Bridging centrality: A new indicator to measure the positioning of actors in R&D networks[1]

Thomas Scherngell*, Iris Wanzenböck* and Laurent Bergé**

*thomas.scherngell@ait.ac.at, iris.wanzenboeck@ait.ac.at
Innovation Systems Department, AIT Austrian Institute of Technology, Vienna, 1220 (Austria)

** laurent.Bergé@parisdescartes.fr
MAP5 (UMR CNRS 8145), Université Paris Descartes & Sorbonne, Paris Cité (France)

ABSTRACT

In the recent past, we can observe growing interest in the STI community in the notion of *positioning indicators*, shifting emphasis to actors in the innovation process and their R&D inter-linkages with other actors. In relation to this, we suggest a new approach for assessing the positioning of actors relying on the notion of bridging centrality (BC). Based on the concept of bridging paths, i.e. a set of two links connecting three actors across three different aggregate nodes (e.g. organisations, regions or countries), we argue that triangulation in networks is a key issue for knowledge recombinations and the extension of an actor's knowledge base. As bridges are most often not empirically observable at the individual level of research teams, we propose an approximated BC measure that provides a flexible framework for dealing with the aggregation problem in positioning actors. Hereby, BC is viewed as a function of an aggregate node's (i) participation intensity in the network, (ii) its openness to other nodes (i.e. the relative outward orientation of network links), and iii) the diversification of links to other nodes. In doing so, we provide an integrative perspective that enables us to achieve a better understanding of the positioning of certain actors in R&D networks. An illustrative example on the co-patent network of European regions demonstrates the performance and usefulness of our BC measure for networks constructed at the aggregated level, i.e. regions in our example. A region's outward orientation and the diversification of its network links moderates the influence of regional scale on network centrality. This is a major strength of the measure, and it paves the way for future studies to examine the role of certain aggregate node's, and, by this, contributes to the debate on positioning indicators in the STI context.

INTRODUCTION

Over the past decade, we have observed considerable progress in the advancement and application of Science, Technology and Innovation (STI) indicators (see, e.g., OECD 2005). In this context, the notion of *positioning indicators* has come into fairly wide use in the STI community. It originates from considerations on new requirements imposed to the production of STI indicators in terms of their adaption from classical input-output to a positioning indicators framework, focusing on flows and linkages between research actors in the innovation system (Lepori 2008). These linkages materialize in form of more formalised collaborations in R&D, such as joint R&D projects (see, e.g., Scherngell and Barber 2009 and 2011, Scherngell and Lata 2013), joint publication activities (see, e.g. Glänzel and Schubert 2004), and researchers mobility (see e.g. Edler et al. 2011). Similarly, they may appear as informal knowledge flows - often referred to as disembodied knowledge spillovers (see, e.g.,

[1] This work has been supported by the Austrian National Bank (ÖNB), Jubiläumsfonds, project No. 16301

Fischer et al. 2006). Despite the fact that a number of works have provided evidence on the crucial importance of R&D linkages, most STI indicators remain rooted in a classical, linear conception of the innovation process.

In this study, we employ a network perspective on R&D linkages. A *R&D network* comprises a set of nodes representing knowledge producing actors inter-linked via edges representing knowledge flows. In Social Network Analysis (SNA), the *positioning* of actors is usually described by the concept of *centrality*, trying to capture a certain function and/or role a node, *i*.e. actor, takes by means of its inter-linking to other nodes (Borgatti 2005). Thus, the concept of *centrality* can be very well related to the notion of *positioning indicators*. Up to now, only a few STI studies have started to utilize the centrality concept to capture the positioning of actors in innovation systems, usually employing most basic analytical concepts, such as degree centrality or betweenness centrality (see, e.g., Wanzenböck et al. 2014 and 2015, Heller-Schuh et al. 2011). However, they somehow neglect conceptual problems that arise if networks are defined at the aggregate level of (large) organisations or even regions and countries, rather than the most relevant level in terms of R&D linkages, usually a research team within an organisation. Furthermore, the used centrality measures are not conceptually adapted to the STI context, such as the incorporation of theoretical considerations on the diversification of links or the relative outward orientation of R&D networks.

Thus, we propose a measurement approach that specifically adapts common centrality measures to STI relevant theoretical considerations, and provides a flexible framework to overcome problems related to node aggregation of the network. We shift attention to the notion of *Bridging Centrality* (BC), based on the concept of inter-nodal *bridging paths*, denoting an indirect connection between two nodes via a third 'bridging node'. However, since bridges are usually difficult to be observed at the level of individual researchers, our proposed BC measure shows properties that allow us to estimate the centrality of an aggregate node based on the underlying micro-structure of the network. The objective of this study is to introduce the conception and formal derivation of BC, and demonstrate its interpretative power by an illustrative example. Our approximation of the number of bridging paths of an aggregate node is given by the product of three components, that is, first, a node´s *participation intensity* in the network, *i*.e. its number of links, ii) a node´s *relative outward orientation*, *i*.e. the ratio of node-internal (loops) vs. node external links, and (iii) the *diversification* of links across other nodes in the network. Emanating from our conceptual discussion, we provide a formal proof on how our measure decomposed into these three components converges mathematically to a node´s expected number of bridges. Since all three components are relevant for STI studies on its own, the measure shows high interpretative power and, by this, significantly enriches our toolset of positioning indicators, not only in terms of a more appropriate centrality measure.

The remainder of this study is structured as follows: The next section introduces the network notation to elaborate in some more detail on the notion of bridges. Afterwards we outline the formal definition of our BC measure based on the three components *participation intensity*, *relative outward orientation* and *diversification*. It shows how we conceptually perceive the number of bridges of a node starting from these three components, before we provide a formal proof that our measurement approach mathematically corresponds to the expected number of bridges of a node. Then we shift attention to an illustrative example, where we apply our measure to the European co-patent network observed at the level of NUTS-2 regions, and compare the results with conventional centrality measures as well as with respect to the three

BC components. The final section closes with some concluding remarks and ideas for a future research agenda.

Network definition and the concept of bridges

In social sciences, analytical strategies employed to deal with the divide between individualistic and holistic approaches for describing social systems are referred to as multilevel analysis (see, e.g., Lazega and Snijders 2015). In traditional sociological literature, this is aptly described as the phenomenon of *ecological fallacy*, pointing to logical failures in the inference of statistical data observed at an aggregated level on the nature and characteristics of individuals (see Robinson 1950). Social Network Analysis (SNA) faces, on the one hand, similar problems when applied to aggregate nodes, in particular in a STI context (see, e.g., Wanzenböck et al. 2014), while on the other hand entails promising potential to overcome such analytical problems (Snijders 2016).

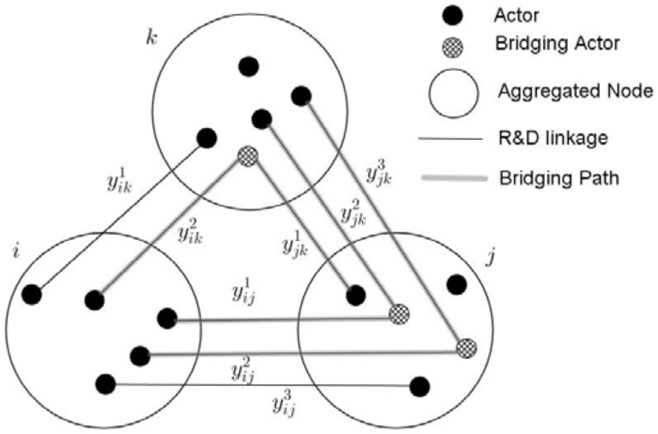
We argue that these aggregation problems prominently occur in the measurement of the positioning of actors in STI studies. Shifting attention to positioning in a network analytic context, we draw on the rich SNA toolbox to evaluate the positioning. The concept of centrality is fundamental in this respect, usually adopted to assign a value to each actor depending on their position within the network (Wasserman and Faust 1994). However, most SNA measures of centrality have been developed for the analysis of social systems, where the nodes of the network are usually identified in terms of individual persons. Accordingly, the original meaning borne by the SNA centrality measures as well as respective interpretations rely on assumptions on the social behaviours of individual persons, and how these persons might influence each other by these behaviours. Centrality measures based on observations at the aggregate level (e.g. organisations, regions or countries) therefore raise important conceptual issues. Most importantly, it implies that every individual actor of an *aggregate node* would homogeneously benefit from the R&D linkages to other nodes, irrespective of who establishes the relations and the strength of these relations.

We propose a flexible analytical approach to address conceptual problems related to unobserved micro-level structures of the observed network. Core in this context is the concept of '*bridging path*' denoting a form of indirect connection between aggregate nodes. For a formal definition, consider a network observed at the level of aggregate nodes, e.g. organisations, regions or countries, and the connections between the aggregate nodes represent the R&D linkages between their individual actors. This represents a weighted network where we define g_{ij} as the number of R&D linkages (*i*.e. micro-level links) between aggregate nodes i and j. Further, each micro-level link between two aggregate nodes is denoted by y_{ij}^{a}, representing the a^{th} link between aggregate nodes' i and j with $a \in \{1, ..., g_{ij}\}$. A pair of links (y_{ik}^{a}, y_{jk}^{b}) forms a bridging path if, and only if, y_{ik}^{a} and y_{jk}^{b} are connected to the same actor of aggregate node k. This concept is depicted by Figure 1 exemplified with three aggregated nodes.

The concept of bridges is of particular relevance in a STI context. A high number of bridging paths implies a more open positioning in the network. In contrast to closed and dense network structures, such a bridging position between other nodes can be related to the access to a more diversified knowledge pool. It is assumed that the sources from which the individual actors draw their knowledge will have an impact on their ability to generate innovations, and knowledge flowing through bridging paths is more likely heterogeneous and non-redundant.

Based on these conceptual considerations on bridging paths, we propose a measurement approach for *Bridging Centrality (BC)* in the section that follows.

Figure 1: Illustration of the notion of bridging path



Notes: The figure depicts three bridging paths formed by the following pairs of links: (y^2_{ik}, y^1_{jk}), (y^1_{ij}, y^2_{jk}) and (y^2_{ij}, y^3_{jk}). So the aggregate node dyads (*j*, *k*), (*i*, *k*) and (*i*, *j*) have respectively 0, 2 and 1 bridging paths stemming from aggregate nodes *i* , *j* and *k*.

Three components of Bridging Centrality

Given the parsimonious and effective formal definition of bridging paths, it could be assumed at a first glance that the definition of a formal BC measure is straightforward. Indeed, this is the case in pure mathematical terms as the *true* measure of BC for an aggregate node *i* would just be the number of bridging actors assigned to *i*, probably normalised by the total of all bridging actors in the network. However, de facto we are often confronted in social sciences with a well-known problem of finding appropriate empirical observations for the objects under scrutiny. This is particularly critical in STI studies, where we usually focus on large-scale networks such as co-patent, co-publication or project networks. Most often information on links at the level of the individual researchers cannot be traced; even when information is available (as e.g. for authors in publications and/or inventors in patents), the observation for large-scale networks is infeasible due to immense efforts for data cleaning, in particular name standardisation over space and time.

Thus, we propose an alternative measure for BC that approximates the number of bridges of an aggregate node. Drawing on theoretical considerations from various STI studies, we assume that the number of bridging actors of an aggregate node may to a large extent depend on three components: the node´s i) *participation intensity,* ii) *relative outward orientation* and iii) *diversification* of network links. We will show that a linear-multiplicative combination of these components formally dissolves to the *expected number of bridges* (see Bergé 2016). At the same time, the three components of BC are highly relevant, each of them having important mechanisms on its own and significant implications on knowledge creation structures.

In our formal description, we denote C_i as the approximated BC for the aggregate *i* node by

$$C_i = q_i \, s_i \, \left(1 - h_i\right) \tag{1}$$

where

q_i is the weighted degree of aggregate node *i*, defined as the total number of links excluding node-internal ones, i.e. $q_i = g_i - g_{ii}$. It refers to the overall *participation intensity* in the network; an aggregate node's size will amplify the probability of yielding more bridges between other nodes.

s_i is the *relative outward orientation* of aggregate node *i* with $s_i = q_i \;/\; g_i$. It reflects the degree of openness of an aggregate node with respect to all established links. Given the focus on bridges, the capacity of an aggregate node to link to other nodes would decrease by a higher number of node-internal links (loops) as it potentially reduces the number of actors connecting different aggregate nodes.

h_i refers to the degree of *diversification* of network links of aggregate node *i* among other nodes. It is measured by the Herfindahl-Hischman (HH) index by $h_i = \sum_{j \neq i} (g_{ij} / q_i)^2$. The term 1- h_i varies between 0 and 1, and indicates how an aggregate node's linkages are distributed along its neighbouring nodes in the network. The more the linkages are concentrated, the less the node is central in terms of BC. Concentration reduces the actors' possibility to build bridges among different aggregate nodes and to draw its knowledge from different sources.

An aggregate node's ability to benefit from new ties in the R&D network or exploit external knowledge sources via the links may be determined by all three components together. Outward orientation and higher diversification in particular may help actors belonging to an aggregate node to develop and renew their knowledge base faster, or prevent lock-in situations in certain technologies (see, e.g., Breschi et al. 2015). Hence, our measure to approximate BC features promising opportunities in terms of interpretation.

However, it is not only conceptually attractive, but also mathematically corresponds very well with the *Expected Number of Bridges* (ENB) measure as introduced by (Bergé 2016) using basic random matching assumptions between aggregate nodes[2]. Mathematically, our measure simply collapses to ENB, given by

$$\begin{aligned} C_i &= q_i \; s_i \; (1 - h_i) = \frac{q_i^2}{g_i}\left(1 - \sum_{j \neq i} (g_{ij} / q_i)^2\right) = \frac{q_i^2}{g_i} - \frac{1}{g_i} \sum_{j \neq i} g_{ij}{}^2 \\ &= \frac{1}{g_i} \sum_{j \neq i} g_{ij} (q_i - g_{ij}) = \frac{1}{g_i} \sum_{j \neq i} (g_{ij} \sum_{k \neq i,j} g_{ik}) \\ &= \sum_{j \neq i} \sum_{k \neq i,j} \frac{g_{ij} g_{ik}}{g_i} \end{aligned} \tag{2}$$

with the latter expression corresponding to the most general form of the expected number of bridges. This can of course be extended to more reasonable assumptions of expected bridges, for instance, by considering the number of actors of aggregate nodes proportional to the

[2] Note in this context that the random matching process is 'noisier' the larger the aggregate node is, e.g. when nodes are countries

number of R&D linkages (see Bergé 2016 for details). This version of the expected number of bridges corresponds to empirically observed cases quite well.

An application to European cross-region patent networks

In this section, we shift attention to a compact illustration of the BC measure in order to demonstrate its behaviour and interpretative power. We use the example of co-patent network data that is observed at the level of European NUTS-2 regions to represent the aggregate level in our network, and compare the BC with three other commonly used centrality measures, that is the degree, the eigenvector and the betweenness centrality (Wasserman and Faust 1994)[3]. A co-patent is regarded as a collaboration of at least two inventors issuing a patent grant, providing us a trail of R&D linkages. Respective data are extracted from the REGPAT database (see Maraut et al. 2008) and consist of all patents applied for at the European patent office (EPO) in the period 2006-2010. Our cross-regional co-patenting network is based on a total of 171,451 patents, producing 121,036 inter-regional collaborations linking 250 NUTS-2 regions (see Bergé et al. 2015 for further details on the data)[4]. In this example, the aggregation problem described in Section 2 clearly applies as we are not able to observe co-patent activities at the level of individual inventors[5].

Table 1 represents the top 30 centralities ordered by the bridging centrality. We focus on commenting the most salient differences. The ranking is clearly dominated by German regions which rank highest for most measures[6]. However, the concentration tendency and high clustering of co-patenting activities at the national level of Germany may point to the fact that economic linkages at the national level prevail. Likely explanations are low cultural barriers as well as lower transaction costs. These factors seem to promote the high regional bridging centrality in German regions[7].

Further interesting specific cases are, e.g., Île de France (FR10) or Brussels (BE10). FR10 ranks at the 16th position for BC, while being ranked first with respect to its degree centrality. Degree centrality may overstate its position; Although the structure of the collaborations of FR10 with its partnering regions is highly distributed (it has a low HH index of 0.04), this region is characterised by a high number of internal collaborations (the outer share of collaborations is only 44%), and thus, do not provide many bridging paths to the inter-regional R&D network. BE10 ranks below 55th for degree and eigenvector centrality, while for BC it ranks 30th. These conventional centrality measures may underestimate its positioning in the inter-regional co-patent network due to its very high outward orientation

[3] The degree is here calculated as the number of unique R&D interactions the agents of a region are involved in. The eigenvector and the betweenness centrality are computed using the package *igraph* available in the statistical software R. Both these two measures are based on the weighted regional co-patent network where the nodes are the regions and where the linkages between any two regions are the number of patents co-invented by agents from these two regions. Due to the nature of the network, we used the weighted version of both the betweenness and the eigenvector centrality.

[4] Note that the use of different time frames to build the dataset, such as 2004–2006 or 2008–2010, imply no important changes on the results.

[5] An aggregation to the organisational level would also be inconsistent, as patents are most often assigned to headquarters of companies which often does not reflect to the locus of knowledge creation.

[6] Note that the performance of German regions is not merely driven by the fact that German NUTS2 regions are usually smaller geographical aggregates than NUTS2 regions in other EU countries, which could drive up their number of inter-regional collaborations at the national level. Indeed, when we redo the analysis taking German regions at the NUTS1 level while keeping other regions at the NUTS2 level, German regions still trust the top of the rankings.

[7] The national versus international nature of collaborations and its effects on regional network centrality might deserve further attention, and constitute an interesting route for the further development of the regional bridging centrality measure.

(its outer share is 94%) and a highly distributed structure of collaborations (it has a low HH index of 0.07); BE10 is likely to provide many bridging paths to the network.

Table 1: Centrality values of the top 30 regions for the co-patent network (ranks in brackets)

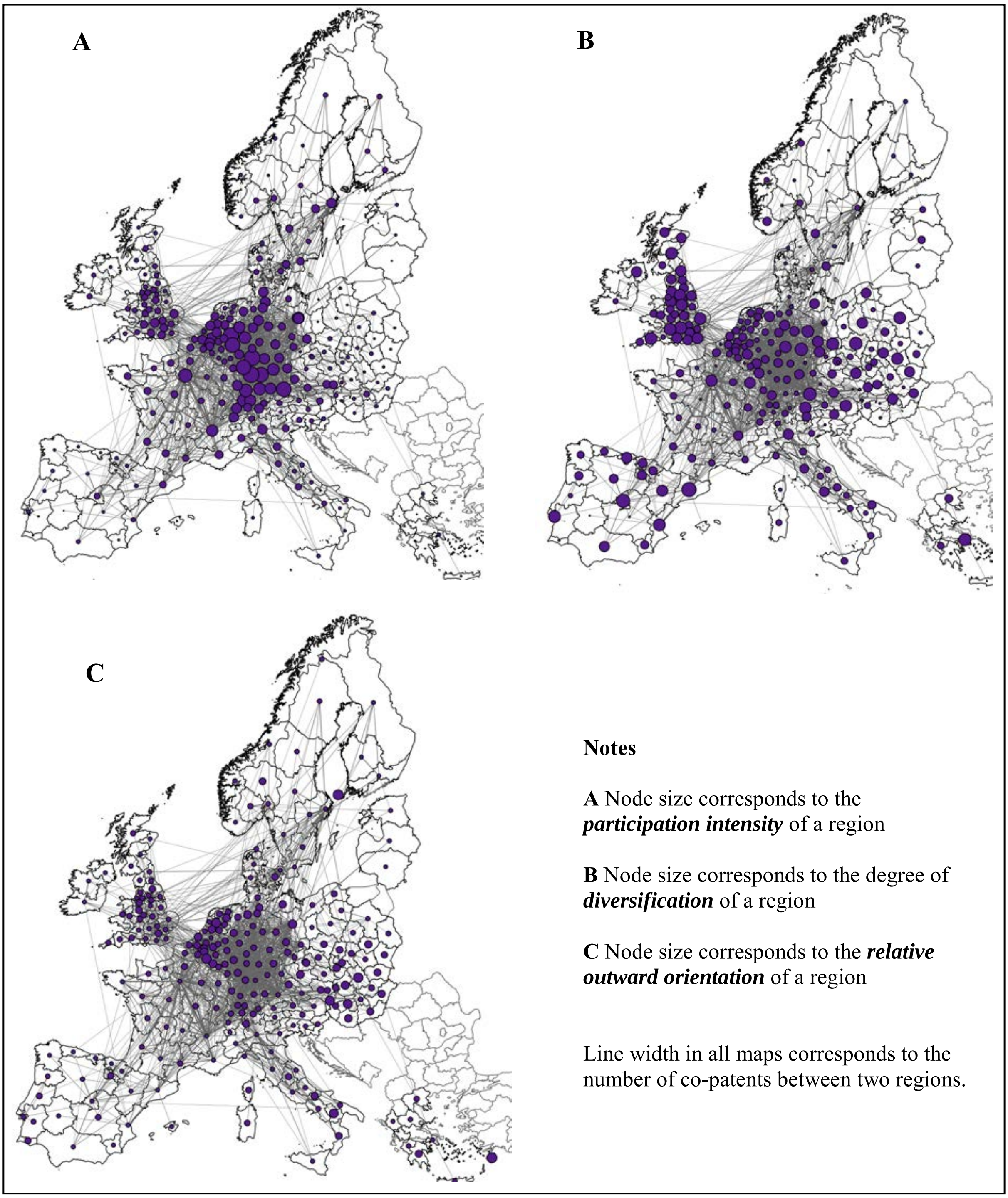
NUTS-2 Code	Region	BC (C_i)	Degree Centrality	Eigenvector Centrality	Betweenness Centrality
DE12	Karlsruhe	1.00 (1)	0.87 (5)	1.00 (1)	0.22 (10)
DE71	Darmstadt	0.93 (2)	0.88 (4)	0.82 (3)	0.45 (4)
DEA1	Düsseldorf	0.84 (3)	0.82 (6)	0.68 (4)	0.22 (9)
DEA2	Köln	0.76 (4)	0.73 (7)	0.63 (6)	0.33 (6)
DEB3	Rheinhessen-Pfalz	0.73 (5)	0.64 (8)	0.85 (2)	0.13 (16)
DE21	Oberbayern	0.63 (6)	0.96 (2)	0.42 (7)	1.00 (1)
DE11	Stuttgart	0.59 (7)	0.95 (3)	0.64 (5)	0.37 (5)
DE13	Freiburg	0.49 (8)	0.52 (10)	0.34 (9)	0.19 (11)
CH03	NW Switzerland	0.43 (9)	0.41 (14)	0.16 (17)	0.10 (24)
DEA5	Arnsberg	0.42 (10)	0.39 (16)	0.33 (10)	0.06 (45)
DE14	Tübingen	0.40 (11)	0.44 (12)	0.38 (8)	0.07 (36)
DE30	Berlin	0.39 (12)	0.40 (15)	0.22 (14)	0.19 (12)
DEA3	Münster	0.39 (13)	0.31 (20)	0.27 (11)	0.05 (49)
DE25	Mittelfranken	0.37 (14)	0.43 (13)	0.20 (15)	0.11 (20)
CH04	Zurich	0.35 (15)	0.34 (18)	0.12 (21)	0.08 (32)
FR10	Île de France	0.34 (16)	1.00 (1)	0.08 (35)	0.93 (2)
DE27	Schwaben	0.33 (17)	0.31 (21)	0.25 (12)	0.03 (71)
DE40	Brandenburg	0.28 (18)	0.22 (30)	0.15 (18)	0.05 (54)
DE60	Hamburg	0.27 (19)	0.23 (29)	0.09 (28)	0.05 (48)
DE26	Unterfranken	0.27 (20)	0.27 (23)	0.25 (13)	0.10 (23)
FR42	Alsace	0.26 (21)	0.23 (27)	0.13 (19)	0.09 (31)
CH02	Espace Mittelland	0.26 (22)	0.27 (22)	0.08 (30)	0.05 (50)
BE24	Vlaams-Brabant	0.25 (23)	0.20 (34)	0.04 (46)	0.10 (25)
DE92	Hannover	0.24 (24)	0.25 (24)	0.12 (22)	0.05 (53)
FR71	Rhône-Alpes	0.24 (25)	0.57 (9)	0.08 (34)	0.33 (7)
DEB1	Koblenz	0.21 (26)	0.17 (46)	0.18 (16)	0.01 (96)
DE93	Lüneburg	0.21 (27)	0.17 (42)	0.07 (37)	0.02 (79)
CH05	Eastern Switzerland	0.21 (28)	0.19 (36)	0.07 (38)	0.01 (97)
BE21	Prov. Antwerpen	0.20 (29)	0.18 (38)	0.05 (44)	0.09 (28)
BE10	Région de Bruxelles	0.20 (30)	0.14 (59)	0.03 (55)	0.08 (34)

To complement the results from Table 1 in this respect, Table 2 provides a snapshot on top-5 regions including Île de France (FR10) and their respective results across the three components. It becomes obvious that the high rankings of German regions result from the fact that they show both a high participation intensity and openness, i.e. a high absolute as well as relative number of inter-regional co-patents.

Table 2: Ranking of top regions decomposed by three components of BC

Rank	NUTS2	BC	Participation Intensity	Outward Orientation	Diversification
1	DE12	1.00	2333	0.85	0.88
2	DE71	0.85	2050	0.78	0.93
3	DEB3	0.80	1831	0.92	0.84
4	DEA1	0.80	1993	0.80	0.87
5	DEA2	0.78	1866	0.84	0.87
13	FR10	0.34	1382	0.49	0.96

Figure 2: Bridging centrality of regions in the European co-patent network decomposed by three components



Notes

A Node size corresponds to the ***participation intensity*** of a region

B Node size corresponds to the degree of ***diversification*** of a region

C Node size corresponds to the ***relative outward orientation*** of a region

Line width in all maps corresponds to the number of co-patents between two regions.

In addition, Figure 2 provides an illustrative overview in form of spatial network maps of the European co-patent network, decomposed by the three components. The results are highly interesting, both in terms of illustrating the functioning of BC, as well as in terms of providing insights into the spatial dynamics of European co-patenting. It demonstrates why some regions, such as Ile de France, do not appear on top in terms of BC due to their lower relative outward orientation. Further, commenting on the overall picture, it can be seen the we observe the classical regions Ile de France as well as regions in Western Germany, the Netherlands und UK to come up with highest participation intensity, while Eastern and Southern European regions show a higher diversification of their links, i.e. actors in that regions seem to be not that selective in the choice of their partners as actors with a high reputation in European core regions. With respect to outward orientation, we also observe high values of some Southern and Eastern European regions. In terms of established co-patent links they seem to be highly open, which could be explained by their reliance on external collaborations and knowledge sources, as well as the lack of internal collaboration structures.

Summary and conclusions

In the STI community, we can observe a lively debate on the notion of positioning indicators, shifting emphasis to actors in the innovation process and their R&D interactions with other actors. However, up to now only few indicators exist which are able to provide a rather comprehensive assessment of an actor's positioning in the innovation system, reflecting structural characteristics of its internal and external R&D linkages. In this study, we suggest a new approach for assessing the positioning of actors in innovation systems relying on the notion of bridging centrality (BC). Based on the concept of bridging paths, i.e. a set of two links connecting three actors across three different aggregate nodes (e.g. organisations, regions or countries), we argue that triangulation in networks is a key issue for knowledge recombination and the extension of an actor's knowledge base.

As bridges are most often not empirically observable at the individual level of research teams, we propose an approximated BC measure that provides a flexible framework for dealing with the aggregation problem in positioning actors. Hereby, BC is viewed as a function of a node's (i) participation intensity in the network, (ii) its openness to other nodes (i.e. the relative outward orientation of network links), and iii) the diversification of links to other nodes. With these three components – which are both intuitive and computationally simple – we provide an integrative perspective that enables us to achieve a better understanding of the role of certain actors in R&D networks.

An illustrative example on the co-patent network for European regions demonstrates the performance and usefulness of our BC measure for networks constructed at the aggregated level. Despite observing similar patterns in basic statistics like correlations of the centralities, we were able to show striking and interesting differences in the structure of the inter-regional co-patent linkages across regions. A region's outward orientation and the diversification of its network links moderates the influence of regional scale on network centrality. This is a major strength of the measure proposed in this study, and it paves the way for future studies to examine the role of certain aggregate node's, not only regions, but also organisations, in R&D networks, and, by this, contributes to the debate on positioning indicators in the STI context.

Of course, there is room for further improvements of the approach. Indeed, a crucial point for future research is to devote higher emphasis to the specific characteristics of R&D network links and our concept could be used to integrate these aspects. For example, extensions of the bridging centrality could include a focus on the fact that some bridging agents indirectly connect national actors with international ones. By focusing on technology related issues, one could consider bridging agents who indirectly connect actors from one specific technology with others from another technology. Moreover, the measure of bridging centrality is not limited to the context of R&D but may prove to be useful also for the application in other types of network structures, such as trade flows or economic value chains.

References

Bergé, L. (2016). Network proximity in the geography of research collaboration. *Papers in Regional Science* [forthcoming].

Borgatti, S.P. (2005). Centrality and network flow. *Social Networks*, 27(1):55–71.

Breschi, S. and Lenzi, C (2015). The Role of External Linkages and Gatekeepers for the Renewal and Expansion of US Cities Knowledge Base, 1990-2004. *Regional Studies*, 49(5): 782–797.

Burt, R.S. (1992). *Structural holes: The social structure of competition*. Harvard University Press, Cambridge, MA.

Edler, J., Fier, H. and Grimpe, C. (2011). International scientist mobility and the locus of knowledge and technology transfer. *Research Policy*, 40(6):791–805.

Fischer, M.M., Scherngell, T. and Jansenberger, E.M. (2006). The geography of knowledge spillovers between high-technology firms in Europe. Evidence from a spatial interaction modelling perspective, *Geographical Analysis* 38(3), 288-309

Glänzel, W. and Schubert, A. (2004). Analysing scientific networks through co-authorship. In *Handbook of quantitative science and technology research*, pages 257–276. Springer.

Heller-Schuh, B., Barber M.J., Henriques, L., Paier, M., Pontikakis, D., Scherngell, T., Veltri, G.A. and Weber, M. (2011). Analysis of Networks in European Framework Programmes (1984-2006). Sevilla, European Commission [ISBN: 9789279197147].

Lazega, E. and Snijders, T. (Ed.) (2015). Multilevel network analysis for the social sciences. Springer.

Lepori, B., Barré, R. and Filliatreau, G., (2008). New perspectives and challenges for the design and production of s&t indicators. *Research Evaluation*, 17(1):33–44.

Maraut, S., Dernis, H., Webb, C., Spiezia, V. and Guellec. D. (2008). The OECD REGPAT Database. *OECD Science, Technology and Industry Working Papers*.

OECD (2005) Oslo manual: Guidelines for collecting and interpreting innovation data. *Organisation for Economic Cooperation and Development (OECD), Paris*.

Robinson, W.S. (1950). Ecological correlations and the behavior of individuals. *American Sociological Review*, 15(3):351–357.

Scherngell, T. (Ed.) (2013). *The Geography of Networks and R&D Collaborations*. Springer-Physica Verlag, Berlin-Heidelberg-New York.

Scherngell, T. and Lata, R. (2013). Towards an integrated European Research Area? Findings from Eigenvector spatially filtered spatial interaction models using European Framework Programme data, *Papers in Regional Science* 92, 555-577.

Scherngell, T. and Barber, M. (2011). Distinct spatial characteristics of industrial and public research collaborations: Evidence from the 5th EU Framework Programme, *The Annals of Regional Science* 46(2), 247-266.

Scherngell, T. and Barber, M. (2009). Spatial interaction modelling of cross-region R&D collaborations. Empirical evidence from the 5th EU Framework Programme, *Papers in Regional Science* 88(3), 531-546.

Snijders, T. (2016). The multiple flavours of multilevel issues for networks. In *Multilevel Network Analysis for the Social Sciences*, pages 15–46. Springer.

Wanzenböck, I., Scherngell, T. and Brenner, T. (2014). Embeddedness of regions in European knowledge networks. A comparative analysis of inter-regional R&D collaborations, co-patents and co- publications, *The Annals of Regional Science* 53, 337-368.

Wanzenböck, I., Scherngell, T. and Lata, R. (2015). Embeddedness of European regions in EU funded R&D networks: A spatial econometric perspective, *Regional Studies* 49(10), 1685-1705.

Wasserman, S. and Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge university press.