Hetesi E. – Vas Zs. (eds) 2015: *New Ideas in a Changing World of Business Management and Marketing*. University of Szeged, Doctoral School in Economics, Szeged, pp. 46-56.

4. Network Revolution in Economic Geography

Sándor Juhász – Zoltán Elekes – János Gyurkovics

A relatively recent development in the field of economic geography, interested in the uneven spatial distribution of economic activities, is the less metaphoric and more formal involvement of network analysis tools in empirical strategies. Furthermore, with the diffusion of innovation systems thinking, and the emerging empirics of evolutionary economic geography, increasing attention is paid to the dynamism of spatial systems and networks. In this paper we review the theoretical background and recent empirical evidence on research topics of economic geography where network analysis and a dynamic perspective were adopted. These topics are (1) local knowledge networks behind clusters and (2) industrial dynamics of regional economies. Overall it is argued that the incorporation of a dynamic network approach in economic geography seems to be a promising line of research for the future.

Keywords: network analysis, economic geography, local knowledge network, evolution

1. Introduction

Economic geography is interested in the uneven spatial distribution of economic activities. The broad field of economic geography has been going through a relational turn lately: it pays even more attention to connections than previously. The use of networks for explanation purposes is not unprecedented in the literature on economic geography, but these researches have used networks in a rather symbolic and metaphorical way. Recently, due to the improvement of methodological and technical tools, both network thinking in conceptual frameworks, and the use of network analysis as a research method are gaining in popularity. Additionally, with the appearance of evolutionary thinking in economic geography, increasing attention is paid to the change in economic systems over time. Dynamic network analysis proves to be highly relevant for this kind of research.

Network analysis in economic geography shed light on the internal dynamics of clusters. It helped understanding the structure of networks behind them, identifying their most influential actors and also following their structural change over time. The growing literature on localised knowledge networks mainly deals with the flow of innovation related knowledge in connection with local learning processes, knowledge spillovers, industrial atmosphere and regional embeddedness. Network analysis opened up new ways to conceptual and empirical research on regional development as well. The diversification of regional economic activities,

often portrayed as a branching process relies on network methodology in identifying technological relatedness of firms and industries.

In this paper we review the literature on the diverse use of network methodology in the dynamic analysis of economic geography. We selected core publications for review based on them dealing with some aspect of economic geography, using network analysis as a research method, and focusing on the change of a network over time. Our paper is structured as follows. In the next section we outline the origin and contemporary significance of networks and network analysis in economic geography. In the third and fourth sections we present three key lines of research relying on network analysis: clusters, localised knowledge networks and regional economic evolution respectively. We end the paper with some concluding remarks.

2. Networks in economic geography

Researches using networks as methodological tools have been very common in natural sciences such as physics or biology for a long time. However since the middle of the 20th century networks as explanatory factors have become particularly popular in social sciences as well. As many social scientific discipline started to use networks (e.g. anthropology, sociology, economics), social network theory advanced in several fronts. Special notions were developed (homophily, preferential attachment) and mathematical methods (matrix algebra or graph theory) were integrated to this evolving field.

By the end of 1900s the network phenomenon has broken into the field of economics as well. This particular interest in networks was part of a general shift in thinking: the individualistic and atomistic approach was replaced by a more systemic and complex view which take into consideration the context of the objects of analysis and their relations (Borgatti – Foster 2003). The appearance and widespread acceptance of evolutionary economics could be one of the best examples in connection with this shift. Furthermore, the innovation system approach that builds on evolutionary theory is also a good example since it deals with innovation as an interactive process where – besides the actors – the relations, connections are equally important (Vas – Bajmócy 2012). We also have to mention Granovetter's work regarding embeddedness. He argues that every process, every economic action is necessarily embedded in their societal, cultural and institutional environment (Granovetter 1986). Therefore these processes always affected by social relations and interactions and they could be understood better if we study them in their context.

Notwithstanding the network theory have been flourishing in organisational researches (Borgatti – Foster 2003, Csizmadia – Grosz 2011) recently it has gained serious attention in economic geography as well (Ter Wal – Boschma 2009). One of the possible antecedents of this debate is the theory of 'space of flows' by Manuel Castells (1996). He discusses whether places or relations, networks are more relevant for the competitiveness of firms. According to his study the notion of 'space of places' refers to that being in the right place matters for learning and innovation while 'space of flows' focuses on relations that is, being part of a network is what matters truly (Ter Wal – Boschma 2009, Castells 1996).

Initially the use of networks in economic geography to explain phenomenon such as regional development, knowledge flows, clusters or industrial change was rather symbolic and neglected any theoretical or methodological underpinnings (Glücker 2007). However as a 'relational turn' has occurred in economic geography network analysis method has become an integrant part of these types of researches. All in all economic geographers started to pay more attention to relations than spatial dimension and started to apply network analysis methods to study inter-organisational interactions and knowledge flows (Ter Wal – Boschma 2009). Thus, network analysis has gone beyond visualization and become an appropriate analytical tool with many proven models and methodologies.

Most of the studies in economic geography that use network analysis as a new method deal with clusters. This is because it was perceived that firms geographically close to each other develop and maintain extensive local networks which affect their economic performance in a positive way. This assumption was implicitly connected to the unrestricted flow of specialised knowledge inside the industry as proposed by Marshall. However as Giuliani (2007) and many others showed it later, these networks are unevenly distributed among firms. Moreover, these (knowledge) networks are rather selective, thus many firms that are involved in the business network are excluded from the knowledge network of the same cluster. In addition firms located in a significant geographical distance may also be part of the cluster's knowledge network. This is because (knowledge) networks are social and not territorial constructs (Ter Wal – Boschma 2009).

However most of these studies have adopted a static analytical perspective, meaning they capture the whole network at a certain point in time. Basically, they provide us a snapshot of the network. These researches mostly focus on computing certain network indicators and compare these indicators to the performance of firms or the whole network, or to identify unique positions in the structure. Nevertheless none of these studies have been interested in how these networks come into existence or how they change over time? More

specifically what drives the formation of networks? How ties are created or dissolved? Thus, a dynamic network approach in economic geography is a rather overlooked field, but it might provide a better understanding for many of its research areas such as the geography of innovation, knowledge flows or industrial evolution.

Dynamic network approach always studies the whole network structure with an analytical focus on dyadic tie formation. On one hand it looks for the changes that a new tie induces or dissolution of an old one causes in the whole network structure. On the other hand it investigates the impact that the structure has on the formation (or dissolution) of the next tie (Glücker 2007). One of the key concepts in the dynamics of networks is preferential attachment (Balland et al. 2013a, Ter Wal – Boschma 2009). This notion explains the growth of networks by arguing that it is more likely that a new node will link to the most central node of the network than to other nodes (Barabási – Albert 1999). In other words a node which has many links to other nodes is more attractive to be connected with (Balland et al. 2013a). This also implies that central nodes become more central while peripheral nodes tend to remain peripheral (Ter Wal – Boschma 2009). However the process of preferential attachment has been often criticized for not providing a sufficient answer for the early phases of network evolution when dominant nodes hardly exist.

Another possible force that might drive network formation could be homophily which is originated from sociology. According to network practitioners homophily refers to tie formation based on similarity between nodes. So nodes will connect not necessarily with the most central node, but with the most similar one in some sense (Ter Wal – Boschma 2009). This similarity could be geographical one (geographical proximity) or any other in connection with the nodes' attributes. In economic geography the term proximity is used to explain this notion (Balland et al. 2013a). Based on the results of the French proximity school Boschma (2005) proposed five proximity dimensions: cognitive proximity that enables communication of actors, organizational proximity means similar structures of decision making, institutional proximity means following a similar set of rules, social proximity means being embedded in similar social context and geographical proximity means co-location. And these concepts are more suitable to explain network formation in economic geography (Boschma – Frenken 2010, Boschma et al. 2014a, Balland et al. 2014b). Thus it could be said that partnering is more probable if the actors speak the same language, share the same knowledge and norms or reside in close proximity to each other since these factors could reduce the risk and the cost of collaboration.

Besides preferential attachment and homophily, triadic closure or transitivity as proposed by Balland et al. (2013a) could be a third mechanism that has an influence on network formation. In a very simple way triadic closure means that partners of partners become partners (Ter Wal – Boschma 2009). Meaning two unconnected nodes that are both connected to a common third node are more likely to become partners.

3. Local knowledge networks behind clusters

What is common in networks is that they display inequalities and they have geography (Maggioni – Uberti 2011). These two characteristics brought the attention of economic geographers to use the methods of network analysis in order to answer primal questions of the field, such as what is behind the spatial concentration of economic activities, firms or innovation. Marshall (1920) introduced the benefits of geographical concentration of firms in specialised industries (here clusters) as positive external economies originating from access to resources, specialised labour pool, favourable industrial atmosphere and knowledge spillovers. In relation to industrial atmosphere, it is often associated that firms operating in clusters are likely to generate a socio-economic environment characterised by dense inter-firm networks. The emergence of successful clusters became increasingly associated with the presence of localised networks that besides helping to lower transaction costs and favouring the diffusion of knowledge also enhances the likelihood of innovation (Iammarino – McCann 2006).

With the help of network analysis it is possible to get a picture about industrial atmosphere and also to catch out knowledge spillovers. In this respect knowledge networks are particular important to capture. Knowledge network could be defined as the network that links firms through the transfer of innovation-related knowledge (Giuliani 2010). Numerous studies have been done in relation to clusters and knowledge networks behind them, focused on the determinants and influential factors of knowledge transfer, learning processes and innovation performance.

Giuliani and Bell (2005) questioned the micro-level determinants of learning and innovation, in a relatively early study using network analysis. They argued that knowledge is not diffused evenly ‘in the air’, but flows within a core group of firms. Social network analysis was applied to explore the overall structure of knowledge network of a wine cluster in Chile and identify different cognitive roles played by cluster firms. Their study focused on absorptive capacity of firms in the cluster defined as their ability to access and absorb external

knowledge. Their final results underpin that knowledge flows within a closed group of firms characterised by advanced absorptive capacity. These technological gatekeepers – as they call them – are firms that have a central position in the knowledge network in terms of knowledge transfer to other local firms (Giuliani – Bell 2005). Boschma and Ter Wal (2007) also highlighted that co-location is not enough in itself for cluster success, rather connectedness may function as key vehicle of knowledge transfer and knowledge diffusion. While studying the footwear cluster of South Italy they also had very interesting findings as strong local knowledge network position of firms impacted positively their innovative performance (Boschma – Ter Wal 2007). Giuliani (2007) also examined the differences existing between the structural properties of knowledge networks and business networks. The findings were that knowledge networks are more selective, less dense and highly uneven compared to business networks. The knowledge-rich linkages increase the likelihood of firms being good performers. The content of the network ties are very important for the economic performance of firms and not networking per se that enhances performance of clusters, but the existence of valuable, knowledge-rich linkages (Giuliani 2010). It indicates that the structure of knowledge-rich networks may affect the quality of regional economic development.

These studies have promising results in relation to central questions of economic geography. Due to the spread of network analysis as a methodology we could better understand what is behind cluster success, local embeddedness, knowledge flow between actors or knowledge spillovers in industrial districts. There are already plenty of studies using network analysis, but most of these applied only a static analytical perspective. Only a few empirical works deal with questions like how these networks change over time or what drives the formation of them. The appearance of dynamic network analysis in economic geography has provided a new tool to answer questions related to the evolution of clusters, knowledge networks or even industries (Maggioni – Uberti 2011, Broekel et al. 2014).

An early work by Giuliani (2013) shows the micro level dynamics underpinning the formation of new knowledge ties among wineries in the wine cluster of Chile. In her analysis she used longitudinal data based on repeated questionnaires in two distant periods of time and the method of stochastic actor-oriented models. She explained structural change and stability of networks by the cohesion effects of reciprocity and transitive closure (or triadic closure). Reciprocity emerges when a firm that has been the recipient of knowledge related advice from another firm, returns (reciprocates) the favour. These two effects increase network cohesion, encourage network growth and capture embeddedness (Giuliani 2013). Main conclusions are that knowledge networks show structural stability over time, but are quite dynamic at the

micro level. Cohesion effects turned out to be key drivers of the formation of many new knowledge ties. This is in line with the literature of regional clusters that describes them as contexts of dense, cohesive and strongly embedded networks.

Balland et al. (2014a) analysed the influence of embeddedness, status and proximity on the evolution of technical (knowledge) and business networks in a toy cluster in Spain. They used primary, retrospective data collection strategy (as requested participants to report information in 2005 and 2010) and the stochastic actor-oriented models to capture the driving forces behind the evolution of knowledge and business networks. Their essential findings are that both network and industrial status drive significantly the formation of business networks. Geographic proximity and cognitive proximity (corresponding to the number of digits two companies share in common in their NACE 4 codes) are significantly important for technical (knowledge) networks. Both structural embeddedness (referred to triadic closure) and social embeddedness (direct observation of social ties) are strong drivers of both the knowledge and business network evolutions.

4. Industrial dynamics and network evolution

The research program of evolutionary economic geography formed around empirical findings of different units of analysis. This line of research is interested in the ways in which the economic landscape is transformed over time (Boschma – Martin 2007). Micro level research focuses on the firm and its routines that are historically formed behavioural patterns of firms that are relatively persistent over time. Meso-level research is concentrated on economic sectors (population of firms) and on networks (relations of firms). Finally, on the macro level the spatial system itself becomes the unit of analysis (Boschma –Frenken 2006). Empirical applications of network analysis appeared in the research program mainly on the meso- and macro-level. On the one hand, the dynamics of industrial change has been linked to the relatedness of firms and industries, which can be viewed as a tie between them. On the other hand, different types of proximity are being combined with dynamic network analysis methodology to track the evolution of heterogeneous nodes, ties and the network structure itself. While some systemic evidence has been gathered in the first case, the second case is still in its formative state. In this section we review empirical research first on industrial dynamics, then on geographically bound economic network evolution.

In the research on industrial dynamics, the main questions are how the relatively stable variety of economic activities, entities and products are affecting the entry and exit decisions

of firms on the short run, and how does variety itself changes due to the entry and exit of firms on a longer time scale. However, as Frenken et al. (2007) argued, it is not variety or specialization of regions *per se* is what matters, but the amount of related variety present. Economic actors, activities or products can be considered related if they are not too close and not too distant in terms of cognitive (technological) proximity, *i.e.* effective communication (learning) can occur between them (Boschma 2005). On a shorter time scale of 4 to 5 years, related variety can be considered relatively stable due to the path-dependent nature of technological change. Empirical evidence shows that the probability of entry increased when firms, technological or scientific knowledge or products were more related to the technological portfolio of regions. The probability of exit was decreased with relatedness to this portfolio. This general pattern was shown for country level export of products (Hidalgo et al. 2007), for the entry and exit of industries in Swedish and Spanish regions (Neffke et al. 2011, Boschma et al. 2012), the appearance of technological classes of patents in U.S. cities (Boschma et al. 2015) and the entry and exit of scientific knowledge (Boschma et al. 2014b).

On a longer timescale related variety itself becomes the dependent variable. As demonstrated by Neffke et al. (2011), a relatively stable amount of related variety concealed significant structural change in the form of a high frequency of entry and exit in the Swedish case. Essletzbichler (2013) also found for the case of U.S. metropolitan areas that technological cohesion was relatively stable with a large amount of turmoil underneath. Following the country level argument of Hidalgo et al. (2007), Frenken and Boschma (2007), Frenken (2009), Boschma and Frenken (2011a) and Boschma and Frenken (2011b) argue that the diversification of the regional economies follows the patterns of technological relatedness, *i.e.* regions diversify into related activities.

Long term evolution of regions based on industry dynamics, network methodology plays a part in the measurement of technological relatedness. While earlier attempts to capture relatedness utilized standard industrial classification of economic activities (*e.g.* Frenken et al. 2007), this method was criticised because it *ex ante* assumes the technological proximity of industries belonging to the same two-digit NACE classification (Neffke – Henning 2008). More advanced approaches rely on the co-occurrence of products (e.g. Neffke et al. 2011) and inter industry labor flows (*e.g.* Boschma et al. 2009) in the ex post establishment of relatedness.

Regarding network dynamics, the main question is how the heterogeneity of nodes, the different dyadic relations and the network structure itself interact and change over time. This sort of research makes use of the newly emerging dynamic network analysis methodology (for

an extensive review see Broekel et al. 2014). Concepts of the aforementioned French proximity school proved useful in this research. Empirical research so far has been focused on specific industries. In the case of the global navigation satellite system industry Vicente et al. (2011), Balland (2012) and Balland et al. (2013b) showed that geographical, organizational and institutional proximity had a positive effect on propensity to collaborate, while the effect of social and cognitive proximity was not significant. In the case of the global video game industry Balland et al. (2013a) found that the role of (1) network endogeneity, stressing the path-dependent nature of change, (2) different forms of proximity, and (3) heterogeneity of firms was significant along the industry life cycle. While the direction of these effects remained the same, their weights changed over the course of the life-cycle. While some case study findings have already been gathered, to our knowledge no systemic evidence has been collected on the dynamic of networks in economic geography. This is partly due to the relative novelty of the methodology involved and partly due to the extreme demand of the method in terms of relational panel data.

5. Conclusions

We have discussed the presence and significance of network analysis in economic geography and emphasized the notability of dynamic network approaches in the field. After the general review of network analysis as a method and its expectations for economic geography, we focused on the growing literature of local knowledge networks behind clusters, industrial dynamics and network evolution in particular. We overviewed some of the most important empirical findings based on network analysis and argued that the incorporation of a dynamic network approach in economic geography seems to be a promising new line of research for the future.

For future research implications, dynamic network analysis could have great potential in many aspects. It could help understanding the role of different local networks in regional development. Since local development is determined by hub positions in key knowledge networks (Broekel et al. 2014), analysing endogenous regional development from a knowledge network perspective seems to be a major challenge for future research. In the context of industrial change, along timeframes of more than 15-20 years, the technological proximity of industries itself can change, which process should be incorporated in future research. A more pronounced use of network analysis tools could also benefit this line of

research. Inclusion of network properties – like centrality or modularity – on their own right into regression models explaining regional economic performance is still underutilized.

References

Balland, P.-A. (2012): Proximity and the Evolution of Collaboration Networks: Evidence from Research and Development Projects within the Global Navigation Satellite System (GNSS) Industry. *Regional Studies*, 46, 6, pp. 741–756.

Balland, P. A. – Belso-Martínez, J. A. – Morrison, A. (2014a): The Dynamics of Technical and Business Networks in Industrial Clusters: Embeddedness, status or proximity? *Papers in Evolutionary Economic Geography*, 1412, Utrecht University, Utrecht.

Balland, P.-A. – Boschma, R. – Frenken, K. (2014b): Proximity and Innovation: From Statics to Dynamics. *Regional Studies*, DOI: 10.1080/00343404.2014.883598

Balland, P.-A. – De Vaan, M. – Boschma, R. (2013a): 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, 5, pp. 741–765.

Balland, P.-A. – Suire, R. – Vicente, J. (2013b): Structural and geographical patterns of knowledge networks in emerging technological standards: evidence from the European GNSS industry. *Economics of Innovation and New Technology*, 22, 1, pp. 47–72.

Barabási A.-L. – Albert R. (1999): Emergence of scaling in random networks. *Science*, 286, pp. 509–512.

Borgatti, S. P. – Foster, P. C. (2003): The Network Paradigm in Organizational Research: A Review and Typology. *Journal of Management*, 29, 6, pp. 991–1013.

Boschma, R. (2005): Proximity and Innovation: A Critical Assessment. *Regional Studies*, 39, 1, pp. 61–74.

Boschma, R. – Balland, P.-A. – De Vaan, M. (2014a): The formation of economic networks: a proximity approach. In Torre, A. – Wallet, F. (eds): *Regional Development And Proximity Relations*. Edward Elgar, Cheltenham – Northampton, pp. 243–266.

Boschma, R. – Balland, P.-A. – Kogler, D. F. (2015): Relatedness and Technological Change in Cities: The rise and fall of technological knowledge in U.S. metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, 24, 1, pp. 223-250.

Boschma, R. – Eriksson, R. – Lindgren, U. (2009): How does labour mobility affect the performance of plants? The importance of relatedness and geographical proximity. *Journal of Economic Geography*, 9, pp. 169–190.

Boschma, R. – Frenken, K. (2006): Why is economic geography not an evolutionary science? Towards an evolutionary economic geography. *Journal of Economic Geography*, 6, pp. 273–302.

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

Boschma, R. – Frenken, K. (2011a): Technological relatedness and regional branching. In Bathelt, H. – Feldman, M. P. – Kogler, D. F. (eds): *Beyond Territory. Dynamic Geographies of Knowledge Creation, Diffusion and Innovation*. Routledge, London – New York, pp. 64–81.

Boschma, R. – Frenken, K. (2011b): Technological relatedness, related variety and economic geography. In Cooke, P. – Asheim, B. – Boschma, R. – Martin, R. – Schwartz, D. – Tödtling, F. (eds): *Handbook of Regional Innovation and Growth*. Edward Elgar, Cheltenham – Northampton, pp. 187-196.

Boschma, R. – Heimericks, G. – Balland, P.-A. (2014b): Scientific knowledge dynamics and relatedness in biotech cities. *Research Policy*, 43, pp. 107–114.

Boschma, R. – Martin, R. (2007): Editorial: Constructing an evolutionary economic geography. *Journal of Economic Geography*, 7, pp. 537–548.

Boschma, R. – Minondo, A. – Navarro, M. (2012): The Emergence of New Industries at the Regional Level in Spain: A Proximity Approach Based on Product Relatedness. *Economic Geography*, 89, 1, pp. 29–51.

Boschma – Ter Wal (2007): Knowledge networks and innovative performance in an industrial district: the case of a footwear district in the South of Italy. *Industry and Innovation*, 14, 2, 177-199. pp.

Broekel, T. – Balland, P.-A. – Burger, M. – Van Oort, F. (2014): Modeling knowledge networks in economic geography: a discussion of four methods. *The Annals of Regional Science*, 53, pp. 423–452.

Castells, M. (1996): *The rise of the network society*. Blackwell, Oxford.

Csizmadia Z. – Grosz A. (2011): *Innováció és együttműködés. A kapcsolathálózatok innovációra gyakorolt hatása.* Magyar Tudományos Akadémia Regionális Kutatások Központja, Pécs – Győr.

Essletzbichler, J. (2013): Relatedness, Industrial Branching and Technological Cohesion in US Metropolitan Areas. *Regional Studies*, DOI: 10.1080/00343404.2013.806793

Frenken, K. (2009): Proximity, Social Capital and the Simon Model of Stochastic Growth. In Reggiani, A. – Nijkamp, P. (eds): *Complexity and Spatial Networks – In Search of Simplicity*. Springer-Verlag, Berlin – Heidelberg, pp. 133–140.

Frenken, K. – Boschma, R. (2007): A theoretical framework for evolutionary economic geography: industrial dynamics and urban growth as a branching process. *Journal of Economic Geography*, 7, pp. 635–649.

Frenken, K. – Van Oort, F. – Verburg, T. (2007): Related Variety, Unrelated Variety and Regional Economic Growth. *Regional Studies*, 41, 5, pp. 685–697.

Giuliani, E. (2007): The selective nature of knowledge networks in clusters: evidence from the wine industry. *Journal Economic Geography*, 7, 2, pp. 139-168.

Giuliani, E. (2010): Clusters, networks and economic development: an evolutionary economics perspective. In Boschma, R. – Martin, R. (szerk.): *The Handbook of Evolutionary Economic Geography*. Edward Elgar, Cheltenham-Northampton, pp. 261-279.

Giuliani, E. (2013): Network dynamics in regional clusters: Evidence from Chile. *Research Policy*, 42, 8, pp. 1406-1419.

Giuliani, E. – Bell, M. (2005): The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster. *Research Policy*, 34, 1, pp. 47–68.

Glücker, J. (2007): Economic geography and the evolution of networks. *Journal of Economic Geography*, 7, 5, pp. 619–634.

Granovetter, M. (1986): Economic Action and Social Structure: The Problem of Embeddedness. *American Journal of Sociology*, 91, 3, pp. 481–510.

Hidalgo, C. A. – Klinger, B. – Barabási A.-L. – Hausmann, R. (2007): The Product Space Conditions the Development of Nations. *Science*, 317, pp. 482–487.

Iammarino, S. – McCann, P. (2006): The structure and evolution of industrial clusters: Transactions, technology and knowledge spillovers. *Research Policy*, 35, 7, pp. 1018-1036.

Maggioni, M. A. – Uberti , T. E. (2011): Networks and geography in the economics of knowledge flows. *Quality & Quantity*, 45, 5, pp. 1031-1051.

Marshall, A. (1920): *Principles of Economics*. MacMillan, London.

Neffke, F. – Henning, M. (2008): Revealed Relatedness: Mapping Industry Space. *Papers in Evolutionary Economic Geography*, 0819, Utrecht University, Utrecht.

Neffke, F. – Henning, M. – Boschma, R. (2011): How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions. *Economic Geography*, 87, 3, pp. 237–265.

Ter Wal, A. L. J. – Boschma, R. (2009): Applying social network analysis in economic geography: framing some key analytic issues. *The Annals of Regional Science*, 43, 3, pp. 739–756.

Vas Zs. – Bajmócy Z. (2012): Az innovációs rendszerek 25 éve. Szakirodalmi áttekintés evolúciós közgazdaságtani megközelítésben. *Közgazdasági Szemle*, 59, 11, pp. 1233–1256.

Vicente, J. – Balland, P.-A. – Brossard, O. (2011): Getting into Networks and Clusters: Evidence from the Midi-Pyrenean Global Navigation Satellite Systems (GNSS) Collaboration Network. *Regional Studies*, 45, 8, pp. 1059–1078.