Centrality of regions in R&D networks: A new measurement approach using the concept of bridging paths*

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Abstract

This paper aims at introducing a novel measure of regional centrality in the context of R&D networks. We first demonstrate some substantial problems of SNA-based centrality measures to cope with regional R&D networks in a meaningful way. Then, we introduce a new measurement approach of regional network centrality based on the concept of inter-regional bridging paths (indirect connections at the regional level). We show that the formal definition of our regional bridging centrality measure can be expressed in terms of three simple components: the participation intensity of a region in inter-regional R&D collaborations, the relative outward orientation in terms of all established links and the diversification of R&D collaborations among partner regions. We illustrate the measure and its behaviour with respect to other conventional centrality measures by using the example of the European co-patent network at the NUTS2 level.

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1 Introduction

Today it is widely recognized that external knowledge sources accessible via networks and collaborations in research and development (R&D) have become an essential component for innovating organisations (see e.g. Powell and Grodal, 2005; Wuchty et al., 2007). Up to now, most studies have emphasized the crucial role of the ability to adopt external knowledge in form of learning capabilities, such as technical or methodological skills, in order to apply the externally tapped knowledge in the organisational innovation process. However, recently also the importance of a particular relative network positioning to access external knowledge has been highlighted and attracted increasing attention (see e.g. Ahuja, 2000; Owen-Smith and Powell, 2004; Gilsing et al., 2008). It is assumed that not only the ability to learn, but also a favourable position for a more efficient access to external knowledge is crucial.

From a network theoretical perspective, such a favorable positioning is referred to as centrality of network vertices (Borgatti, 2005), where – in terms of R&D – these vertices represent knowledge producing actors interlinked via edges representing knowledge flows. Actors showing a more central network position will more likely benefit from network advantages. This argument has been taken up at the regional level in recent regional science literature, where regions – constituting the aggregate of its knowledge producing organisations – are treated as relevant units of observation. In this context, the notion of inter-regional R&D collaboration networks has come into use (see e.g. Autant-Bernard et al., 2007) where regions are the network nodes representing distinct pools of knowledge, which are assumed to get into motion via the R&D relations between these regions, constituting the edges in the network.

Such a network representation has developed to an analytical vehicle that has been applied to investigate the geography of R&D networks (Scherngell, 2013), in particular how knowledge diffuses between regions (see e.g. Maggioni et al., 2007; Ponds et al., 2010). Compared to studies focusing on the structural properties of network linkages established within actors in single region (see e.g. Fleming et al., 2007a; Giuliani, 2007; Crespo et al., 2014; Ter Wal, 2014), these studies mainly investigate the structure of linkages in a multi-regional system.

Given this recent focus on regional R&D networks, network analytic techniques have been increasingly applied at the regional level in order to characterize the inter-regional connectedness of a region (see e.g. Maggioni et al., 2007; Sebestén and Varga, 2013; Wanzenböck et al., 2014). For observing a region's centrality, up to now the most common analytical approaches from Social Network Analysis (SNA) have been utilized, such as degree centrality or betweenness centrality (Wanzenböck et al. 2014; 2015). However, these studies somehow neglect conceptual problems that arise for networks defined at the aggregate level of regions. In particular, such problems are related with the loss of information regarding the structure of network relations and with that, information on the real channels through which knowledge flows. In this context, the question of how to adequately reflect regions in weighted

network structures such as R&D networks become even more important.

As we argue in this paper, the specific characteristics of regions – regarded as aggregate units – have to be taken into account and reflected in some way when designing analytical measurement approaches for regional centrality. Relevant questions in this context are (i) how can we conceive the centrality of regions in a network that is composed of several research actors in its underlying structure, and (ii) what are then the main building blocks that might characterize the centrality of regions, in particular when we consider R&D networks?

This paper is one of the first that deals explicitly with the drawbacks and insufficiencies related with conventional approaches to represent networks and measure centrality at the level of regions. Against this background, the objective is to propose a new measurement approach of regional centrality that is explicitly designed for aggregated networks at the regional level, based on the concept of inter-regional *bridging paths*. Here a bridging path is defined as an indirect connection between two regions via a third 'bridging region'. From a simple random matching process that models the collaborations among the micro-level actors based on the information provided at the aggregated level, we derive a closed form of the expected number of bridges between two regions stemming from a specific bridging region. On this basis we are able to define a new measure of regional centrality that not only depends on the number of links one region has, but also on the structure and intensity of its cross-regional collaborations.

In its fundamentals, our measure of *regional bridging centrality* builds upon several network- and knowledge-related arguments, referring to the relevance of bridging path between network actors in light of diversified knowledge sourcing strategies and increasing need for technological recombinations (see e.g. Kogut and Zander, 1992; Fleming, 2001; Singh, 2005). Moreover, the role of bridges between regions as mechanisms for network evolution and inter-regional knowledge diffusion is addressed. We show how such a measure defined for aggregated networks can be meaningfully related to the regional dimension. Our measure of bridging centrality of a region can be easily interpreted as a function of (i) the participation intensity of a region in inter-regional R&D collaborations, (ii) the relative outward orientation in terms of all established network links, and (iii) the diversification of network partner regions and knowledge relations to them. Hence, it views network centrality as a multi-dimensional problem, and integrates different region-specific aspects of the regional linking structure that might only together determine the visibility and importance of regions in R&D networks.

To illustrate our regional centrality measure we use a large-scale dataset on the European co-patent network in the years 2006–2010 at the NUTS2 level. The comparative analysis with three common SNA-based measures (degree, betweenness and eigenvector centrality) is based on basic statistics on distribution and correlations between the four centrality measures observed for the regional network. Despite striking similarities in correlations and distributional

aspects on a more general level, the in-depth analysis of regional ranks reveals interesting differences which emphasize the advantages of the regional bridging centrality measure, in particular in terms of its interpretative power for region-level analyses.

The remainder of this study is structured as follows: Section 2 discusses in some detail the conventional approaches to measure the centrality of regions in R&D networks. Section 3 introduces the concept of bridging paths, constituting the main essence of the measurement approach proposed in this study, before Section 4 formally derives the bridging centrality measure for regions. Section 5 shifts attention to the illustrative example, applying our measure to the European co-patent network and comparing results with conventional measures, before Section 6 concludes with a summary of the main results and some ideas for future research.

2 The conventional measurement approach

The notion of the centrality of regions in R&D networks has come into use just recently. A rising body of literature deals with the distinct knowledge transmission channels than span across regions, so-called global pipelines, and their role for the innovativeness and growth performance of localities (see e.g. Bathelt et al., 2004; Giuliani and Bell, 2005; Trippl et al., 2009; Balland et al., 2013; Morrison et al., 2013). It is argued that the knowledge creation ability within a region depends not only on internal resources and capabilities but to a large extent also on the ability of the region-specifc actors to efficiently access and integrate region-external knowledge. Inter-regional R&D collaboration networks are regarded as effective means in this regard with network links representing direct channels to a specific (region-external) source of knowledge that actors otherwise would not have access to. Moreover, the links in networks can also be seen as vehicles of information, for example information on who would be a suitable and reliable partner to collaborate with, in particular across regional borders (see e.g. Gulati and Gargiulo, 1999; Cassi and Plunket, 2015). Against this background, need has been expressed to derive analytical approaches to measure a region's centrality in such networks, enabling the empirical researcher to characterize whether a region has a favourable position in the network, whether it takes a specific – for instance 'brokering' – role from a global network perspective, or how a region's network positioning changes over time.

The concept of centrality originates from Social Network Analysis (SNA). It is used to assign a value to each actor of a network, depending on their position within the network (Wasserman and Faust, 1994). Most measures of network centrality have been developed for their application on social networks, where the nodes of the network are clearly identified in terms of individuals. Accordingly, the original meaning borne by the SNA centrality measures as well as respective interpretations rely on the context of individuals and their social beha-

viours. It is assumed that such individuals participate in social systems connecting them to other individuals, whose relations comprise important influences on one another's behaviours, affecting actors' perceptions, beliefs and actions through a variety of structural mechanisms that are socially constructed by relations among them. In the context of centrality, the main SNA assumptions are that direct contacts and more intensive interactions enable the actors to dispose of better information, a greater awareness, and a higher propensity for influencing or being influenced by others. Indirect relations through intermediaries may also bring exposure to new ideas and access to useful resources that may be acquired through interactions with others (Barber et al., 2011).

The traditional SNA centrality measures are directly derived from these assumptions. If these measures focus only on the importance of direct connections they are referred to as local centrality measures (e.g. the degree centrality just counts the number of direct links). In contrast, global measures, such as betweenness centrality, also take account of indirect links and structural properties of the network (see Wasserman and Faust, 1994, for an overview and definition of various centrality measures). Empirical works focusing on regional centrality usually apply these conventional measures – derived in a SNA context with the specific assumptions discussed above – to regions. Hence, the underlying system of interaction, i.e. the micro structure consisting of actors which actually 'take the decisions' on how to behave in the network, is more or less neglected.

Thus, the conventional measurement approach of calculating regional centrality based on a regional R&D network raises important conceptual issues that should be tackled. *First*, it implies that every actor within a region would homogeneously benefit from the R&D connections to other regions, irrespective of who establishes the relations and the strength of these relations. Such an approach is based on the assumption that region-internal knowledge flows are 'in the air' (Breschi and Lissoni, 2001). However, this assumption appears heroic and can hardly be made; it remains unclear how the actors located in a central region benefit from the region's centrality. *Second*, a specific conceptual problem refers to global centrality measures, for instance in the case of regional betweenness centrality. A region with a high betweenness, i.e. being on many shortest paths, assumes that this translates into all its actors being on shortest paths, as if they were only one entity. Also this assumption does not hold.

Some recent empirical works have recognized this problem and have tried to overcome it by putting higher emphasis on the underlying micro structure of regional R&D networks. For example, Wanzenböck et al. (2015) define the centrality of a region as the sum of the centrality of its actors. However, the approach of aggregating micro-level network centralities may be also flawed, with considerable problems stemming from the links occurring internally to regions. Consider for instance a case where a region shows a very dense structure of internal connections but no link to any other region (see Figure C.1 in appendix). In this case, the region can have a high value of centrality (due to the high centrality of the actors in

the region) despite being isolated from an inter-regional perspective. This is fundamentally problematic since a measure of regional centrality should not be able to assign a high rank to a region which have no external links. The centrality of a region should clearly relate to its position within the inter-regional network. On the other hand, if one cuts all internal linkages, regions appear to be equivalent despite considerable differences in the region-internal structure (see Figure C.2 in appendix).

Given these considerations, there is a need for developing alternative centrality measures applicable for regional R&D networks and resting on more robust conceptual grounds. In what follows, we provide a first attempt for the development of novel measurement approaches that explicitly address the conceptual problems discussed above by taking into account the underlying micro structure of regional R&D networks.

3 The concept of bridging paths

There is a strong need for overcoming the duality in analysing R&D networks of regions concerning the micro level which encompasses the actors participating in R&D collaborations, and the aggregate, i.e. regional, level where the analysis focuses on. As has been discussed in the previous section, major problems arise in applying and interpreting conventional SNA-based centrality measures. The purpose of this section is to provide a new concept that is *meaningful* in the context of inter-regional R&D networks. We introduce the notion of 'bridging path' denoting a form of indirect connection between regions, i.e. regions are indirectly connected in the network thanks to their micro-level actors. We first define this concept before providing an approach to derive the expected number of bridging paths from aggregate flows of R&D interactions. The expected number of bridging paths between regions will be the major building block of the regional centrality measure we introduce in the next section.

For introducing the bridging path concept, consider a network where the nodes are the regions and the connections between the regions represent the R&D interactions between their actors. This represents a weighted network where we define g_{ij} as the number of R&D interactions (i.e. micro-level links) between regions i and j. Further, each micro-level link between two regions is denoted by y^a_{ij}, where y^a_{ij} represents the ath link between regions i and j with $a \in \{1, \ldots, g_{ij}\}$. A bridging path is then regarded as a set of two links at the micro level connecting three actors from three different regions. Speaking in social network analytical terms, the micro-level actor in one region act as a 'broker' (Burt, 1992) for two other not directly connected actors; he/she has a bridging role in the network of regions linking indirectly the micro-level actors of two other regions. This triangulation between actors located in three different regions leads to the notion of an inter-regional bridging path. Formally, a bridging path is defined as a set of two links from two different regions, say i and

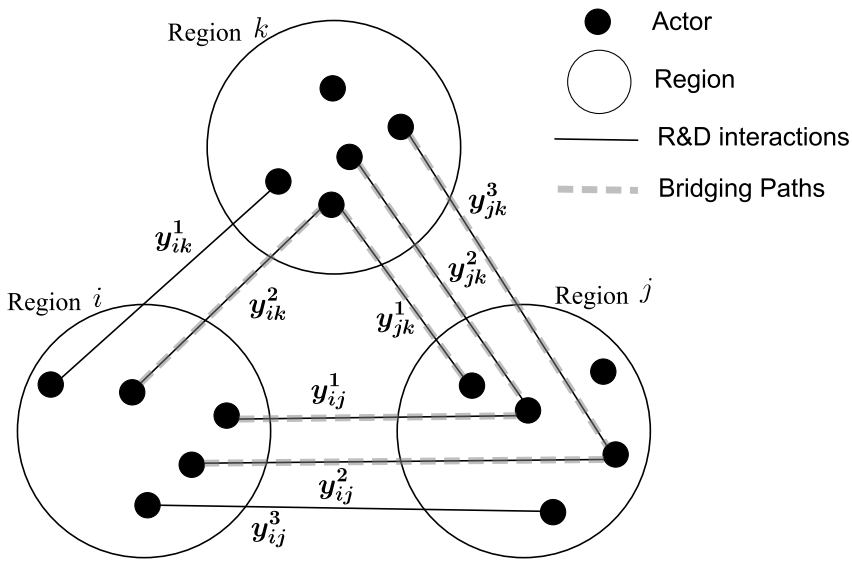

Figure 1: Illustration of the notion of bridging path

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 regional dyads (j,k), (i,k) and (i,j) have respectively 0, 2 and 1 bridging paths stemming from regions i, j and k, respectively.

j, with a third one, say k, so that the actors from i and j are both connected to the same actor in k. This means that a pair of links (y^a_{ik}, y^b_{jk}) forms a bridging path if, and only if, y^a_{ik} and y^b_{jk} are connected to the same actor in region k.

This notion is depicted by Figure 1 which represents a regional network of three regions. In this figure, the pair of links (y^2_{ik}, y^1_{jk}) is a bridging path between regions i and j stemming from k because the actor from k maintains both links y^2_{ik} and y^1_{jk}. Although both regions j and k do have links with region i, there is no bridging path between them because the actors from i of the links y^1_{ik} and y^2_{ik} are neither connected to y^1_{ij}, y^2_{ij} nor y^3_{ij}. Hence, region i provide not any bridging path between regions j and k in this set-up. We see that the notion of bridging path is about indirect connections. Accordingly, the region with most bridging paths is region j, as it provides two bridging paths between regions i and k.

Different strands in the literature dealing with the geography of R&D networks and knowledge diffusion deliver arguments of why inter-regional bridging paths are important. These arguments may be related to both the knowledge creation performance of individual regions and the diffusion of knowledge through network evolution in an inter-regional context. For regions, a high number of bridging paths implies a more open positioning in the inter-regional network, similar to a structural hole positioning as brought forward in SNA theory (Burt, 2005). In contrast to closed and dense network structures, such a bridging position between other regions can be related to the access to a more diversified knowledge pool. It is assumed that the sources from which the actors draw their knowledge will have an impact on

their ability to generate innovations, and knowledge flowing through bridging path is more likely heterogeneous and non-redundant. Hence, an inter-regional bridging path might be important for a region as it provides greater opportunities that, on the one hand, new ideas and information from network partners can flow faster into the region through short path length (Fleming et al., 2007a), and on the other hand, the knowledge already existing in the network can be recombined to develop new ideas and applications (see e.g. Kogut and Zander, 1992; Cassiman and Veugelers, 2006). Studies have confirmed in this context that radical innovations are indeed more often the result of different sources and a high diversity in (local and non-local) knowledge linkages (see e.g. Trippl et al., 2009; Fitjar and Rodriguez-Pose, 2011; Fitjar and Huber, 2015). However, the degree of how an entire region might benefit from its portfolio of global pipelines, i.e. the diversity of the knowledge pool, depends on the internal capacities for exploiting the external knowledge brought into the regional system and transferring it between the regional actors (see e.g. Giuliani, 2007; Morrison et al., 2013; Wanzenböck and Piribauer, 2015).[1]

Furthermore, there is an increasing body of literature on R&D networks that place the duality of local and non-local network linkages in light of the the technological regime and the different stages of the knowledge value chain. Balland et al. (2013), for example, show that global linkages in the GNSS industry are more often market-oriented relations predominantly devoted to knowledge exploitation and technological diffusion at a higher stage of maturity of the field. Ter Wal (2014) and Owen-Smith and Powell (2004) come to similar findings for the field of biotechnology. Their investigations show that the spatial scale of R&D linkages highly depends on the degree of codification and the nature of the knowledge being exchanged (basic vs. industrial and mutually purposeful knowledge), and may be subject to change over the life cycle of a distinct field (Ter Wal, 2014). Hence, similarly important from the perspective of regional development is the ability of regional actors to identify technological transformations and new market opportunities at an early stage. An open position in the network is assumed to help a region in adapting oneself to such transformations, dealing with uncertainty or preventing regional lock-in (Eisingerich et al., 2010). To this effect, inter-regional bridging paths are assumed to contribute to a region's enduring ability to produce new knowledge and innovations.

From the perspective of inter-regional knowledge diffusion and integration, bridging paths may also be of significance when we consider network formation and network evolution processes across regions. Indeed, several recent studies have put at the forefront the consideration

[1]The effectiveness of inter-regional network linkages is further driven by other dimensions working at the micro-level and assignable to the characteristics of organisations within a region, such as the distinct institutional background and capabilities (Singh, 2005; Ponds et al., 2007) as well as the degree of cognitive proximity of partners (Nooteboom et al., 2007). The individual knowledge base, the absorptive capacity and the internal ressources of actors to manage a wider range of (explorative and exploitative) network ties might further play a decisive role in how R&D linkages are established and in which way regional organisations can benefit from them (Giuliani, 2007).

that the structure of network links plays an important role in explaining future states of the network (see e.g. Barabási et al., 2002; Jackson and Rogers, 2007). The network structure is assumed to influence the level of knowledge being exchanged throughout the network, for example between the core and the periphery (Cowan and Jonard, 2003, 2004; Fleming et al., 2007a; Crespo et al., 2014), and with this, a region's ability to activate new network ties and participate in inter-regional knowledge diffusion. For instance, hubs in the network may hold short path lengths to many other nodes in the network. If they form new collaboration linkages across regional boundaries, i.e. pursue inter-regional bridging strategies, this could accelerate knowledge diffusion across different network components and different regions.

Moreover, recent research in the context of R&D networks has shown that two actors are more likely to collaborate together if they share a common collaborator (that is if they are indirectly linked in the network, see e.g. Fafchamps et al., 2010). There are good reasons to assume that bridging paths matter for the evolution of the whole network. They create network proximity and opportunity for (triadic) closure. Indeed, if bridging paths represent indirect connections between actors from different regions, then we can assume that those regions which provide the bridging paths are in a position to facilitate the connectivity between other regions in the network. Such inter-regional closure structures may be of particular importance for the development of distinct technological networks, where knowledge integration between different components is crucial and the need for intensified and trust-based collaborations is high (Ter Wal, 2014). Bridging paths can thus be seen as important for regions not only in the context of accessing a diversified knowledge pool, but also in a network formation perspective. It helps establishing inter-regional R&D connections and with that inter-regional integration of (technological) knowledge.

4 A new measure of regional centrality

By proposing the significance of the bridging path concept for measuring regional centrality in regional R&D networks, the question of how this concept can be incorporated into regional centrality measures arises at this point. Usually, empirical researchers focusing on regions as units of observations face the problem that the underlying micro structure of the R&D network may be either undefined or unobservable. Concerning the latter, one may consider the example of co-patenting networks (see e.g. Lata et al., 2015), for which the relevant actors are individual persons (inventors) that are hardly identifiable as homogeneous nodes over time. Thus, we introduce a random matching process that will allow us to approximate the underlying micro-structure by deriving an expected number of bridging paths (ENB) between two regions.[2]

[2]This model is an adaptation of the one in Bergé (2016).

To introduce and illustrate the random matching process, take the case of three regions, A, B and C whose actors have R&D interactions. The term "link" will denote an R&D interaction between two actors and is seen as a collaboration between these actors. The random matching process uses only the aggregate flow of collaborations between A and B and the one between B and C. It hinges on the assumption that any observed link with the bridging region was randomly assigned to one actor from that region. Therefore, if there are two actors in region B and one link with region A, we consider that each actor of B would have a 50% chance to be connected with an actor from A. This assumption is very similar to the one used by Bloom et al. (2013), who provide a measure of technological similarity between firms' patenting activity introducing a model which considers random encounters between pairs of scientists. The random matching process reflects the ex post probability to be matched, i.e. the probability that two actors from two particular regions have been matched conditional on the structure of the inter-regional flows of collaborations. It simply relates to the fact that the higher the number of R&D interactions with a particular region, the higher the likelihood that an actor has collaborated with that region. The very intention is to give a baseline for a micro-network that was likely to occur, with respect to what is observable at the meso level.[3]

On this basis, it is now possible to derive the expected number of bridging paths stemming from a given region by using directly the aggregate flows of collaborations occurring between regions. First, denote by n_i the number of actors active in R&D collaboration in region i. Then the expected number of bridging paths, ENB^i_{jk}, between the two regions j and k stemming from the bridging region i along the random matching process is:[4]

$$ENB^i_{jk} = \frac{g_{ij}g_{ik}}{n_i}. \tag{1}$$

The expression related by equation (1) simply states that the more connections two regions, j and k, have with a third common region, i, the more likely they will have indirect connections at the micro level (bridging paths) thanks to the actors located in i.

Based on this, we are able to construct a new measure of the centrality of regions in R&D networks, denoted as *regional bridging centrality (BC)*. The BC is defined as the number of bridging paths stemming from a region between all dyads of the network. Formally, this means that the BC of region i is equal to:

[3]Note that assuming that the matching mechanism is based on preferential attachment instead of being purely random would not lead to any significant changes to the closed form of the expected number of bridging paths. Indeed, the ENB under preferential attachment would merely be an inflation of the ENB under the random matching (the theoretical details are provided in Appendix B of Bergé, 2016).

[4]The proof is given in Appendix A.1.

$$BC_i = \sum_{j \neq i} \sum_{k \neq i,j} ENB^i_{jk}, \tag{2}$$

where ENB^i_{jk} is defined by equation (1).

The interesting point of our measure is that its definition can be pretty much simplified and interpreted meaningfully in a regional context. Assume that the number of actors (n_i) is proportional to the number of R&D interactions (g_i);[5] then equation (2) decomposes to a notion of centrality of a region that entails a combination of three different components, reflecting i) a region's *participation intensity,* ii) a region's *relative outward orientation* and iii) a region's *diversification of network links* (see Appendix A.2 for a formal proof). It is defined as

$$BC_i = \bar{g}_i \, s_i \, (1 - h_i), \tag{3}$$

where

$\bar{g}_i$ is the number of outer collaborations (i.e. outer degree, that is $\bar{g}_i = g_i - g_{ii}$ which is the total number of collaborations of i, noted g_i, excluding the internal ones, noted g_{ii}). It refers to a region's *participation intensity* in inter-regional R&D collaborations, which affects positively the centrality of the region. It is a general measure of how well a region is embedded in the particular R&D network. Note that a region's size will amplify the probability of yielding more bridges between other regions. The participation intensity could therefore be interpreted as a broad measure of the relational capacity of the regional network nodes, which should be taken into account.

s_i is the share of outer collaborations with $s_i = \bar{g}_i / g_i$. It can be related to the *relative outward orientation* of all established network linkages, i.e. the relative degree of external R&D interactions. It refers to the openness of a region with respect to knowledge sourcing strategies. Given the fact that the BC focuses on the capacity of one region to link other regions, a high number of region-internal collaborations would have a negative influence as it potentially reduces the number of actors connecting different regions.

h_i refers to the Herfindahl-Hischman (HH) index of the distribution of i's outer collaborations defined as $h_i = \sum_{j \neq i} (g_{ij} / \bar{g}_i)^2$. The term $1 - h_i$ varies between 0 and 1 according

[5]Note that the assumption of proportionality between the number of actors and the number of R&D interactions is not limiting. Indeed, to empirically assess whether this was the case, we used data on patents, detailed in Section 5. Here we identify the R&D interactions as co-patents and the actors of the network as the inventors. Further, we used a simple algorithm to identify the inventors (two inventors from the same region are considered identical if they have the same first and last names). The results show a 98% correlation between the number of inventors in a given region and the number of patents produced by this region.

to the degree of *diversification of network links* to other regions, and indicates how a region's R&D collaborations are distributed along its neighboring regions in the network. In this case, the more the collaborations are concentrated, the less the region is central. Concentration reduces the actors' possibility to build bridges among different regions. This also relates to the fact that the more the outer collaboration pool is diversified over different regions, the more the region can draw its knowledge from different sources.

One especially promising property of the measure is that it takes account of the peculiar characteristics of regional networks. Indeed, regional networks are characterised by the structure of region-internal and region-external links and this feature cannot be dealt with adequately by using a single (a-spatial) SNA centrality measure. A region'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 a region to develop and renew the regional knowledge base faster, or prevent lock-in situations in certain technologies (see e.g. Breschi and Lenzi, 2015).

Finally, it is worth noting that the concept of bridging path is flexible and can easily be adapted to fit other forms of network centrality, depending on the context that is to be highlighted, as shown in Appendix B. In the analysis of R&D networks, for instance, it may be important to account for different categories of network linkages, such as intra-national vs. inter-national links when the R&D network under consideration crosses countries. However, in the illustrative example that follows, we stick to the regional level demonstrating an application of the original measure introduced in this section.

5 An illustrative example: an application to the European co-patent network

Given the promising features of the regional bridging centrality (BC) measure as defined in the previous section, an application to empirical regional R&D networks is required in order to illustrate the behaviour of the measure as compared to the conventional ones. To this end, we will employ co-patent data, comparing the regional BC with three other commonly used centrality measures, that is the degree, the eigenvector and the betweenness centrality.[6] We use the European co-patent network, a network of inter- and intra-regional collaborations in patent production observed at the regional level. A co-patent, that is a collaboration

[6]The degree is here calculated as the number of unique R&D interactions the actors 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 actors from these two regions. Due to the nature of the network, we used the weighted version of both the betweenness and the eigenvector centrality.

issuing a patent grant, is a visible trail of a successful R&D collaboration and is defined as an invention implying at least two inventors. This data are extracted from the REGPAT database (Maraut et al., 2008) and consist of all patents applied for at the European patent office (EPO) in the period 2006–2010.[7] We make use of the information contained in each patent record to build the co-patent network. Particularly, we use the address contained in each inventor's byline to map every patent to a set of NUTS2 regions. That is, the NUTS2 regions represent the place of residence of the inventors when the patent was applied for.[8] The number of inter-regional collaborations between two regions results from co-patents having at least one inventor from each of these two regions. Collaborations occurring strictly within the regions are counted as intra-regional patents.

The network consists of collaboration flows between 250 NUTS2 regions. This cross-regional co-patenting network is based on a total of 171,451 patents, producing 121,036 inter-regional collaborations linking the 250 NUTS2 regions. As a starting point, the three components of the BC are described by Table 1a. The participation intensity is on average 968, which means that the regions show on average 968 co-patent links to other regions in the network. This is much higher than the median of 368, confirming the right-skewed distribution of the number of co-patent links the individual regions hold to other regions.

More interestingly is the relative outward orientation. Here, the median is 73%, meaning that for half of the regions, more than 73% of their patents are of inter-regional nature, being invented with at least one partner outside the regions. Also diversification is relatively high, with an average at 0.88 (as indicated by 1 minus the HH index), meaning that the co-patents are rather distributed along several regions. Hence, the regions resort – on average – to a rich portfolio of partner regions leading to a diversified structure of inter-regional knowledge exchanges in patenting. In contrast to the participation intensity, the other two components, the relative outward orientation and the structure, are slightly left skewed, and can be seen as moderators of the scale of a region. Indeed, being a large region with a high network participation intensity does not necessarily lead to a high centrality value, if either the share of intra-regional collaborations is very large or inter-regional links are concentrated among only a few regions.

Table 1 reports some statistics on the BC measure as compared to the conventional measures, and the correlations among them. Note that for the sake of comparison, all measures

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

[8]We use the location of inventors to map the inter-regional collaboration network. This choice is made in order to insure that a patent's location matches the place where it has been produced. Indeed, an alternative way to locate the patents would have been to use the applicants' addresses. However, the applicant's address often refers to the firms headquarters, whose location is likely to be different to that of the place of production. Therefore using applicants addresses to locate the patents would have yielded another network that could have been interesting to analyse. Nevertheless, we here stick to inter-regional collaborations between "places of production", in line with the literature (see e.g. Fleming et al., 2007b).

Table 1: Descriptive statistics of the components of the BC and of the centrality measures applied on co-patenting data.

(a) Descriptive statistics of the three components of the bridging centrality measure.

	Min	Q1	Median	Q3	90%	Max	Mean	SD	Skewness	Kurtosis
Participation intensity	1	129.5	368.0	1096.7	2218.2	9550.0	968.2	1570.1	3.16	11.30
Relative outward orientation	0.15	0.62	0.73	0.83	0.88	1.00	0.71	0.15	-0.60	-0.05
Diversification	0	0.86	0.9084	0.9351	0.9505	0.97	0.88	0.09	-4.52	31.38

(b) Summary statistics.

	Min	Q1	Median	Q3	90%	Max	Mean	SD	Skewness	Kurtosis
Bridging Centrality	0.0000	0.0102	0.0311	0.0928	0.2173	1.0000	0.0893	0.1512	3.3548	13.2547
Degree	0.0000	0.0141	0.0410	0.1300	0.2361	1.0000	0.1064	0.1708	3.1677	11.2178
Eigenvector	0.0000	0.0014	0.0043	0.0199	0.0990	1.0000	0.0452	0.1313	4.7771	25.0188
Betweenness	0.0000	0.0016	0.0072	0.0372	0.0957	1.0000	0.0407	0.1070	6.0531	44.7149

(c) Correlations.

	Bridging Centrality	Degree	Eigenvector	Betweenness
Bridging Centrality	1.0000	0.9168	0.9376	0.6124
Degree	0.9168	1.0000	0.8295	0.8176
Eigenvector	0.9376	0.8295	1.0000	0.4994
Betweenness	0.6124	0.8176	0.4994	1.0000

Notes: The *participation intensity* is the outer degree. The *relative outward orientation* is the share of outside collaborations over all collaborations, it varies between 0 and 1. The *diversification* is $1 - h_i$ where h_i is the Herfindahl index of the distributions of region i's collaborations over all other regions; it varies between 0 and 1, the more the collaborations are concentrated, the lower is the measure.

are normalized so that the highest value is one and the lowest zero.[9] While there is no large difference in the summary statistics provided by Table 1b, it can still be noted that the eigenvector and the betweenness centrality are highly skewed, in contrast to the BC and the degree centrality. Table 1c further shows that the correlation between the bridging centrality and the other measures ranges from 61% to 93%. Those high levels are reassuring as they show that the BC does not completely reorder the regional positioning. The difference in the distribution of the four centrality measures is also illustrated by Figure 2 which reports the cumulative distribution of each measure. The graph of the cumulative distributions depicts two groups. On the one hand, the betweenness and the eigenvector centrality are close and at the top of the other distributions. On the other hand, both the degree centrality and the BC are at the bottom, with the distribution of the BC being above the distribution of the degree. Overall, the differences are higher at the beginning of the distribution (below 0.50) than at the end, where the distribution of all the centrality measures become much closer. However, the differences with existing measurements are real and it is worthwhile to point out the changes occurring to some particular regions. Moreover, it becomes obvious from this basic statistics that the bridging centrality is a combination of three components. It depends not only the scale of a region, like it might be the case for the degree centrality, or the quality of partners, i.e. whether they are located at the very core of the network, as for the eigenvector centrality. Therefore, it might be of particular interest how differently the three components are distributed across the individual regions.

Table 2 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.[10] Interestingly, we find 13 German regions among the 15 best ranked regions for the bridging centrality.[11] This results from the fact that they show both a high participation intensity as well as high openness from an inter-regional perspective; they show a high absolute as well as relative number of inter-regional co-patents. 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 language / cultural barriers as well as lower transaction costs. These factors seem to promote the high regional bridging centrality in German regions.[12]

Another interesting case is the region of Île de France (FR10) which ranks at the 16th po-

[9] Formally, the transformation applied to each centrality measure is: $(x - x_{min})/(x_{max} - x_{min})$.

[10] The spatial distribution of all four centrality measures over the EU is shown by Figure C.3 in appendix.

[11] 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.

[12] 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. We thank an anonymous reviewer for raising this issue.

Table 2: Centralities of the top 30 regions for the co-patent network, ranked by bridging centrality.

	NUTS2	Bridging Centrality value (rank)	Degree Centrality value (rank)	Eigenvector Centrality value (rank)	Betweenness Centrality value (rank)
Karlsruhe	DE12	1.00 (1)	0.87 (5)	1.00 (1)	0.22 (10)
Darmstadt	DE71	0.93 (2)	0.88 (4)	0.82 (3)	0.45 (4)
Düsseldorf	DEA1	0.84 (3)	0.82 (6)	0.68 (4)	0.22 (9)
Köln	DEA2	0.76 (4)	0.73 (7)	0.63 (6)	0.33 (6)
Rheinhessen-Pfalz	DEB3	0.73 (5)	0.64 (8)	0.85 (2)	0.13 (16)
Oberbayern	DE21	0.63 (6)	0.96 (2)	0.42 (7)	1.00 (1)
Stuttgart	DE11	0.59 (7)	0.95 (3)	0.64 (5)	0.37 (5)
Freiburg	DE13	0.49 (8)	0.52 (10)	0.34 (9)	0.19 (11)
Northwestern Switzerland	CH03	0.43 (9)	0.41 (14)	0.16 (17)	0.10 (24)
Arnsberg	DEA5	0.42 (10)	0.39 (16)	0.33 (10)	0.06 (45)
Tübingen	DE14	0.40 (11)	0.44 (12)	0.38 (8)	0.07 (36)
Berlin	DE30	0.39 (12)	0.40 (15)	0.22 (14)	0.19 (12)
Münster	DEA3	0.39 (13)	0.31 (20)	0.27 (11)	0.05 (49)
Mittelfranken	DE25	0.37 (14)	0.43 (13)	0.20 (15)	0.11 (20)
Zurich	CH04	0.35 (15)	0.34 (18)	0.12 (21)	0.08 (32)
Île de France	FR10	0.34 (16)	1.00 (1)	0.08 (35)	0.93 (2)
Schwaben	DE27	0.33 (17)	0.31 (21)	0.25 (12)	0.03 (71)
Brandenburg	DE40	0.28 (18)	0.22 (30)	0.15 (18)	0.05 (54)
Hamburg	DE60	0.27 (19)	0.23 (29)	0.09 (28)	0.05 (48)
Unterfranken	DE26	0.27 (20)	0.27 (23)	0.25 (13)	0.10 (23)
Alsace	FR42	0.26 (21)	0.23 (27)	0.13 (19)	0.09 (31)
Espace Mittelland	CH02	0.26 (22)	0.27 (22)	0.08 (30)	0.05 (50)
Prov. Vlaams-Brabant	BE24	0.25 (23)	0.20 (34)	0.04 (46)	0.10 (25)
Hannover	DE92	0.24 (24)	0.25 (24)	0.12 (22)	0.05 (53)
Rhône-Alpes	FR71	0.24 (25)	0.57 (9)	0.08 (34)	0.33 (7)
Koblenz	DEB1	0.21 (26)	0.17 (46)	0.18 (16)	0.01 (96)
Lüneburg	DE93	0.21 (27)	0.17 (42)	0.07 (37)	0.02 (79)
Eastern Switzerland	CH05	0.21 (28)	0.19 (36)	0.07 (38)	0.01 (97)
Prov. Antwerpen	BE21	0.20 (29)	0.18 (38)	0.05 (44)	0.09 (28)
Région de Bruxelles-Capitale Brussels Hoofdstede	BE10	0.20 (30)	0.14 (59)	0.03 (55)	0.08 (34)

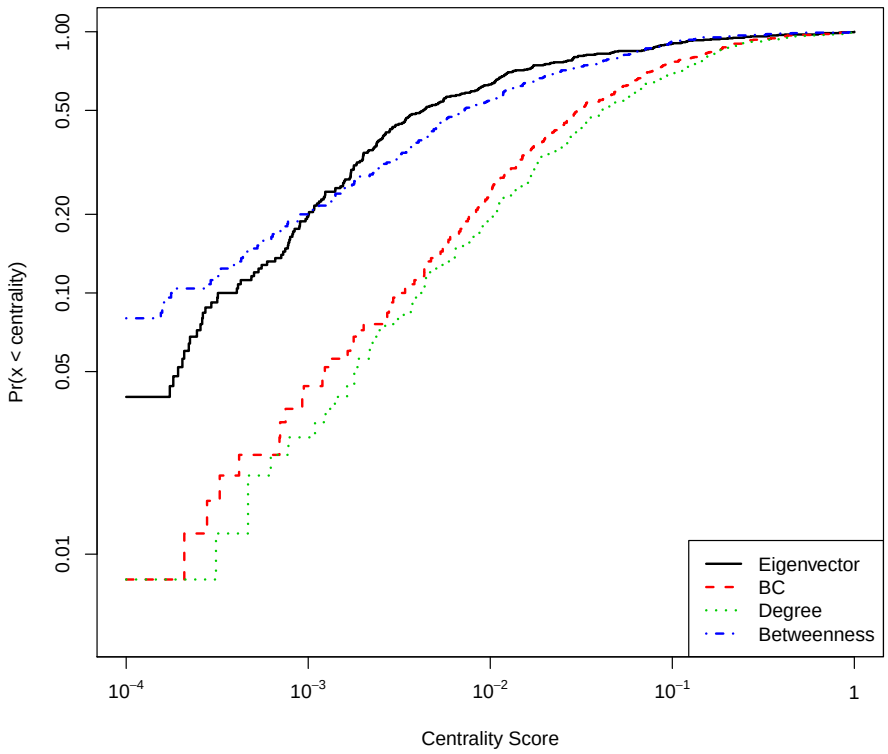

Figure 2: Cumulative distributions of the centrality measures in log-log.

sition for the bridging centrality, while being ranked first with respect to its degree centrality. We see that the measure of degree centrality may overstate its position in the inter-regional co-patent network. 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. By contrast, the eigenvector centrality may understate the importance of FR10; it ranks only 35 as it is linked to a lesser extent to the core regions. For the same reason as for FR10, some regions that are ranked high in the degree centrality end up much lower in the BC; i.e. they show high embeddedness in the inter-regional R&D network but are less open and diversified in the structure of their inter-regional collaboration, thus receiving lower values of bridging centrality.

Following the criteria of openness and diversification, interesting is also the case of Brussels (BE10) which ranks after the 55th place for the degree and the eigenvector centrality. With the BC, BE10 ranks 30th, gaining at least 25 places compared to these measures. However, these SNA-based centrality measures may underestimate its positioning in the inter-regional co-patent network: due to its very high outward orientation (its outer share is 94%) and a highly distributed structure of collaborations (it has a low HH index of 0.07), this region is

likely to provide many bridging paths to the network and may therefore be an important bridge for the whole network and for inter-regional knowledge diffusion.

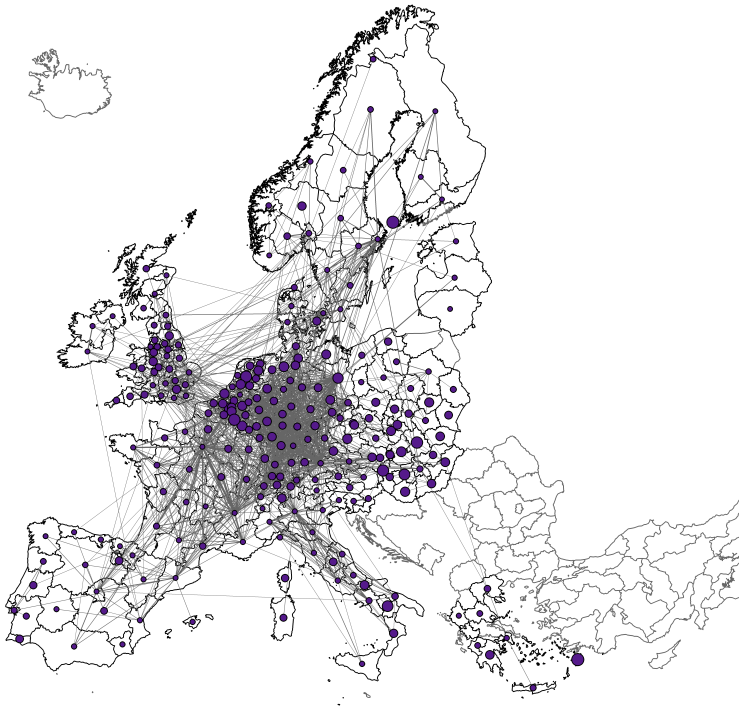

Figure 3: The European co-patent network

Notes: Node size corresponds to the relative outward orientation of a region, line width corresponds to the number of co-patents between two region.

Figure 3 illustrates the European co-patent network for the European NUTS2 regions, with the node size corresponding to the relative outward orientation of a region. It confirms the very dense network structure between core regions clustered in Germany, which hold intensive connections among each other. From a regional perspective, the bridging centrality is high for these regions, i.e. they yield high values for all three components, despite the fact that most of the links are confined at the national level. Furthermore, we observe a high relative outward orientation of some South 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. Nevertheless, inter-regional linkages are generally weak for these regions.

6 Concluding remarks

The notion of centrality is ubiquitous in debates on the role of regions in R&D networks. Quantitative approaches to measure regional centrality, however, are often based on micro-

level centrality measures as introduced in Social Network Analysis (SNA). The empirical analysis of regional networks requires accounting for the network structure originally defined at the micro level or by the linkages between different actors, which often limits the usefulness and conclusive identification of regions in the network. A further unavoidable problem relates to the considerable loss of information regarding network structure and meaning when regions are regarded only as aggregate units. In this study we address this micro / meso-level duality in how we view regional networks and define a region's structural network positioning, questioning the conventional measurement approaches for region-level analysis.

By introducing the notion of regional bridging centrality we suggest a new approach for assessing the centrality of regions in R&D networks; one that is able to cope with the regional dimension in measuring the centrality. Based on the concept of bridging paths, i.e. a set of two links connecting three actors in three different regions, we develop a measure of centrality that satisfies the requirements of both R&D networks and region-level applications: A bridging path between regions characterizes a situation where regional actors represent bridges or brokers in the network of regions as they connect indirectly the actors located in two other regions. Such a triangulation in regional networks, as we argue, is a key issue for knowledge recombinations, the extension of a region's knowledge base as well as inter-regional knowledge diffusion.

We further show that centrality in terms of bridging centrality can be viewed as a function of (i) the participation intensity in inter-regional R&D collaborations, (ii) its openness to other regions (i.e. the relative outward orientation of network links), and iii) the diversification of network links to other regions. With these three components – which are both intuitive and computationally simple – we argue that regional network centrality has to be viewed from a multidimensional perspective. Only with such an integrative approach we can achieve a better understanding of the role of certain regions in inter-regional R&D networks.

The comparative analysis with three standard SNA-centrality measures confirms the performance and usefulness of our measure of regional bridging centrality. We chose the inter-regional co-patent network for European NUTS2 regions as an illustrative example. Despite observing similar patterns in basic statistics like correlations of the centralities or the skewness, we were able to show striking and interesting differences in the structure of the inter-regional co-patent linkages across regions. The results reveal that thinking only of the degree of participation is not enough. Rather, the most central regions show simultaneously high embeddedness, high relative outward orientation and high diversification of their network links (e.g. Karlsruhe). In contrast, regions that may be strongly embedded (i.e. high participation intensity) may show low openness or diversification of links, thus yielding lower centrality values (e.g. Île de France). Hence, 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 regions in R&D networks. Viewing network positioning of regions in terms of regional bridging centrality might further elevate our understanding of which regions are the most central, show high visibility and at the same time are most important for the network and the inter-regional diffusion of knowledge.

There is room for further improvements of the concept of bridging path. 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, as shown in Appendix B, extensions of the bridging centrality can include a focus on the bridging actors that indirectly connect national actors with international ones. Focusing on technology related issues, one could consider bridging actors who indirectly connect actors from one specific technology to others from another technology.Therefore, depending on the R&D links' characteristics one wants to focus on, there are different ways to extend the notion of regional network centrality by using the concept of bridging paths.

Furthermore, the bridging centrality measure may contribute to the development of a multi-dimensional typology of regions, based on structural network criteria according to their levels of embeddedness, openness and diversification of links in inter-regional networks. Such a typology might enhance our understanding of how different the roles of regions in networks might be, and how they contribute to the arrangement and evolution of the inter-regional structure. Moreover, it seems natural that an application of the bridging centrality measure on other types of knowledge networks according to different technological fields might reveal interesting patterns of the most central network nodes. Hence, the measure of bridging centrality is not limited to the context of R&D collaborations but may prove to be useful also for the application in other types of network structures, such as inter-regional trade flows or inter-regional economic value chains, also regarding their evolution over time.

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A Proofs

We here show how to derive the results of equations (1) and (3).

A.1 The expected number of bridging paths

This proof is taken from Bergé (2016), the agents are the actors of the R&D network. Let L^a_{ik} to represent the ath link, $a \in \{1, \ldots, g_{ik}\}$, between agents from regions i and k, and L^b_{jk} to be the bth link, $b \in \left\{1, \ldots, g_{jk}\right\}$, between agents from regions j and k. By definition, the pair of links (L^a_{ik}, L^b_{jk}) forms a bridging path if and only if they are both connected to the same agent in region k (as depicted by Figure 1). Let the Greek letter ι, $\iota \in \{1, \ldots, n_k\}$, to designate agent ι from region k. Hence, from the random matching process, we know that the probability that agent ι is connected to any incoming link is $p_\iota = 1/n_k$. Thus, the probability that agent ι is connected to both links L^a_{ik} and L^b_{jk} is $p^2_\iota = 1/n^2_k$. Then the pair (L^a_{ik}, L^b_{jk}) is a bridging path with probability $p = \sum_{\iota=1}^{n_k} p^2_\iota = 1/n_k$ (summing over all the agents of region k, because each agent can be connected to both links). Let X_{ab} to be the binary random variable relating the event that the pair of links (L^a_{ik}, L^b_{jk}) is a bridging path. This random variable has value 1 with probability p and 0 otherwise, so that its mean is $E(X_{ab}) = p$. The random variable giving the number of bridging paths between regions i and j via region k is then the sum of all variables X_{ab}, a and b ranging over $\{1, \ldots, g_{ik}\}$ and $\left\{1, \ldots, g_{jk}\right\}$, that is ranging over all possible bridging paths. It follows that the expected number of bridging paths is $ENB^k_{ij} = E(\sum_{a=1}^{g_{ik}} \sum_{b=1}^{g_{jk}} X_{ab})$. From the property of the mean operator, it can be rewritten as: $ENB^k_{ij} = \sum_{a=1}^{g_{ik}} \sum_{b=1}^{g_{jk}} E(X_{ab}) = \sum_{a=1}^{g_{ik}} \sum_{b=1}^{g_{jk}} p = \sum_{a=1}^{g_{ik}} \sum_{b=1}^{g_{jk}} (1/n_k) = (g_{ik} g_{jk})/n_k$. □

A.2 The Bridging Centrality

Assume that the number of actors of region i,n_i, and the number of R&D interactions of that region, g_i, are proportional so that $n_i = \alpha g_i$. then the bridging centrality can be rewritten as:

$$\begin{aligned}
BC_i = & \quad \textstyle\sum_{j\in\{\Omega/i\}} \sum_{k\in\{\Omega/\{i,j\}\}} ENB^i_{jk} & = \sum_{j\in\{\Omega/i\}} \sum_{k\in\{\Omega/\{i,j\}\}} \frac{g_{ij}g_{ik}}{\alpha g_i} \\
= & \quad \tfrac{1}{\alpha}\tfrac{1}{g_i} \textstyle\sum_{j\in\{\Omega/i\}} \left[g_{ij} \sum_{k\in\{\Omega/\{i,j\}\}} g_{ik} \right] & = \frac{1}{\alpha}\frac{1}{g_i} \sum_{j\in\{\Omega/i\}} g_{ij}\left(\bar{g}_i - g_{ij}\right) \\
= & \quad \tfrac{1}{\alpha}\tfrac{\bar{g}_i^2}{g_i} - \tfrac{1}{g_i} \textstyle\sum_{j\in\{\Omega/i\}} g_{ij}^2 & = \frac{1}{\alpha}\frac{\bar{g}_i^2}{g_i}\left(1 - \sum_{j\in\{\Omega/i\}} \left(\frac{g_{ij}}{\bar{g}_i}\right)^2\right) \\
= & \quad \tfrac{1}{\alpha}\bar{g}_i s_i \left(1 - h_i\right)
\end{aligned}$$

Further, as the α is common to all regions, we lose no generality to setting it to $\alpha = 1$. Which yields the result. □

B Extensions using bridging paths

In this section we show how the concept of bridging path can be used to create other forms of network centrality. We first introduce one possible extension in general terms and then provide two examples.

General definition. Consider the general case in which regions, which are the nodes of the network, can belong to different categories (think to countries for instance). Let C_i denote the category of node i. By definition, nodes i and j are of the same category only if $C_i = C_j$. Depending on the context, it can be interesting to assess how much a region provides bridging paths between the nodes of its category and nodes of other categories.Then the number of bridging paths that node i provides between the two kind of categories, noted BC_i^{subset}, can be simply written as:[13]

$$BC_i^{subset} = \sum_{\substack{j \neq i \\ C_j = C_i}} \sum_{\substack{k \neq i \\ C_k \neq C_i}} ENB^i_{jk} = \frac{g_i^{\nabla} g_i^{\Delta}}{g_i}, \tag{4}$$

where g_i^{∇} represents the number of connections between node i and the other nodes of its category, and g_i^{Δ} connections between i and all other nodes that are not of its category. This

[13]This result can be obtained using simple rewritings as in Appendix A.2.

measure is significantly different from the Bridging centrality of Section 4 since here only bridging paths between a *subset* of all pairs of nodes are considered: the ones that are of different categories.

Examples. In the context of the European research area, regions that are connected to both i) other national regions and ii) international ones can be of particular importance. In this context, the natural categories are the countries to which the regions belong. The measure of centrality defined by Equation (4) then represents the expected number of bridging paths stemming from the central region between its national collaborators and its international ones.

Another illustration relates to organizations, when they are considered to be the nodes of the network. On could differentiate two kind of actors (or categories): public and private. This dichotomy can allow to have a form of centrality reflecting the idea of who is the most central in terms of providing bridging paths between public and private institutions, which is the measure defined in Equation (4).

C Figures

See figures C.1, C.2 and C.3.

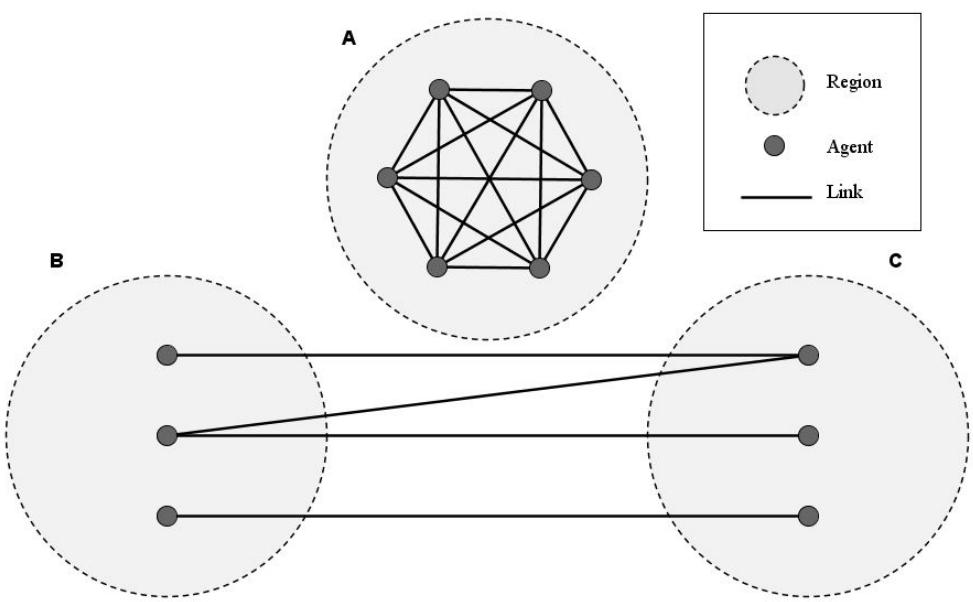

Figure C.1: Illustration of a regional network where a region has a strong internal structure yet no link with the outside.

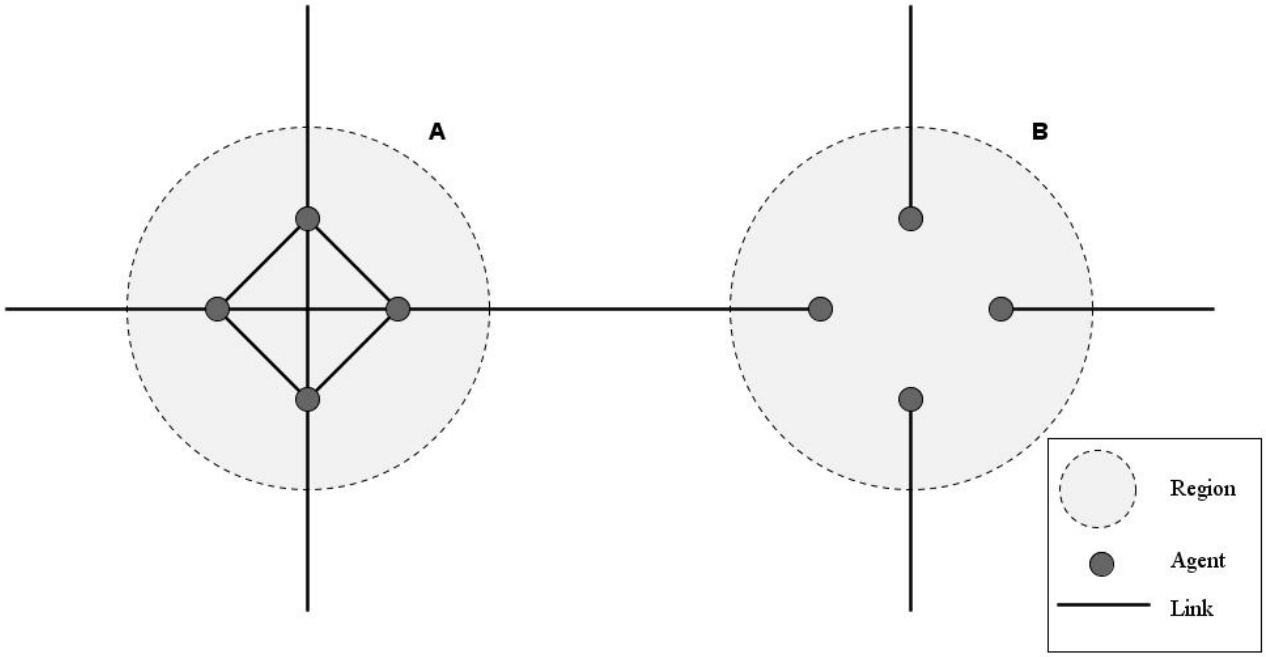

Figure C.2: Sample of a regional network. Illustration of two regions with external links, differentiated with respect to their internal links.

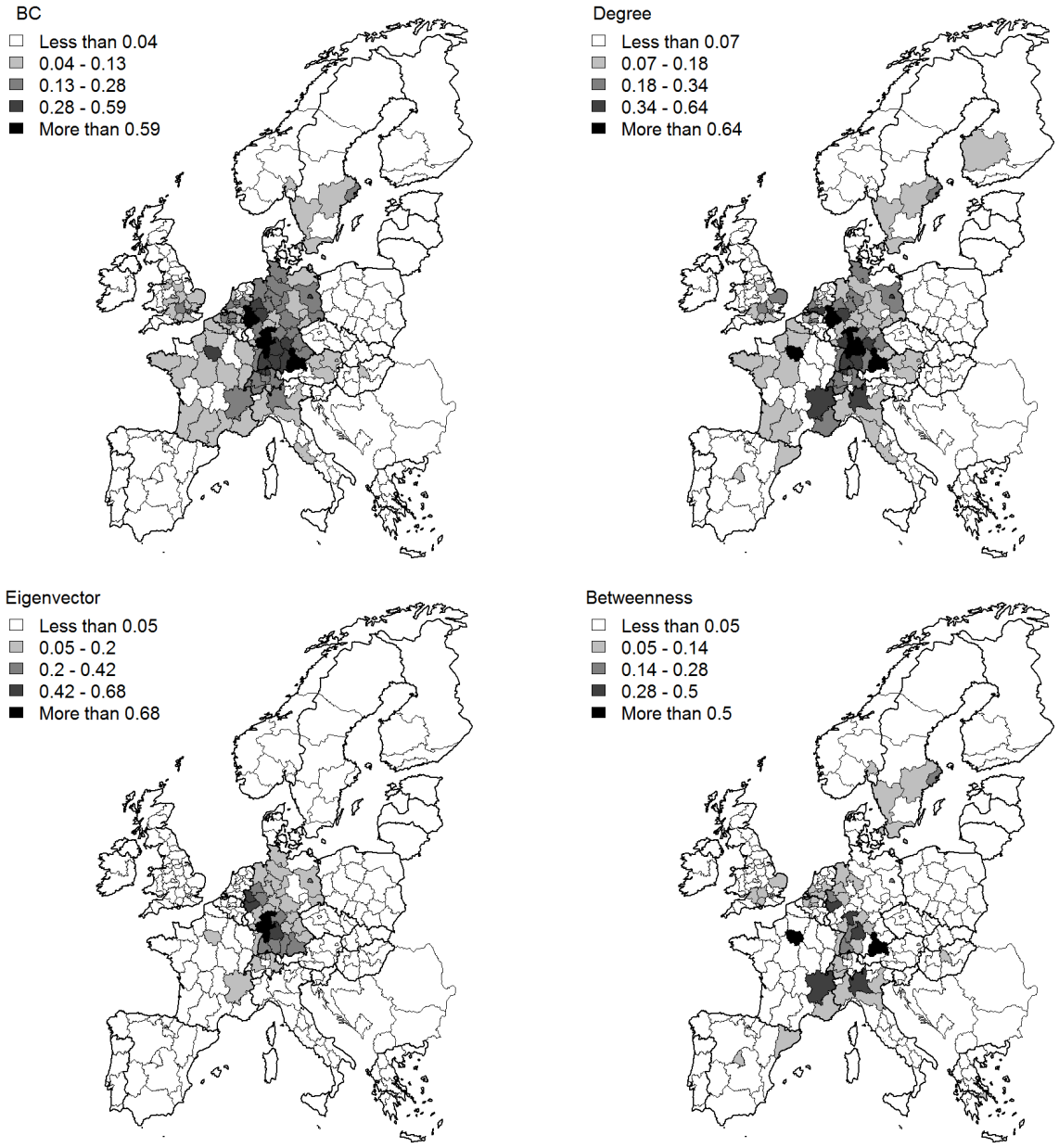

Figure C.3: Distribution of the centrality measures over the European regions for co-patenting data.