

Applying social network analysis in economic geography: framing some key analytic issues

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Abstract Social network analysis attracts increasing attention in economic geography. We claim social network analysis is a promising tool for empirically investigating the structure and evolution of inter-organizational interaction and knowledge flows within and across regions. However, the potential of the application of network methodology to regional issues is far from exhausted. The aim of our paper is twofold. The first objective is to shed light on the untapped potential of social network analysis techniques in economic geography: we set out some theoretical challenges concerning the static and dynamic analysis of networks in geography. Basically, we claim that network analysis has a huge potential to enrich the literature on clusters, regional innovation systems and knowledge spillovers. The second objective is to describe how these challenges can be met through the application of network analysis techniques, using primary (survey) and secondary (patent) data. We argue that the choice between these two types of data has strong implications for the type of research questions that can be dealt with in economic geography, such as the feasibility of dynamic network analysis.

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1 Introduction

Since the last decade, networks have gained a great deal of attention in regional economics and economic geography (Grabher and Ibert 2006). Only recently, social network analysis techniques have been applied in an effort to examine how the structure of interaction in regions and geographical clusters looks like. More and more researchers get convinced that networks are an appropriate conceptualization of inter-organizational interaction and knowledge flows. Hence, social network analysis is viewed upon as a promising tool for future directions in regional research. That is to say, now that it is possible to empirically assess the structure of networks, new possibilities have arisen to investigate inter-organizational interactions and their evolution over time in a more quantitative manner.

Virtually all existing empirical studies on networks in clusters (e.g. Morrison 2008; Giuliani and Bell 2005) take a static perspective, depicting the network at a certain point in time. The wider field of network theory, on the other hand, recently experienced an upsurge of interest in the dynamics of networks (e.g. Snijders 2001; Baum et al. 2003). In this dynamic network analysis, concepts like preferential attachment play a key role. However, the application of dynamic network theory to inter-organizational networks (e.g. Orsenigo et al. 1998; Gay and Dousset 2005) still lacks a geographical component (Glückler 2007). Hence, it is especially in the combination of both trends where important theoretical and empirical challenges remain. In this paper, we claim that economic geography could contribute greatly to combining both trends, when taking an evolutionary perspective to networks within and across regions.

The aim of our paper is twofold. The first objective is to shed light on the untapped potential of social network analysis techniques in economic geography. We aim to set out in Sect. 2 some theoretical challenges concerning the static and dynamic analysis of networks in regional research. Doing so, we claim that especially three types of literature in economic geography can potentially benefit from social network analysis: the cluster literature, the regional innovation system literature, and the literature on agglomeration economies and knowledge spillovers. The second objective of our paper is to describe how these challenges can be assessed through the application of social network analysis techniques, using primary (survey) and secondary (patent) data. We argue in Sect. 3 that the choice between these two types of data has strong implications for the type of research questions that can be dealt with in economic geography. Section 4 draws some conclusions.

2 Theoretical challenges: the role of networks in economic geography

Notwithstanding the growing number of regional studies applying social network analysis, the potential for the useful application of network theory and methodology is far from exhausted. Theoretical and empirical challenges remain, particularly in the application of network theory in three related fields of study in economic geography: inter-firm networks in clusters, regional innovation systems, and agglomeration

economies. How network theory can contribute to a better understanding of these concepts will be explained in this section.¹

A fundamental debate in economic geography concerns the question whether places are more relevant for the competitiveness of firms, or whether networks matter more (Castells 1996). While the concept of ‘space of places’ expresses the idea that the location matters for learning and innovation (being in the right place is what counts), the concept of ‘space of flows’ focuses more on the idea that networks are important vehicles of knowledge transfer and diffusion (meaning that being part of a network is crucial). Surprisingly, this debate has, however, not been a real issue in the cluster literature until quite recently.

In a nutshell, the cluster literature claimed that regions are drivers of innovation and economic development: firms in clusters benefit almost automatically from knowledge externalities that are ‘in the air’, as Marshall once put it. This is because tacit knowledge travels more easily across short distances, and shared institutions at the cluster level further facilitate the effective transfer of knowledge. This is not to say that the cluster literature overlooked the importance of networks. On the contrary, extensive local networks connecting specialised firms were considered a key feature of clusters that contributed to their economic success. The problem was, however, that the cluster literature suggested that the space of place and the space of flows showed a great deal of overlap (Boschma and Ter Wal 2007). Knowledge externalities were geographically localized because knowledge networks were assumed to be confined to the boundaries of the cluster: all cluster firms were connected with each other and engaged in interactive learning, and no significant extra-cluster linkages were likely to exist (Boschma and Lambooy 2002). Cluster borders were conceived to enclose knowledge networks, and collective learning processes were tied to the place of the cluster.

When applying network theory, some of these strong assumptions of the cluster literature may be seriously questioned. Network theory suggests it is unlikely that a knowledge network encompasses all cluster firms: it is a rule rather than an exception that networks will be unevenly distributed among firms (e.g. Giuliani 2007). In addition, (knowledge) networks are not territorial but social constructs that may cross the boundaries of regions. Knowledge diffuses through social networks which may be dense between local agents, but may also span across the world. Only recently, there is increasing awareness that extra-cluster linkages may be crucial for overcoming processes of lock-in in clusters (Asheim and Isaksen 2002). In addition, clusters have been analysed from a static perspective. A key question is how the configuration of a network in a cluster evolves over time, and what mechanisms might be held responsible for that. So, it is no wonder that clusters have become one of the key themes in economic geography in which network theory is applied. However, particularly in the application to regional issues, network research is still in its infancy. Currently, regional network research is involved in broadly three different sets of questions.

¹ We basically associate networks with inter-firm settings in which knowledge creation, knowledge diffusion and innovation take place. This implies we are not considering potential applications of network theory in other topics in economic geography, such as urban systems and infrastructure networks (Guimera and Amaral 2004).

The first set of questions concerns the structure of interaction in a cluster. What does the structure of a cluster-based network look like? And what are the determinants of this structure? In the last decade, a number of network studies in clusters has been carried out. [Giuliani and Bell \(2005\)](#) showed on the basis of network analysis that firms in a Chilean wine cluster differ largely in their centrality in the local network of knowledge diffusion, and that quite a number of firms acted completely isolated from this network. In addition, they found that some cluster firms were also extremely well connected to organizations beyond the cluster's boundaries. A study of [Morrison \(2008\)](#) identified the structure of knowledge-based interaction in the furniture district of Matera in Southern Italy. In particular, he showed that some large firms that were well-connected to organizations outside the district were acting as gatekeepers, passing the acquired external knowledge on through a network of local firms.

Further insight is needed in what explains the unequal distribution of network centrality across firms. Explanations can be found either at the micro-level of the firm or at the meso-level of the dyad (a pair of firms). At the micro level heterogeneity among firms in terms of their cognitive capabilities—a central feature of evolutionary economic theorising—might play a key role ([Gulati 1999](#)). For instance, [Gay and Dousset \(2005\)](#) found empirical evidence that firms with cutting-edge technology are usually positioned in the core of inter-firm collaboration networks. [Giuliani \(2007\)](#) argued that a firm's absorptive capacity is an important determinant of a firm's network position in a cluster. At the meso level various forms of proximity can be brought forward as a possible explanation to why links exist between some firms and not between others ([Boschma 2005](#)). Geographical proximity may affect the network structure: geographical distance may act as a barrier, and geography may also enhance other forms of proximity that enable firms to connect more easily. Social proximity may be a driver of network formation ([Granovetter 1973](#)): there is a higher probability that firms connect to individuals in other firms with whom they are socially connected ([Sorensen 2003](#)). Geography may still be relevant. A source of social connectedness between individuals is, for example, a shared working past. When an employee leaves a firm to work for another firm (labour mobility) or to start his own company (being a spin-off), social relationships are often maintained with their former colleagues, and these may induce the establishment of a knowledge network relationship between the firms involved. Since spin-off processes and labour mobility are mainly local phenomena, these are most likely to contribute to the formation of local networks.

Social network analysis has the potential to contribute further to the analysis of regional innovation systems ([Cooke 2001](#)). This literature claims that the innovation process is harmed when complementary organizations like research institutes, educational facilities and capital suppliers are not well developed and not well connected in a region. Conducting social network methodology, the concept of regional innovation system can be disentangled more systematically by mapping the network relations of these key agents with other agents within and outside the region. Doing so, key information is collected on how well these major organizations are connected, and at what spatial levels: do the key agents indeed form a system of innovation; which relationships are not well developed and, thus, form a bottleneck for the innovation process; and to what extent are these connections non-local and, thus, depend on non-local

organizations and connections? An additional challenge for a network approach is to determine how place-specific institutions affect the structure of the network.

The second set of questions concerns how networks change over time (see also [Ter Wal and Boschma 2008](#)). Virtually no studies on the dynamics of the structure of networks in space exist. It is hardly ever questioned whether the network structure that is observed in static network studies is stable over time, or just a snapshot view of a volatile and evolving structure. In the dynamics of networks, preferential attachment might play an important role ([Barabasi and Albert 1999](#)). The process of preferential attachment describes the growth of a network in which the probability that a new node will link to a certain other node is proportional to the number of links that node already has. An outcome of this probabilistic process is that central firms tend to become more central, whereas peripherally positioned firms tend to stay peripheral. Since some evidence suggests that inter-firm cooperation networks show a great deal of stability in terms of core-periphery structures ([Orsenigo et al. 1998](#)), preferential attachment processes might have played a role in driving the evolution of the network. An interesting hypothesis, which has hardly been thoroughly tested, then would be that early entrants in a new industry, with superior technological capabilities, are the ones that are most central in the network. A contrasting line of thought is that preferential attachment is unlikely to shape the formation of a new knowledge network during the early stages of the industry life cycle: networks may be rather volatile, because there is no dominant design in the industry, among other reasons. Another issue that questions the relevance of preferential attachment is that current network theory is mainly concerned with the formation and growth of networks: hardly any attention has been paid to the causes and consequences of changes in network size ([Glückler 2007](#)).

Beside preferential attachment there might be other structural forces at work that shape the evolution of inter-firm networks. Network theorists—and particularly those from the sociological tradition—argue that the partnering decision of actors in a network is often based on homophily ([Skvoretz 1991](#); [Powell et al. 2005](#)). That is to say, the choice of partner is biased towards actors that are ‘similar’. In the context of inter-firm networks one can easily imagine that firms that are similar in terms of geographical location—i.e. that are located in the same region—are more likely to get linked than firms further apart. Hence, network formation does not only leave an imprint on geography: geography itself also impacts on network evolution. In addition to preferential attachment, geographical proximity may be a key driver of network formation. In that case, new firms will connect not necessarily with the most central firms, but will connect to those that are close by in a geographical sense. This tendency to choose geographically proximate partners might be subject to change over time, being dependent, for instance, on the extent to which an industry’s knowledge base has been codified ([Cowan et al. 2004](#)). However, it has been hardly assessed empirically what implications the changing importance of geographical proximity has for the structure of knowledge networks over time.

Similarly the mechanism of homophily as a potential driver of partnering decisions can be applied to other forms of proximity, like social and cognitive proximity. Firms tend to select partners that are socially or cognitively similar. A third structural force in network evolution can be triadic closure. Closure describes tendency that partners of

partners become partners among themselves. In contrast to the mechanism preferential attachment a tendency towards closure produces dense cliques of strongly interconnected actors (Skvoretz 1991). In sum, no systematic research exists that has tested the effects of preferential attachment, homophily and closure on the spatial evolution of networks. It is still rather unclear what role firms' cognitive capabilities, geographical proximity and social connectedness play in the spatial formation of networks. There is no doubt social network methodology provides a rich toolbox for testing these key propositions (Carrington et al. 2005).

Consequently, further research is needed on how the structure of networks evolves over time and space and, particularly, how the evolution of networks is related to the evolution of clusters (Iammarino and McCann 2006; Ter Wal and Boschma 2008). It can be easily suggested that, for example, the importance of local versus non-local linkages for cluster development might change over time, for instance when during the course of the industry life cycle, knowledge shifts from being mainly tacit to more codified forms of knowledge (Cowan et al. 2004). Similarly, the structure of a network might change through entry and exit of firms, which might result in the creation or disappearance of a critical mass of firms engaged in local collective learning. Glückler (2007) suggested that the evolution of networks in industries or regions will be the outcome of an interplay between path-creating and path-disruptive forces. Whereas path-creating forces lead to the formation of dense components in a network—which in turn might lead to cognitive lock-in, path-disruptive forces enable a firm to escape such a situation by bridging itself to other components of a network (Burt 2004). However, these views need thorough empirical validation, in which social network analysis techniques might play a crucial role.

A third set of questions in network research focuses on the effects of a certain network structure. Here one could distinguish between the effects on its individual actors at the micro level and the effects on the population as a whole at the macro level. At the micro level, studies measure the effect of network position on firm performance. Uzzi (1996) found that a mixture of embedded trust-based ties and arm's length market-based ties was positively associated with firm survival. Similarly, Mitchell and Singh (1996) found that firms with inferior network positions were more likely to end their business. Later work in the field of organization studies confirmed a positive affect of network position on firm performance in terms of innovation. Whereas Ahuja (2000) found that both direct ties, indirect ties and structural holes matter for innovation, Zaheer and Bell (2005) demonstrated that particularly firms that bridge structural holes in a network tend to be better capable to exploit their internal capabilities and innovate. In one of the first regional studies on the network effect Giuliani (2007) proved for firms in local knowledge networks in wine clusters that centrality of firms in the network positively affected their innovative performance. However, large scale and convincing evidence on a positive or curvilinear (inverted U-shaped) relationship between network centrality and firm performance—as Uzzi (1996) suggested—has not been shown yet. Only a longitudinal view on networks will reveal the stability or volatility of the positions firms take in these networks and whether a relationship with firm performance or firm survival can be detected. To the best of our knowledge, such a hypothesis has not been tested yet. Supposing a strong and significant positive relationship between network position and firm survival exists,

the evolution of the network has implications for the evolution of an industry. In case firm exits are selective as to where they occur, the relationship between networks and survival directly affects the spatial pattern of an industry. Consequently, a synthesis between industrial dynamics and network evolution is a promising avenue for future research in economic geography.

At the macro level, the concept of cognitive lock-in comes into play. Dense parts of a network in a cluster, for instance, carry the risk of getting locked in established ways of thinking and a lack of new knowledge coming in. Social network analysis techniques could be applied for empirically testing this phenomenon, which, till today, has been mostly addressed in theoretical and more qualitative terms. Doing so, network analysis could enrich a body of literature in economic geography that analyses the relationship between agglomeration economies and economic growth (Ellison and Glaeser 1997). Basically, it investigates whether sectoral specialisation of a region is a good or a bad thing, and whether a more diversified regional economy generates more knowledge spillovers (i.e. Jacobs' externalities). Since this literature exclusively focuses on the regional level, it does not account for (inter-sectoral) linkages with other regions that may bring new variety in the region. Doing so, the agglomeration economies literature overlooks the fact that new knowledge may flow into the region through the establishment of extra-local linkages, such as a diversified set of linkages with non-local partners. As such, sectoral lock-in at the regional level may be counterbalanced by the inflow of a high variety of knowledge through inter-regional connections. In addition, it may matter what kind of knowledge flows into a region: when the extra-regional knowledge is related, but not similar to the existing knowledge base of the region, it might particularly enhance interactive learning and regional growth (Boschma and Iammarino 2007). Network analysis may be a promising tool here, because it accounts for those effects in these models.

In sum, we expect that the use of social network techniques will enrich the literature on clusters, regional innovation systems and knowledge spillovers both theoretically and empirically in the years to come. However, huge analytical challenges remain, both in the static and dynamic analysis of networks within and across regions. When using primary and secondary network data, strict conditions have to be met in order to be able to apply social network analysis effectively. The next section will address these conditions for both types of network data and explain which approach is most appropriate for which type of network research. Even then, we will argue that both types of network research have important pitfalls that need to be acknowledged when interpreting the results obtained from network analysis.

3 Methodological and empirical challenges in network analysis in economic geography

In the previous section, we argued that network analysis plays an increasing role in economic geography. This development, facilitated by the application of social network analysis in cluster research, has opened up new insights in how the structure of inter-firm interaction looks like and, more importantly, it has enabled empirical research on the antecedents and effects of the differential positions firms occupy in

such networks. However, the application of network theory—and hence of social network analysis techniques—is far from fully exploited. In this section, we explain how network methodology can contribute to a better empirical understanding of these applications. In Sect. 3.1, we discuss the roster-recall methodology, which is a prime example of primary data collection. Although we acknowledge there exist other ways of collecting network data, for instance through a snowball method, for the purpose of this paper we will exclusively concentrate on the roster-recall methodology. The main reason for doing so is that a snowball method will not identify isolates in the network. Hence it is considered inappropriate for network research in clusters, where isolates are likely to exist. In Sect. 3.2, we concentrate on a widely used source of secondary network data, that is, patent data. Other sources of secondary network data are also used and exploited in the literature, such as strategic alliance or joint-venture databases (Stuart 1998), co-publications (e.g. Ponds et al. 2007), European Framework Programmes (e.g. Maggioni 2002) and internet flows (e.g. Oinas and Malecki 2002). Due to a lack of space, these will not be considered in this paper. Both the roster-recall methodology and patent data will be discussed extensively in terms of their potential for applying network analysis in economic geography.

3.1 Primary data collection: roster-recall methodology

In a number of studies on networks in clusters (e.g. Morrison 2008; Giuliani and Bell 2005; Boschma and Ter Wal 2007), networks have been built on the basis of primary data collection. Data have been collected by means of interviews, in which the so-called ‘roster-recall methodology’ played a major role. This methodology aims to collect full network data—as opposed to ego network data—on a pre-defined population of actors. In this methodology, each of the actors of the population is provided with a list of actors of the population. Preferably this *roster* includes all actors of the population, since listing just a selection might cause a bias of those firms being pre-indicated more often as a partner. In many cases, however, only principal actors are pre-listed, the list of actors otherwise getting too extensive. For each of the pre-listed firms in the roster, the respondent firm has to indicate whether or not he had a relationship of a pre-defined type.

In addition, the respondents is asked to *recall* all other firms they had this type of relationship with and add them to the list. First, this ensures that the complete network will be identified as long as all population firms take part in the survey. Doing so, one compensates for the fact that not all local actors are pre-listed on the roster. Second, the ‘recall’ part of the methodology makes it possible for the respondents to add external linkages. Although the population under investigation is regionally (or sectorally) bounded, this does not imply that the actors do not have relevant relationships beyond the survey area. In other words, information on links beyond the survey area indicates the importance of region-external interaction in comparison with regional interaction. Therefore, it is necessary to put the identified regional network in a wider context. However, measures of network structure like density, cliques or measures of the individual position of actors (forms of centrality or structural holes) can be computed

only for the regional population of actors, for which complete network data have been gathered.

Primary network data research provides ample opportunities to empirically assess important issues for the study of regional networks. However, the methodology described is characterized by several strengths and weaknesses that make the procedure more appropriate for some kinds of network research than for others.

First, social network analysis on the basis of primary data certainly is the most statistically robust procedure when different kinds of relationships among the same set of actors need to be compared. Beside the fact that is virtually impossible to find a dataset that comprises two kinds of relationships across the same set of actors, with the roster-recall methodology, one can relatively easily ask for two different kinds of relationships contemporarily and hence generate two or more networks for the same population. For instance, [Giuliani \(2007\)](#) identified both a network of business relations and a network of knowledge-based relationships. She found that the first comprises virtually all local actors, whereas the latter is much more 'uneven and selective'. Similarly, it can be investigated to what extent different kinds of networks show overlap. For instance, one can analyse the extent to which a social network of technicians of different firms is related to a network of cooperation at the level of the respective firms.

Second, the roster-recall methodology offers the opportunity to ask for several characteristics for each of the links. One might think of the importance, the frequency or the amount of money involved in the interaction. These data may serve as an input for a valued graph, in which each of the links is provided with a strength. In this way, one can prevent, for instance, that a cooperation project that lasted for only a week gets the same impact in the computations as a collaboration that continued for five years. Alternatively, it is possible to decide ex-post to include only ties with an impact above a certain threshold. Databases of existing links (like strategic alliance databases) often do not contain further details on the links or the partners involved. Similarly, the survey-based nature of the methodology provides opportunities to gather additional information on the population that might otherwise be unknown. For instance, such information is crucial when investigating why some links exist whereas others are absent—the so-called determinants of matching in a network (see e.g. [Cantner and Meder 2006](#)), or when explaining why firms turn out to be more central than others.

However, network research on the basis of primary data suffers from a number of shortcomings as well. First of all, a research on the basis of the roster-recall methodology will only be successful in case of a very high response rate. Social network analysis presupposes that complete network data are available. That is to say, all measures assume that *all* relationships for *all* actors of the population are included in the network. It is easy to imagine that the structure of the identified network will look rather different when one of the most central actors in the network did not collaborate with the survey. However, part of the non-response might be compensated by the fact that, ideally, each link should be mentioned twice, by each of the two partners. In case this reciprocation occurs for (most of) the response part of the survey, one can still assume that the links of the non-respondents are identified when mentioned by their partners. On that condition, a response rate slightly below the maximum might still be sufficient to ensure the network data are complete. If this condition cannot be satisfied, one is forced to rely on ego-network data. These data only take the direct

links of an actor (and the links between his direct associates) into account. On the one hand, this reduces the potential of social network analysis in terms of the centrality measures that can be used; the value of social network analysis precisely resides in the possibility to reveal the complete structure of a network and the position of actors in a wider structure. On the other hand, for large-scale surveys ego-network data will be a good alternative. Development of new software for the analysis of ego networks, like the E-Net program (Borgatti et al. 2002), will further stimulate the application of ego-network data in economic geography.

A second and related shortcoming is the time-intensive nature of the methodology. In order to ensure a high response rate, a postal survey usually is no option. In most cases, it will be rather complicated to use the roster-recall methodology by means of a telephonic survey, during which firms might not be willing to provide confidential information like the names of their cooperation partners. The best results are likely to be obtained through interviews. Due to the time-consuming character of interviews, such a survey method highly limits the size of the population that can be investigated. As a consequence, network analysis on the basis of primary data is most appropriate for small clusters of firms or relatively small sectors within a region. Then, it needs to be acknowledged again that the relevance of such a local network exercise depends on the importance of local linkages in comparison to cluster-external linkages. Decreasing the size of population under investigation will likely increase the relative share of relationships to actors beyond the population.

Third, there might be other reasons than non-response that make it questionable whether the identified network is a valid representation of the complete network. Which type of relationship a respondent will mention is dependent on the exact formulation of the type of relationship. Hence, asking for concrete relationships like ‘who do you go to for technical advice?’ (Giuliani and Bell 2005) or ‘with whom do you commonly develop new products?’ are to be preferred above questions of the type of ‘who do you cooperate with?’ or ‘who do you exchange knowledge with?’. But even when precisely formulated, respondents might not come up with a complete list of links, simply because they are not able to remember all relationships they had in the period under investigation. This might be particularly problematic when the ‘recall’ part of the methodology is relatively large in comparison with the ‘roster’ part. In addition, in case of large organizations, the respondent might not even be aware of all relationships a firm has had. Thus the proper identification of the network depends to some extent on who you speak with within the firm.

The fourth and final drawback we bring forward here concerns the static nature of the networks one can identify. Although, it is possible to collect longitudinal network data by organizing a survey at multiple points in time, to the best of our knowledge such studies hardly exist (Van der Valk 2007). Furthermore, it is simply unfeasible and unrealistic to ask respondents about their relationships in the (remote) past. Consequently, it is difficult to use primary network data for analysing how the network structure or the network position of actors have changed over time, while from an evolutionary point of view, the dynamics of a network constitute a crucial object of study. An alternative for primary data collection in network research is the use of patents as relational, secondary-data. How networks can be generated from patent

data as well as the strengths and weaknesses of the methodology will be discussed in the next section.

3.2 Secondary data collection: patents as a source of network data

Notwithstanding its limitations, network research in economic geography on the basis of primary data has become a considerable research field. Another trend is the application of patent data as relational data. [Jaffe et al. \(1993\)](#) used patent citations to trace knowledge spillovers and examine their geographical reach. In response to their work, [Breschi and Lissoni \(2003\)](#) argued that it is not geographical proximity itself that causes knowledge spillovers to be localised. Instead, it is the underlying social networks of inventors and the mobility of inventors across firms that tend to be geographically localized and in turn cause knowledge spillovers to have a limited geographical reach. In providing empirical evidence, they were among the first to use patent data as relational data (see also [Breschi and Lissoni 2004](#)), provoking a trend in research on inventor networks ([Balconi et al. 2004](#); [Cantner and Graf 2006](#); [Ejermo and Karlsson 2006](#)). We build on their inventor-oriented approach to discuss the methodology that reconstructs networks on the basis of secondary data.

Patents contain a rich bulk of information that has scientific applications in various fields, ranging from scientometrics and technology studies to business administration and regional economics. Besides a detailed description of the patented product and many of its technological details, patent records provide information about the actor possessing the patents, the people that have been involved into its realization, as well as several citations to previous patents or scientific work. Furthermore, a patent record exhibits information on the technology class by means of an IPC-code (International Patent Classification) and on the year the patent was applied for and has been granted. Generally, the application year is used in order to date the patent. It might take some years before the granting procedure has been completed. Moreover, the application date is closer to the date of innovation.

For the purpose of building a network on the basis of patent data, particularly the information about the patent applicant and the inventors is valuable. Patent applicants or patent holders are the actors that legally possess the patent. These can be either firms, research institutes or private persons, although the vast majority of patents is held by private companies. Inventors are the people that have been involved in the development of the patented product. Both for the patent applicant and for its inventors, name and address details are provided.

This information is necessary for selecting the patents belonging to the region under investigation. Generally, the inventor's home address is used to determine to which region a patent should be allocated and whether or not a patent should be included in a regional network analysis. The underlying reason for taking the inventor address as the selection criterion for localizing patents, is that patents of multi-establishment companies are generally assigned to the company's headquarter. Therefore, patents realized in the firms' R&D subsidiaries will exhibit the headquarter address as the applicant's address, whereas most of its inventors will be resident in the subsidiaries' region ([Verspagen and Duysters 2004](#)).

Patents differ strongly in terms of their monetary value. According to a survey among 10,000 inventors in 6 European countries, about 40% of patents is neither commercially exploited within the patent-holding organization nor licensed to other organizations (Giuri and Mariani 2005). Except for the fact that patented innovations inherently differ for their market potential, another underlying reason might be that firms have other strategic motives than the legal protection of intellectual property. Such strategic motives might relate to building up a patent portfolio in order to improve the position in negotiations with other firms or to improve the firm's reputation and technological image (Blind et al. 2006). In the patent document itself, no information on its monetary value is available. However, there are various ways for measuring the value of patents, for instance by the number of citations it received (Trajtenberg 1990), or by the number of years the annual renewal fee has been paid (Pakes 1986). Such procedures can be useful in order to create a valued graph for a co-patenting network, in which the cells take differential values according to the 'impact' of a patent.

Depending on the purpose of the network analysis, the node in the network can be either the individual inventor or the patent applicant. Most regional network studies take the inventor as the node in the network. A regional network study at the inventor level fits well the argument of communities of practice. In high-tech clusters, communities of technicians and the social relationships within them are argued to play a crucial role in the innovation dynamics of the cluster (Dahl and Pedersen 2004).

Inventors are interlinked when they have worked together on a single patent (Breschi and Lissoni 2003). Assuming that inventors that worked on the same patent know each other, the complete network structure resulting from this exercise represents the underlying social network of inventors of the population under investigation. A social network of inventors that has been identified in this way does not take into account the boundaries of the firm. Since the inventors mentioned on a patent document do not necessarily work for the patent assigning company, a two-mode network that distinguishes between an inventor level and a patent level might compensate for this shortcoming. Such a network supposes links between inventors to exist in case they have worked on the same patent.

An alternative approach in patent-based regional network studies is taking the firm as the node in the network. The basic assumption in patent-based network research at the firm level is that links can be established in two different ways. A link between two patent applicants exists in case of co-patenting, or in case of multi-applicant inventorship.

A co-patent is a patent applied for by two or more actors. Generally, this is a sign of innovation-based cooperation activity. However, the number of co-patents is relatively limited. In a survey among 10,000 inventors in 6 European countries, only 3.6% of all patents were a co-patent, whereas in 15% of the patents, inventors from another organization than the patent-holder had been involved. More than 20% of all patents even turned out to be the result of a collaboration with an external organization (Giuri and Mariani 2005). According to Hagedoorn (2003), this is due to the fact that companies view co-patenting as a 'second best option'. Cooperating companies prefer to divide the patents resulting from a joint R&D project among them over applying jointly for all patents, because co-possessing a patent is legally complex, particularly when partners come from different countries. Mainly in case a limited number of

patents result from short-term and relatively informal joint R&D-projects, firms tend to jointly apply for a patent. Due to this behaviour, quite a substantial extent of inter-organizational cooperation remains invisible when just taking co-patenting as a proxy for joint R&D projects. This shortcoming might be partly—though considerably—compensated for when taking multi-applicant inventorship as an additional means of retracing inter-organizational knowledge-based relationships.

Multi-applicant inventorship is the case in which one or more inventors have been involved in the development of a patent at two or more different patent applicants. As a consequence, one inventor turns up at patents possessed by different applicants within the patent data file. Generally, this is interpreted as labour mobility (Laforgia and Lissoni 2006). When a technician moves from the R&D department of one firm to the R&D department of another firm, he will be listed as an inventor for multiple firms. However, this argumentation only holds when the patents of the different firms are subsequent in time. In many cases, this turned out not to be true. This is not really surprising bearing in mind that job mobility of European inventors is relatively low. Almost 80% of the inventors in a large-scale European inventor survey did not change jobs at all in a period of 6–10 years after the patent application (Giuri and Mariani 2005). Laforgia and Lissoni (2006) found in the study of patents of European biotechnology firms that only 20% of multi-applicant inventorship can be explained as a pure case of labour mobility. The other 80% should have alternative explanations, two of which will be brought forward here.

First, firms engaged in a strategic alliance or any other innovation-based cooperation activity often decide to divide the patents resulting from the cooperation among them in order to avoid legal complexity in case of co-patenting (Hagedoorn 2003). In these cases, the inventors being involved in joint innovation projects will turn up at single-owned patents of different companies. Consequently, in many cases multiple-applicant inventorship can be considered a hidden act of cooperation.

Second, multi-applicant inventorship might occur when patents are sold on the market for technology (Arora et al. 2001). Particularly small- and medium-sized firms might decide not to take the risk of – and make substantial investments for—exploiting the patent by bringing the product on the market, but to sell the patent to other, generally larger, firms and take immediate gains of the patent (Giuri and Mariani 2005). In such cases, the buying firms turn up as the patent applicant, whereas the inventors involved in the patent's realization are working for the selling firm. Then, if the selling firm also applied for patents on its own, its inventors are likely to create a case of multiple-applicant inventorship, being caused by a market for technology relationship. For instance, as shortly noted already, most software patents are assigned to large manufacturing firms (Bessen and Hunt 2007). This might be the result of smaller software firms selling their patents as a license on the market for technology.

In general, up to 10% of all patents is a co-patent, but this figure shows major variation over time, over space and across industries. The amount of cases identified as multi-applicant inventorship depends on the spatial scale of the analysis, since the larger the amount of patents under investigation, the higher the chance an inventor will turn up at multiple patents. Whether or not multi-applicant inventorship and co-patenting are both interpreted as a link in the reconstruction of the network depends on the purpose of the network analysis. Whereas taking only co-patenting gives the

'purest' picture of regional cooperation activity, it is not complete, because cooperation hidden in multiple-applicant inventorship will be left out of the analysis. However, putting multiple applicant inventorship widens the interpretation of the linkages in the network, since not all cases represent cooperative relationships. However, since they all represent some form of knowledge flow between patent applicants—also in case of market for technology or pure labour mobility—the networks reconstructed on the basis of both types of relationships can be applied in research more generally investigating a region's knowledge infrastructure.

Networks that are detected on the basis of patent data have opened up new opportunities for empirical research in the field of regional innovation systems and clusters. The main advantage of this methodology in comparison to the use of primary network data is the possibility to detect networks back in time. In combination with the development of new software for the dynamic analysis of social networks, like the SIENA program developed by [Snijders et al. \(2007\)](#), the treatment of patent data as relational data has enabled the dynamic analysis of inter-firm networks. Whereas applying the roster-recall methodology results in a 'snapshot' view of a network, patent-based networks give insight in forces towards stability and change in network evolution. The SIENA software can estimate parameters for these structural forces—including preferential attachment, closure and homophily—by simulating how the network evolved from one state into the other (for more technical details, see [Snijders 2001](#)). Particularly within regional studies with an evolutionary focus, the time-dimension is highly relevant. For instance, the relationship between the life cycle stage of a cluster and the structure and geographical reach of its knowledge network has been hardly assessed empirically. Patent-based networks enable the empirical investigation of such a relationship.

However, patent-based networks suffer from a number of shortcomings that limit the number of applications in regional research and have strong implications for the interpretation of the reconstructed networks. As in the case of network research on the basis of primary data, social network analysis techniques presuppose that complete network data on a certain population are available. Again, it needs to be questioned whether this is really the case.

First, the suggested procedure only reveals the cooperative links that have led to a patent. As regards to the inventor level research, the technicians that are not involved in patenting will remain invisible, whereas in fact they might still play a major role in a network of technicians. At the level of the firm, only relatively formal inter-firm cooperation agreements will turn up in the network. More informal, though sometimes valuable, ways of inter-firm interaction will not be captured by this methodology. At the same time, the methodology is biased towards cooperation in applied and product-oriented innovation projects at the expense of more fundamental research in cooperation.

Second, patenting behaviour varies strongly across sectors. In some sectors, patents are a much more common way of protecting intellectual property than in others. Some sectors will more rely on secrecy or trademarks in order to protect their innovations. Since the methodology assumes to result in a complete network, this implies that the methodology is only appropriate for sectors in which most innovations are patented. As a consequence, the pharmaceutical and semiconductor industries, for instance, are

relatively good candidates for this methodology, whereas it is less appropriate for software industries and services. In the particular case of software, the number of patents in this field has increased substantially over the last decades (at least in the US). However, most software patents are possessed by large manufacturing companies and much less so by smaller software publishing firms. These large manufacturing firms generally have a large patent portfolio and generally apply for these patents for strategic reasons (Bessen and Hunt 2007).

Third, patenting behaviour is closely related to firm size. Generally, large firms show a higher propensity to patent than small firms. This difference is partly explained by the relatively high cost of patenting. Both the money and the time needed to apply for a patent might be more easily gathered by larger firms that might have built experience in applying for patents through a broad patent portfolio (Giuri and Mariani 2005). In addition, larger firms are much stronger inclined to patent for strategic reasons (Blind et al. 2006). As a result, the networks that result from patent data are biased towards larger firms. Smaller firms will be underrepresented in the network. Their centrality in the network will be lower in the reconstructed network than in the complete, though partly invisible, network.

Finally, universities and research institutes are underrepresented in patent data as well. Universities do not have strong incentives to patent, since their aim is to diffuse rather than protect the generated knowledge. However, over the last years, a trend towards more university patenting is observed. This trend is visible both at university-owned and university-invented patents (in the sense that at least one inventor at a non-university-owned patent is employed at a university) (Blind et al. 2006; Geuna and Nesta 2006). Still only a limited part of the innovations generated at universities will be patented. That is why some network studies, and particularly those interested in the role of universities in regional innovation systems or science-industry relationships, use co-publication data to reconstruct inter-organizational networks in which universities and other research institutes will play a bigger role (Ponds et al. 2007; Blind et al. 2006).

In synthesis, reconstruction of regional innovation networks on the basis of patent data needs to be carried out with extreme care. Only when applied to the right sectors, patent data provide us with ample opportunities for a dynamic investigation of knowledge networks. Even then, one needs to acknowledge the limitations of the procedure as to which part of a network has been revealed and which type of actors and which type of links will be over- or underrepresented in the reconstructed network. However, when bearing in mind its limitations, treating patent data as relational data provides us with considerable opportunities to study the dynamics of regional innovation networks, which is, till today, a rather unexplored though promising field of study.

4 Conclusions

Inter-organizational interaction has always played a crucial role in the literature on regional innovation systems and clusters. However, the structure of this interaction has hardly been assessed empirically in more quantitative terms. At the same time, existing empirical studies on clusters and regional innovation systems have been mostly static.

Whereas static network studies incorporating social network analysis techniques have emerged in the field of economic geography in the last couple of years, dynamic studies of spatial networks are virtually non-existent. However, both in terms of static and dynamic network research, a lot of challenges remain. These challenges can be organized along three sets of questions that should form the backbone in future regional network research.

The first set of questions refers to how interaction within and across clusters is structured and particularly how this structure has come into being. Further insight is needed how micro-level capabilities and meso-level proximities affect the spatial configuration of inter-firm networks. Related to this is the second set of questions, which concerns the evolution of networks across time and space. To what extent do inter-firm networks evolve along the general principles of preferential attachment and homophily as set out by network theorists? And how do these drivers of network evolution relate to economic geographical factors like geographical proximity, social connectedness and cognitive capabilities? Finally, a third set of questions refers to the effects of networks on performance. At the micro level economic geographers can further contribute to the growing literature on the positive and negative effects of the positions firm occupy in local and non-local networks on their innovative performance. At the macro level, economic geographers can bring in a network approach to the literature on agglomeration economies and cluster development. There is increasing awareness that a dense local system of interactions may lead to cognitive lock-in and economic decline when it is not complemented by a wider network of non-regional linkages. Network analysis will further contribute to a better understanding of which types of extra-regional linkages matter most in economic terms.

Social network analysis constitutes an appropriate analytic toolbox for economic geographers to meet these challenges and has created a growing demand for empirical network data. Both empirical network research on the basis of primary data and secondary data can play a central role in meeting these challenges. When carried out thoroughly (i.e., resulting in a very high response rate), primary data network research can generate a detailed network that reveals the real and complete structure of a spatial innovation network. However, due its highly time-intensive nature, it can only be applied to very limited samples. Moreover, the high requirements concerning response—to ensure that one identifies the complete network—makes this methodology unfeasible for large scale empirical work. Since asking organizations for the relationships in the past will not result in reliable information, this methodology is also inappropriate for longitudinal network analysis. Patent-based networks in this case are a better alternative. In these networks, links between firms can be identified back in time through co-patenting and co-inventing. However, this methodology is only appropriate for industries in which intellectual property is generally protected by patents. In addition, it is biased towards explicit and successful forms of inter-firm knowledge exchange.

Bearing these shortcomings in mind, we believe that social network methodology has a huge potential to enrich the literature on clusters, regional innovations systems and knowledge spillovers in the years to come. Basically, it has the potential to tackle some key problems these bodies of literature have been struggling with. In addition, network theory provides ideas for formulating new research questions, and social

network methodology offers an advanced toolbox to address these questions empirically. The time has come to fully exploit these opportunities in economic geography.

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