusters are the ones that are able to build and maintain a variety of channels for knowledge sharing across members, which is largely shaped by social networks.

A great deal of studies on clusters and networks is focused on knowledge networks. *"Knowledge network is defined as the network that links firms through the transfer of innovation-related knowledge, aimed at the solution of complex technical problems. The knowledge network thus is based on the transfer of knowledge among firms, which occurs informally for problem-solving and is promoted by the local community of technicians and entrepreneurs"* (Giuliani 2010, p. 265). Studying local knowledge networks has already brought novel understanding of the underlying mechanism of knowledge sharing in clusters in two prominent way. On the one hand, knowledge is not automatically accessible for everyone in clusters, but its spread is determined by trust-based relationships of actors (Giuliani – Bell 2005, Giuliani 2007, Morrison – Rabellotti 2009). On the other hand, prominent position of actors in knowledge networks are associated with higher innovation performance (Boschma – Ter Wal 2007), as firms can get new knowledge easier and earlier.

Even though the need to understand evolutionary aspects related to clusters and their underlying networks are highly pronounced (Iammarino – McCann 2006, Glückler 2007, Boschma – Fornahl 2011), there are not much empirical studies concerned on the dynamic effects influencing the change of cluster knowledge networks. The few research on the evolution of these networks have identified that the embeddedness of actors, their status in the network and the different proximities between firms are the most influential factors of change (Giuliani 2013, Balland et al. 2016). However, none of the existing studies deal with transition economy cases, which could be especially interesting from the evolutionary economic geography point of view. Because of the post-socialist transition setting, cooperation willingness and the lack of trust-based relationships can have a particular effect on network evolution (Grabher – Stark 1997). Moreover, there is still no empirical evidence about the dynamics of knowledge networks behind declining clusters (Menzel – Fornahl 2010). Since most of the related papers deal with empirics of developing or sustaining clusters, cases with diminishing knowledge linkages behind clusters can emphasize the importance of different effects on network dynamics. We argue that it is crucial to understand the latter phenomena because competition in the cluster may undermine the willingness to share innovation-related knowledge with co-located firms.

In this paper we try to answer the question: what drives the evolution of knowledge networks behind declining clusters in transition economy setting? In studies on clusters a central tenet is that embeddedness of actors in cohesive webs of relationships yield positive returns to its members (Asheim 1996). On the one hand, the embeddedness of firms in local networks has been considered crucially important in reducing transaction costs, as they build on personal, trust-based relationships among them (Granovetter 1986). On the other hand, embeddedness is particularly relevant for knowledge sharing between firms of clusters (Uzzi 1997). From a dynamic network point of view, embeddedness could be understood as the relationships of firms become more complex. A widely used network analogy for embeddedness is the notion of triadic closure (Giuliani 2013, Balland et al. 2016), as partner of partners become partners. In our view, this is such an influential effect on knowledge network evolution, that even in cases of diminishing networks it remains determinate. This leads to the following hypothesis:

H1: Despite the decline of network relations, embeddedness (triadic closure) is important for the dynamics of the local knowledge network.

Besides achieving higher embeddedness, the change of network relations behind clusters is also influenced by the hierarchy of the network. In social networks, new ties are established most likely with actors having the highest number of connections (Barabasi – Albert 1999), so as the dynamics of networks are strongly shaped by the network status of actors. In case of advice networks, actors ask advice from other members of a community who have higher status, more connections and therefore more direct linkages to other sources of knowledge (Lazega et al. 2012). There are several empirical evidence on the influence of central actors with the highest status of cluster network on the dynamics of knowledge diffusion (Giuliani 2007, Morrison – Rabellotti 2009). However, the few studies concerned about the dynamics of knowledge networks behind clusters did not find any significant influence of status on knowledge network evolution. Even though all the empirically examined clusters were in a growing or sustaining stage and therefore the preferential attachment mechanism looked as an obvious dynamics, it could have a more important effect when the knowledge network behind the cluster declines. The above discussion leads to the following hypothesis:

H2: Despite the decline of network relations, network status (in-degree popularity) is important for the dynamics of the local knowledge network.

One of the core conceptual and also empirical elements of the discussion on clusters is the role of different proximities in knowledge sharing. In this literature, geographical proximity is an essential part of the cluster concept because it facilitates face-to-face interactions, communication between agents, and the exchange of knowledge (tacit knowledge, in particular). However, another question remains whether geographic proximity is sufficient for knowledge linkages and innovation too? Boschma (2005) proposed five different proximity dimensions (cognitive, institutional, organizational, social and geographical) that could influence knowledge exchange and therefore innovation performance and emphasized that geographical proximity is more likely to become effective indirectly through the other types of proximity. By now, not much study scaled down and tried to understand the role of geographic proximity behind clusters from a micro-level perspective (Pratt 2011), even though it could help the easy and fast physical contacting of actors and therefore facilitate the transfer of tacit knowledge. However, the importance of geographic proximity on knowledge network dynamics still has contradictory results (Ter Wal 2014, Balland et al. 2016). All these lead us to the following hypothesis:

H3: Micro-level geography plays an important role in the dynamics of the local knowledge network.

Since knowledge resides mostly in skills of individual workers and routines of firms (Nelson – Winter 1982), it makes difficult to be transferred across organizations. Even in clusters, where firms are related to the same sector, the difference of their knowledge bases makes the transfer of know-how difficult. Therefore, the similarity of firms knowledge bases, so as cognitive proximity of firms is relevant for the transfer of knowledge, thus could significantly influence the development of knowledge linkages between firms of a cluster. This leads to the following hypothesis:

H4: Cognitive proximity plays an important role in the dynamics of the local knowledge network.

The relevance of external relationships of clusters is long established in the literature (Bathelt et al. 2004, Morrison 2008). Many studies indicate that the innovative performance of industrial districts are related to their ability to reach and absorb external knowledge. Firms who build and maintain linkages with other actors outside their region with the purpose of learning and knowledge sharing are often called ’pipelines’ in the literature (Owen-Smith – Powell 2002, Bathelt et al. 2004). These firms with external linkages can impregnate the cluster with new knowledge and therefore foster local learning processes, increase international competitiveness and avoid the (technological) lock-in of the cluster. These firms are often associated with a central position in cluster network (Morrison 2008), however, there is still no empirical evidence on how external knowledge ties impact firms local connections over time and therefore the evolution of the local knowledge network. This lead us to the following hypothesis:

H5: Firms with more external knowledge ties are more likely to form local knowledge linkages than firms with less external knowledge ties.

3. The study setting

3.1. Printing and paper product industry in Kecskemét

In the centre of our empirical analysis is the printing and paper product industry of Kecskemét. This dynamically developing town is about 80 km south from Budapest, the capital city 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). The geographical unit of the analysis is the urban agglomeration of Kecskemét, which is joined by 9 settlements and accounts for about 140.000 inhabitants. Printing and paper product industry has a long tradition in the region of Kecskemét. The first printing-house called Petőfi Press was established in the 1840s by Szilády Károly and it still works under this name. Since the 1990s, basically after the planned economy collapsed and it became possible to found self-owned firms, numerous small and medium enterprises (SMEs) was born around the town of Kecskemét and created a strong local base for the industry. International companies have also located their facilities (e.g. Axel-Springer). By now, 58 firms operate in the sector around the town resulting a high concentration of both printing and paper product creation in the urban agglomeration of Kecskemét. The location quotient (LQ) based on the number of employees in the region, compared to other manufacturing industries at national level 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 (1.059)[1]. The high concentration and the simultaneous presence of small and big firms resulted in an intensive local competition, which requires flexible specialisation 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).

The printing and paper product industry in Kecskemét has several features – such as tradition, concentration, SMEs, specialization – that can help the establishment of a successful regional cluster. One can argue that the type of the organization should be an old social network based cluster (Iammarino – McCann 2006) due to its specific characteristics. The reason for the typology is that these clusters characteristically deal with customised traditional goods; these clusters are built on mature technological knowledge and smaller, customer-driven process oriented innovations are typical in order to satisfy the customers' unique needs. In case of social network based clusters social and historical ties play a crucial role in cluster governance and information and knowledge transfer.

3.2. Data collection

The study is based on primary micro level data collected at the firm level on the basis of face-to-face interviews with skilled workers (mostly with co-founders, operational managers or foremen) in two time points at 2012 and 2015. The interviews were structured by a questionnaire in order to get necessary information for the network analysis. The actual firms the analysis was concentrated on were those that have at least 2 employees, had a seat in the

[1] Location quotient is considered to be high above 1.00.

urban agglomeration of Kecskemét and the main activity was classified under the 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 datas, 38 firms suited the above conditions and we merged those firms that had identical addresses and similar names. Finally, there were 35 firms in the roster for the 2012 questionnaire and at the end of the list 3 opened questions tried to explore the linkages to partner organisations, schools and other important actors not mentioned in the roster. To the actual identification of the firms the database of the Hungarian Central Statistical Office was used. The questionnaire contained some additional control questions about the firms' main activities, the number of employees, total revenue and the proportion of export in total sales in the given year.

We managed to get answers from 26 different companies in 2012 and in order to examine the evolution of the network, we repeated the interviews in 2015 with the same 26 firms who responded in 2012. Due to the opened questions at the end of the roster we successfully managed entries and exits of firms, therefore, we collected 26 responses in 2016 too. These are especially good response rates (more than 70% of the local firms in the industry were reached at both time points) to capture and analyse the patterns of knowledge flow and the evolution of the network behind the local cluster.

The relational data was collected through the so called roster recall method (Wasserman – Faust 1994, Ter Wal – Boschma 2009, Maggioni – Uberti 2011) where each firm were presented with a complete list (roster) of the other firms and was asked to report about their relations to all the other firms. The question formulated to collect knowledge network data – as used in several studies (Giuliani – Bell 2005, Morrison – Rabellotti 2009) – were as follows:

If you are in a critical situation and need technical advice, to which of the local firms mentioned in the roster do you turn?
[Please rate the importance you attach to the knowledge linkage established with each of the firms according to its persistence and quality, on the basis of the following scale: 0= none, 1 = low, 2 = medium, 3 = high].

This question is related to the transfer of innovation-related knowledge and only reveal the inter-firms linkages that are internal to the cluster. They specifically address problem solving and technical assistance because they involve some effort in producing improvements and change within the economic activity of a firm (Giuliani – Bell 2005). This is meant to capture not only the bare transfer of information which is by now easily accessible by many other channels (such as specialised reviews, the internet, etc.), but instead the transfer of contextualised complex knowledge which is eventually absorbed by localised firms. As an example, knowledge is transferred by providing a suggestion about how to set up a printing-press for a special type of paper or which lighting process is the best for specific materials. Accordingly, the knowledge transferred is normally the reply to a query about a complex problem that has emerged and that the firm seeks to solve (Giuliani – Bell 2005).

The questions related to firms' knowledge transfers have been used to construct two n x n matrix (where n stands for the number of respondents) for the two time points, in which each cell reports the existence of knowledge being transferred from firm i in the row to firm j in the column. As a result of these, the cell (i, j) contains 1 if firm i has transferred knowledge to firm j with the weight of at least 1. Cell (i, j) contains a 0 when no transfer of knowledge has been reported between firm i and j. Therefore, the outcomes of these questions are two directed adjacency matrices.

To have a more complex view on what are the driving forces of network evolution we used additional question on firms characteristics. We asked them about their size, ownership, export ratio, external knowledge linkages and their foundation (if they are spin-off firms or not). The statistical techniques we used to model the dynamics of the knowledge networks and the exact variables we used are described in the next section.

4. Methodology and variables

As we addressed above, knowledge in clusters is transferred by informal contacts between actors to solve technical problems or get professional advice. To explain how these local knowledge networks change over time, we have to model how the actors choose to ask for advice, and how its patterns change over time. Therefore, the dependent variable in this analysis is the formation of knowledge ties between actors (Balland et al. 2016). To analyse the evolution of the cluster knowledge network we apply stochastic actor-oriented models (SAOMs) because they allows simultaneous analysis of different effects on network change (Snijders et al. 2010). Concretely, we use SAOMs implemented in the RSiena statistical software for network analysis (Ripley et al. 2015). This 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). For a more detailed introduction of SAOMs see Snijders et al. (2010).

SAOMs can take account of three classes of effects. Firstly, endogenous or structural effects which came from the network structure itself (e.g. network closure effects, degree-related effects, reciprocity). Secondly, dyadic covariate effects based on the existence of similarity or proximity between pairs of actors in the network. If the dyadic covariate is larger, a linkage between two actors is more likely to be established. Thirdly, individual characteristics of actors is also taken account as influential effects of network evolution. An actor related ego-effect expresses the tendency that an actors with higher values for a given characteristic has higher network degree. SAOM model the change of the whole network by a time-continuous Markov chain and assumes that the further evolution of the network is determinable by a probability function based on the present state of the network. The model is actor-oriented, it explains the structural change of the network by the micro level decisions of actors, as they control their outgoing ties. The probability of changes is modelled by a multinomial linear regression which contains structural, dyadic and individual effects. The evolution of the network is simulated by a Monte Carlo algorithm, thereby it tries to connect the states of the network in the different times observed by simulating the internal steps. This stochastic approximation algorithm estimates the parameters that minimize the deviation between observed and simulated networks. For the deeper understanding of SAOMs see Snijders et al. (2010) and Broekel et al. (2014).

To estimate how structural effects or network cohesion shapes the evolution of the knowledge network behind the examined cluster we investigate the role of embeddedness (H1). Embeddedness is often operationalized by triadic closure (Giuliani 2013, Balland et al. 2016). Triadic closure is the notion when partner of partners become partners so as a triad is created by linkages. To capture the role of network status (H2) as a structural effect on network change we investigate the importance preferential attachment mechanism (Barabasi – Albert 1999) as in-degree popularity of actors. We used structural control variables along the estimations just as the out-degree density of the network, the reciprocity of ties and directed cycles (3-cycles) of ties.

To capture the importance of dyadic effects on knowledge network tie formation, we focus on geographical (H3) and cognitive (H4) proximities. Proximities are frequently used as dyadic effects in SAOM based studies on knowledge network evolution (Balland 2012, Balland et al. 2013, Ter Wal 2014, Balland et al. 2016). We measured geographical proximity as the physical distance between two firms. We created a valued measure for cognitive proximity corresponding to the number of digits the two firms share in common in their NACE 4 codes (Balland et al. 2016). This assumes that two firms have similar knowledge bases and therefore are in cognitive 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 (H5). To measure the effect of extra-regional connections as an individual characteristics, we used the number of external knowledge ties (both in other regions of Hungary and abroad). Additionally, we used actor related control variables as ownership, age (or experience) and the number of employee for firm size. In the following section, we present the characteristics of the examined knowledge network in the two time periods and the results of the dynamic network analysis.

5. Empirical results

This section presents the results of our empirical analysis on the knowledge network evolution of the printing and paper product cluster of Kecskemét, Hungary. 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 3 years, but two other companies joined to the sample by 2015. Spin-off activity is very important in our setting as nearly half of the questioned firms said that they were founded by a former employee of an incumbent firm of the industry. The number of firms operating in printing and paper product creation decreased between 2012 and 2015. Pre-printing processes became the main activity of more firms by 2015 than before. The examined firms are mainly SMEs and only a minority of them is foreign owned. The external orientation of firms, both as there export ratio from the net revenue and their extra-regional knowledge exchanges is decreased from 2012 to 2015.

As we can clearly see on Table 2, the knowledge network behind the cluster became less dense by 2015. From the 223 knowledge ties only 110 linkages maintained. Although, 113 edges dissolved after 2012, no firms became isolated by 2015. On average, actors only asked for technical advice to nearly 8 firms in 2012 and about 6 firms in 2015.

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	
Spin-off firm	11		12
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: own construction

Table 2 Descriptive statistics of the knowledge network in 2012 and 2015

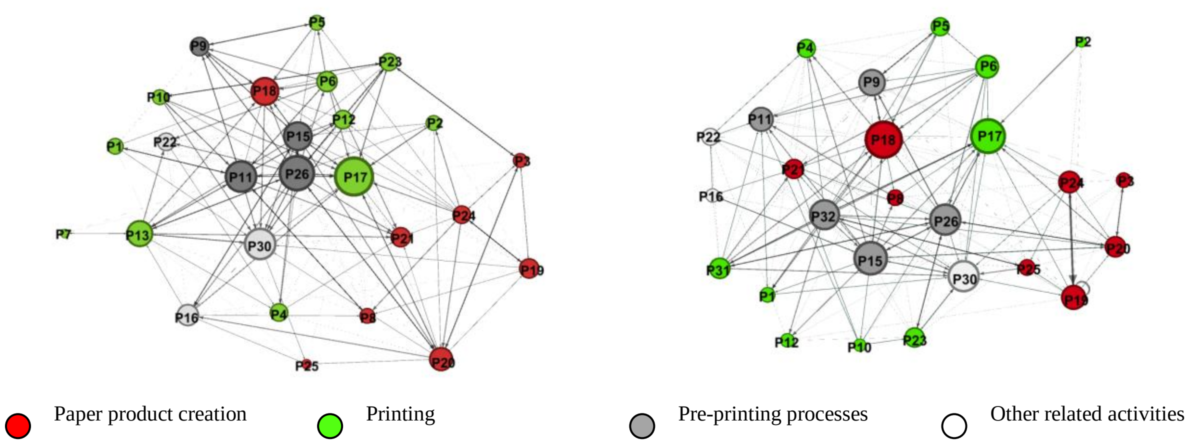
	2012	**2015**
Nodes	26	26
Ties	223	180
Density	0,295	0,238
Average degree	7,964	6,429
Tie created	-	70
Tie maintained	-	110
Tie dissolved	-	113
Isolates	0	0

Source: own construction

Even the visual representation of the knowledge networks (Figure 1) suggests that the knowledge network of the cluster is declining. However, in both cases the network is hyerarchical 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). The descriptive statistics of the network emphasized that the case of the printing and paper product cluster of Kecskemét is special in a sense that the network is not growing or sustaining like in previous similar studies (Giuliani 2013, Balland et al. 2016), but rather shrinking. This makes our main question more interesting on what are the driving forces behind the network evolution. What characteristics are still important in a situation when the cluster knowledge network is declining?

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

2012 2015



Source: own construction

In order to test our hypotheses and capture the driving forces behind network change, we applied SAOM in RSiena. All parameter estimations are based on 2000 simulation runs. The convergence of the approximation algorithm is good for all the variables in the different models (all the t-ratios are smaller than 0.1) and there was no problem with multicollinearity. Estimations can be interpreted straightforward as they are non-standardized coefficients come by 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 a simple t-statistics following normal distribution. Therefore, estimate coefficients are 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). The results of parameter estimations of SAOM applied for the knowledge network are presented in Table 3.

Table 3 Dynamics of the knowledge network evolution

	Estimates	SD	t-value
Embeddedness			
Triadic closure	0.126**	(0.061)	2.083
Cyclicity	– 0.132**	(0.066)	– 1.985
Network status			
Indegree - popularity (sqrt)	0.344**	(0.163)	2.102
Outdegree - activity (sqrt)	0.058	(0.143)	0.403
Proximity			
Cognitive proximity	0.097**	(0.045)	2.155
Geographical proximity	– 0.018	(0.037)	– 0.492
External linkages			
External ties	0.081***	(0.029)	2.759
Control variables			
Ownership	– 0.015	(0.246)	– 0.062
Age (experience)	– 0.021	(0.013)	– 1.633
Employment	– 0.000	(0.001)	– 0.285
Density	– 2.525***	(0.787)	– 3.207
Reciprocity	0.678***	(0.219)	3.100
Rate parameter	11.869	(1.240)	.

Note: Results of the stochastic approximation. Estimated parameters based on 4060 iterations. The convergence of the models was good in all cases, all the t-ratios were smaller than 0.064 (<0.1). The coefficients are significant at the * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$ level.
Source: own construction

Our first hypothesis refers to embeddedness as an influential effect on knowledge tie formation. As shown in Table 3, the coefficient of triadic closure is positive and significant. This means that even if the number of ties decrease, actors willing to ask their partners's partners for technical advice. This is consistent with the literature on clusters that describes them as dense, cohesive networks. This finding confirms H1, as structural embeddedness is a strong driver of knowledge networks behind clusters, even if a network diminishes.

Our second hypothesis concerns about the effect of preferential attachment on local knowledge network dynamics. The coefficient for network status (measured by indegree) is positive and significant. This suggests, that despite the overall network is getting smaller, those actors who receive more requests for technological advice tend to attract even more new requests in the following period. This suggests that professional reputation is important for knowledge seeking. This result confirms H2.

The third and fourth hypotheses concern about the role of proximities – as geographical (H3) and cognitive proximity (H4) – on cluster knowledge network evolution. In our case, the dynamics of the knowledge network seem to be driven by cognitive proximity, as its coefficient is positive and significant. However, micro-level geography does not affect new tie creation in our case. Our finding on the role of cognitive proximity is in line with previous studies, however, the role of geographical proximity seems to be contradictional (Balland et al. 2016).

Our fifth hypothesis is about how the number of external knowledge linkages influence the tie formation of firms in cluster knowledge networks. The coefficient for external knowledge ties are positive and highly significant, which means that firms who can reach more external sources of knowledge forms more local knowledge ties over time. This could mean that in cases when the local knowledge network diminishes, firms in the cluster try to avoid the technological lock-in and renew or strengthen their knowledge base by incorporate more new knowledge.

As for our control variables, 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 its stability over time. The positive and relatively high value suggests that there were significant changes in the formation of new ties, while the negative and highly significant coefficient of density indicates that firms tend not to establish knowledge linkages with just any other firm in the cluster (Snijders et al. 2007, Ripley et al. 2015). The negative and significant effect of cyclicity indicates, that there are a certain hierarchy in triads, but knowledge is not just circulates, rather there is a dominant actor who provides knowledge to the other two. Reciprocity came out to be positive and highly significant, which confirms in our case too, that knowledge is sensitive to stable, mutual ties between actors (Giuliani 2013, Balland et al. 2016). Additionally, we controlled for out-degree activity, which came out not significant at all. It means that the excessive activity of firms does not shaping the knowledge network. This is confirmed by our interviews with the local firms who unfold that because of the more and more intensive local competition, they became less opened for knowledge sharing and tend to ask less advice from local competitors. We also included control variables for firms ownership, age and employment, none of which turned out to be significant.

6. Conclusion and discussion

In this study we examined the driving forces behind the local knowledge network of the printing and paper product cluster of Kecskemét, Hungary. Our empirical setting was special in two ways. Firstly, the number of knowledge linkages behind the cluster drastically decreased by time. Secondly, this was the first dynamic network analysis related to a cluster in transition economic environment, where trust based relationships and the attitude to cooperate considered to be different. However, we found that in line with the literature, embeddedness of firms is very important for the evolution of the cluster knowledge network. Against other studies where network status did not significantly influence the change of knowledge exchanges, in our case, it was very influential on network evolution. The reason behind it could relate to the transition economy setting as firms have a higher willingness to cooperate with firms who are asked for technical advice by many and therefore they are proved to be reliable. Due to the complexity of technical knowledge, cognitive proximity seems to be crucial for its exchange in our case too. As external linkages of firms seems to influence the local knowledge tie creation of firms, it suggests that firms who are the ’gatekeepers’ of new knowledge are more attractive for cooperation.

The effect of preferential attachment mechanism on network formation suggest the concentration of knowledge in few firms, as suggested in recent studies on knowledge networks behind clusters (Giuliani 2007, Giuliani 2013). We argue that a successful cluster should concentrate on the firms who are in the centre of the knowledge network, who have the most influence on knowledge tie formation and therefore on knowledge flow. The understand of the main driving forces of knowledge network evolution helps to appreciate the different roles in the cluster and to create better and more customized strategies for the development of local industry clusters.

This paper has some important limitations, which provide opportunities for further research, but also suggest careful interpretation for findings. Even though there are more and more empirical studies on knowledge network evolution behind clusters, further empirical investigations are needed for comparison. Our study is based only a single case, what makes generalization not possible. Additionally, the examined knowledge ties are assumed to be equal in a sense, that we do not have an understanding on the value of the transferred knowledge. Furthermore, the incorporation of change in individual characteristics could result a more complex understand on whether structural or individual effects are more important for knowledge network evolution behind clusters.

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