

## The spatial component of R&D networks

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**Abstract** We study the role of geography in R&D networks by means of a quantitative, micro-geographic approach. Using a large database that covers international R&D collaborations from 1984 to 2009, we localize each actor precisely in space through its latitude and longitude. This allows us to analyze the R&D network at all geographic scales simultaneously. Our empirical results show that despite the high importance of the city level, transnational R&D collaborations at large distances are much more frequent than expected from similar networks. This provides evidence for the ambiguity of distance in economic collaboration which is also suggested by the existing literature. In addition we test whether the hypothesis of *local buzz and global pipelines* applies to the observed R&D network by calculating well-defined metrics from network theory.

**Keywords** Complex network · Geographic distance · R&D · Collaboration

**JEL Classification** F60 · F23 · O30

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## 1 Introduction

Networks and their evolution over time have been studied extensively from different academic perspectives. Recently, much effort has been devoted to understand the structure of economic networks from a complex systems view. The complex systems approach, rooting back to physics and computer science, provides new perspectives on economic questions, since it allows to observe both the micro level (behavior and properties of a single economic actor) and the macro level (global outcomes, dynamics) in a unified way (Schweitzer et al. 2009). Different economic networks have been the topic of recent studies, such as ownership, financial, trade, or collaboration networks (Garas and Argyrakis 2008; Garas et al. 2010; Vitali et al. 2011; Battiston et al. 2012; Tomasello et al. 2013). Whereas this view led to the discovery of some stylized facts about economic networks, the actual role of geography in their formation requires further investigation.

This is quite surprising since geography has been a major topic of research in both economics and network science. From the economic perspective, it is widely agreed upon that geography has a prominent role in the formation of economic networks. Spatial proximity eases face to face contact, reduces costs and favors the building of trust. Geographers, economists and sociologists have provided a rich body of literature on how spatial proximity influences economic structures, starting from Marshall's Industrial Districts (Marshall 1895) to Porter's Cluster concept (Porter 1998) and Urban Economics (Glaeser et al. 1992; Glaeser 1999), just to mention a few.

While all these theories stress the importance of spatial proximity, there is also a bulk of literature that favors the opposite: Internationalization, standardization, global transport routes and new communication technologies constantly reduce the costs for transnational collaboration. At least since the end of 1980s, there is a strong trend toward international R&D collaborations (Kang and Sakai 2000; Gassmann and von Zedtwitz 1999; Georghiou 1998). In economic theory, the ambiguous role of geographic distance has been labeled with the term *Glocalization*, describing the high relevance of a firm's local environment in a globalized economy. A third stream of literature that can be labeled as "regional innovation system studies" takes an intermediate point of view; it puts special emphasis on the 'region', normally larger than a city and smaller than a nation, as the driver of innovation, interaction and learning (Cooke 2001; Doloreux and Parto 2004).

Despite these theoretical insights, the existing literature – as far as we know – does not provide any empirical analysis of R&D collaborations at *all spatial scales, simultaneously*. Existing studies focus on one specific geographical level, such as cities (Acs et al. 1999b), regions (Fritsch and Franke 2004; Bode 2004) or nations (Coe and Helpman 1997). However, this view is incomplete since the nature of R&D networks allows the co-existence of collaboration at different distances.

Additionally, it is considered a "stylized fact" in economics that R&D activities depend both on the type of industries and on properties of the firms, i.e. their size or their growth rates (Cohen and Klepper 1996; de Jong and Freel 2010), and this is reflected in the spatial component of their collaborations. For instance, small and medium-sized firms are usually more dependent on spatial proximity within their

knowledge-acquisition (Davenport 2005). Concerning the type of industry, literature has paid much attention on the role of service firms, in particular Knowledge-Intensive Business Services (KIBS), as catalysts of innovation (Strambach 2001). For KIBS, R&D collaborations are characterized by cyclical interactions and a high importance of tacit knowledge that favors the establishment local collaborations (Muller and Doloreux 2009). Besides the firm and industry specific properties, the temporal component should have a notable influence as well. As literature suggests, we expect to find a shift toward international R&D collaborations with our analysis, given that we have R&D collaboration data spanning a time period of 25 years.

In sum, the spatial component of R&D collaborations seems to be rather heterogeneous and multifaceted. Whereas the existing literature lacks empirical investigations, this issue has been tackled from a theoretical perspective in the paper of Bathelt et al. (2004). By means of their hypothesis of *local buzz and global pipelines*, the authors explain the *co-existence* of different spatial scales in collaboration networks. However, as far as we know, the existing literature does not provide an empirical analysis of this theory at a global scale.

With this paper we address the role of geographic distance in R&D collaborations by providing a detailed analysis of the spatial component of R&D networks. Our contribution to the current literature is twofold. First, we analyze the network of R&D alliances, which, in order to function properly, requires ongoing coordination and trust (Kang and Sakai 2000). These are complex social processes that should have traceable effects in the network's spatial component. Second, we push the geographic scale to a micro level, using refined localization for each firm in our dataset. This treatment allows to investigate the spatial component of R&D networks for all different spatial scales simultaneously, and goes beyond what has been reported so far in literature. In addition, we are able to use well-defined network measures (like betweenness centrality) to test the existence and the function of the *local buzz and global pipelines*, which are expected to play an important role in the process of knowledge creation (Bathelt et al. 2004). In sum, we contribute to the literature on R&D networks by focusing on the quantitative evaluation of one specific aspect: the geographic distance between collaborating firms.

## 2 Literature

Studies of the spatial component of networks are actually not new, but have been a research topic of many early quantitative geographers in the 1960s (Haggett 1967; Haggett and Chorley 1969). However, they were limited due to lack of access to large databases and computational power (Barthélemy 2006). Today, user- and commercially generated databases provide new possibilities to investigate the spatial component of complex networks, shedding light to the way geography affects human behavior.

During the last two decades, regional scientists have provided a remarkable amount of literature that applies network theory in the context of spatial innovation studies. Starting from the insight that geography and the way agents are connected to each other have a remarkable impact on innovation activities of firms or regions

(e.g. Acs et al. (1992a), Feldman (1994), and Porter (1998)), scientists have included network theory in their investigations to model innovation networks in a more reliable way. Much of this work can be labeled with the term *regional regression-based network theory*: network measures are computed and then integrated in a regression model to determine the factors why one region is more innovative than others (e.g. Broekel et al. 2014; Graf and Krüger 2011; Paier and Scherngell 2011; Whittington et al. 2009).

While our paper also deals with networks, space and innovativeness, there are two main differences to the aforementioned stream of literature. First, our operational unit is not the “region” but a single actor, i.e., a node in a network representation, and its geographical position is given by its latitude and longitude. Second, our empirical method does not rely on a spatial econometric approach where network measures are included in regression models. Instead, we focus our analysis on a very basic but nonetheless often disregarded question: What is the geographic distance of nodes inside a collaboration network and which conclusions on industrial innovation mechanisms can be derived from such an analysis? More precisely, we study the distribution of distances between nodes in the observed R&D network. In contrast to the mentioned stream of literature, such an analysis is more common in physics and complex systems literature. For example, Brockmann et al. (2006) analyzed the circulation of dollar bills, in order to investigate human travel for all different modes of transport simultaneously. Gonzalez et al. (2008) analyzed data from mobile phone users to explore patterns in human mobility, while Lambiotte et al. (2008) used mobile phone data to study the geographical component of human communication. Similarly, Bianconi et al. (2009) studied the role of distance for the global airline network, (Vitali and Battiston 2011) studied how distance affects corporate ownership networks, and Hennemann et al. (2012) collected geocoded information from the Thompson Scientific® database to explore the influence of geography on scientific collaborations.

All these works found that distances between nodes in the network follow a heavy-tailed distribution. More precisely, in most of them the distribution of distances  $r$  decays as a power law

$$P(r) \sim \frac{1}{r^\gamma} \quad (1)$$

with some small variations in the exponent,  $\gamma$ . As extensively discussed in literature, such broad distance distributions have important implications. For example, Hennemann et al. (2012) showed that national borders still have the highest impact on where scientific collaboration takes place. This contrasts with the popular belief that scientific collaboration has evolved into a joint global process and, as such, becomes independent from spatial distances. But, while distance plays a significant role at the national level, it is almost irrelevant for cross-country collaboration at the same time. Therefore, the authors conclude that low coordination costs and national funding systems tie researchers to local science clusters. But, going beyond the national level, increasing costs seem to be unimportant when collaborators can benefit from access to complementary knowledge or equipment (Hennemann et al. 2012).

Due to the functional similarities between scientific collaborations and R&D activities, heavy-tailed distributions of distances seem to be plausible for R&D networks

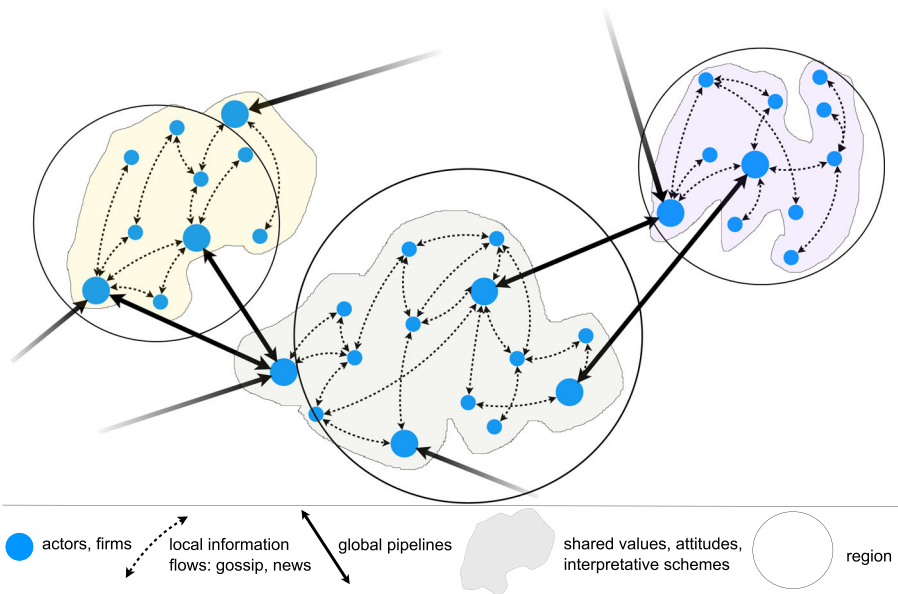
as well. This means that most of the collaborations take place between partners that are geographically close to each other, because collaborations usually imply that the economic actors know each other and meet frequently. However, collaborations are not fixed only to a narrow geographical scale. Large distances between actors may be more cost-intensive but also increase the chance of obtaining complementary knowledge.

Despite this intuitive explanation, economic theory provides only few models to explain a heavy-tailed distribution of distances in R&D collaborations, since most papers only deal with specific geographic levels. Bathelt et al. (2004) criticize the sole focus of many theories on localized knowledge spillover, since geographical proximity alone cannot explain the information flows within clusters of firms. Notwithstanding the importance of the surrounding environment, even very successful clusters, such as Silicon Valley, depend on knowledge flows from other remote clusters. The authors explain this ambiguity by means of what they call *local buzz and global pipelines*. Although their paper deals with the conversion of explicit and tacit knowledge and is not about network theory from quantitative point of view, it is often cited in the stream of regional regression-based network theory (e.g. Graf and Krüger 2011; Morrison and Rabellotti 2009; Whittington et al. 2009).

The term *local buzz* stands for short distance flows of information, face-to-face contact, gossip and every day communication of people and firms within the same region. Local buzz can be seen as a relatively informal way of communication that does not require particular investments and that affects all firms within a local cluster. This buzz can lead to common locally shared routines, similar technology attitudes and trust (Bathelt et al. 2004). On the other hand, *global pipelines* represent connections of individual firms inside a local cluster to other places around the world, as illustrated in Fig. 1.

In contrast to the local buzz, global pipelines represent a more formal way of interaction and can be seen as strategic partnerships. They are highly relevant for local clusters, since a cluster's competitive advantage is not only determined by its own innovative capacity but also by its ability to quickly absorb and adapt technology created elsewhere (Bathelt et al. 2004). Local buzz and global pipelines should not be seen as two distinct ways of accessing knowledge flows, but as aspects interacting with each other. Knowledge gained through global pipelines is accessible to all firms in a local cluster through the local buzz. In the paper of Bathelt et al. (2004) it is not clear, whether two collaborating firms of a global pipeline are both located inside a local cluster. However, the related literature clearly favors the idea of global pipelines being bridges between remote clusters (Amin and Thrift 1992; Giuliani 2005), since a costly pipeline is more efficient when it can benefit from local buzz from both of its sides.

Here we would like to highlight the conceptual similarity of the local buzz and global pipelines model to the small-world network model of Watts and Strogatz (1998). Both models discuss the existence of links that bridge different parts of a network, but the small-world network model does not make any claim about the role of geographical distance. More precisely, the distinctive characteristic of small-world networks is their combination of high clustering with short characteristic path length, but this length is measured by the number of links that separate two nodes.



**Fig. 1** Graphical representation of the local buzz and global pipelines model, following Bathelt et al. (2004)

On the other hand, the local buzz and global pipelines model was built to discuss how the actual geographic proximity affects the process of knowledge creation and knowledge access.

How the two main aspects of the local buzz and global pipelines model are combined seems to provide a promising theoretical explanation for observing heavy-tailed distributed distances of R&D collaborations: Local buzz is easy to access and facilitates the development of local trust, which is highly important for R&D collaborations (Ryan et al. 2004). Thus, local buzz can explain the strong focus of R&D collaborations on short distances. In order to adopt crucial knowledge created elsewhere, firms also invest in building up global pipelines. However, global pipelines are less frequent since they require intense efforts on both sides, are costly and harder to establish and to maintain.

Because the *local buzz and global pipelines* hypothesis describes the heterogeneity of network distances in a convincing manner, we plan to test it against our dataset and derive conclusions about the way R&D networks are structured. However, observing a broad distribution of distances alone does not imply that a R&D network follows a *local buzz and global pipelines* pattern. It only shows that remote connections exist but we do not know whether they bridge local clusters. If a network is characterized by separated local clusters with some pairs of firms being bridges that bring together different clusters, as shown in Fig. 1, it should also have a heavy-tailed distribution of the network's edge betweenness centrality ( $b_c(e)$ ) values (see Section 4). But, this will only show the existence of pipelines which by construction should have high  $b_c(e)$  values. To actually test how global they are, we should be able to detect

correlations between their  $b_c(e)$  values and their length in terms of actual geographic distance.

### 3 Data

For our analysis, we use the Thomson Reuters SDC Platinum database. This database records all publicly announced R&D partnerships between different kind of economic actors (including firms, investors, banks and universities) for the time period of 1984 to 2009. Hereafter, we use the standard view of complex networks literature, to represent economic actors as nodes and any relations between them as edges in an R&D network. In general, these edges can be directed or undirected. Given that R&D collaborations are usually bilateral processes, we assume that the network is undirected. With this abstract view we map actor differences to node properties, while all aspects of their relationship (like number of alliances between the same set of nodes, their geographical distance, etc.) are mapped to edge properties.

For each alliance relation we know the date of its announcement, the participating nodes, their 4-digit SIC<sup>1</sup> codes, and their country of residence. Because the nodes' geographic information is highly aggregated in our database, we used on-line queries in search engines to retrieve the address (house number, street name, postal code and city) of 3598 nodes. This allows us to calculate their exact spatial position through the geographical latitude and longitude. This way, we circumvent the Modifiable Areal Unit Problem (MAUP), a well-known issue in spatial statistics that describes a general bias when working with spatially aggregated data (Openshaw 1984). For our type of analysis, even small scaled spatial units may lead to distortion when processing global data. For instance, postal codes that are quite often used for geographically detailed research, normally refer to a single dwelling in the UK, while they range between 12 and 1,400 square kilometers in the US (Grubestic 2008). In summary, knowing the exact location of each node enables us to conduct a global analysis for all spatial scales, simultaneously. Additional to the 4-digit SIC-code, we matched our nodes with the Bureau Van Dijk's 2007 Orbis database to obtain information about its size, as reflected by the number of employees.

### 4 Methods

**Centrality measures** A graph  $G$ , is an abstract representation of what in this work we call network, and it is defined as a tuple of vertices (or nodes)  $n \in V$  and edges  $e \in E$  connecting the nodes. The way nodes are connected, i.e. the topology of the network, determines its properties, which can be expressed by various network metrics. The most frequently used metrics are related to *centrality* (Newman 2010), which can be defined in many different ways. In this work we will only consider node degree centrality and edge betweenness centrality. The degree centrality of a

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<sup>1</sup>Standard Industrial Classification.

node is simply given by its number of edges,  $k$ , and is called node degree. The edge betweenness centrality is given by

$$b_c(e) = \sum_{s \neq t} \frac{\sigma_{st}(e)}{\sigma_{st}} \quad (2)$$

where  $\sigma_{st}$  is the total number of shortest paths from node  $s$  to node  $t$ , and  $\sigma_{st}(e)$  is the number of those paths passing through edge  $e$ . This centrality metric is of particular interest to identify edges that act as pipelines, since by definition edges with high betweenness centrality are those that act as bridges between different communities.

**Null model** For different purposes, we have to compare the outcome of the observed R&D network to that of a random network. For instance, in order to make statements on the pipelines properties, we have to compare the distribution of  $b_c(e)$  values of the observed R&D network to a random one, keeping the main properties of the network (number of edges and nodes, degree distribution) constant except for the allocation of edges to nodes. To construct such a network, we randomly pick two edges,  $e_{ij} = (n_i, n_j)$  and  $e_{kl} = (n_k, n_l)$ , and swap the connections to obtain  $e_{ik} = (n_i, n_k)$  and  $e_{jl} = (n_j, n_l)$ . This step has to be repeated at least as many times as there are edges in the network. Here, following (Hennemann et al. 2012), we repeat this procedure five times the observed number of edges to ensure a sufficient randomization.

**Point pattern analysis** Since our dataset provides refined information about the location of firms, it can be studied with techniques that have been established for point pattern analysis. For the point pattern analysis of economic activities, the  $\hat{K}(d)$ -index of Duranton and Overman (2005) is the most established one in spatial econometrics.  $\hat{K}(d)$  allows to test whether, and at which exact distances, firms in an industry under investigation are spatially more concentrated or dispersed relative to what would be expected from the overall industrial agglomeration. The first step to compute  $\hat{K}(d)$ -values is to build the geographical distances between all possible pairs of firms so that one gains  $N(N-1)/2$  unique bilateral distances, where  $N$  is the number of firms in the observed industry. In the next step, one estimates the density of neighborhoods of firm pairs at distance  $d$  by means of a kernel density estimation (KDE). Thus the formula reads:

$$\hat{K}(d) = \frac{1}{n * (n-1)h} \sum_{i=1}^{n-1} \sum_{j=i+1}^n f\left(\frac{r - d_{i,j}}{h}\right), \quad (3)$$

where  $d_{i,j}$  is the distance between firm  $i$  and  $j$ ,  $h$  is the optimal bandwidth and  $f$  is the Gaussian kernel function. To test whether the computed  $\hat{K}(d)$  values show significant concentration or dispersion at a distance  $d$ , they have to be compared to confidence bands that are constructed by a Monte-Carlo approach: Let  $N$  be the number of firms in the industry under investigation, then we draw  $N$  locations out of the population of all possible firm locations in the area under investigation. These firms represent a random industry localization, whose  $\hat{K}(d)$  values are computed. The basic idea behind this procedure is that the spatial localization of industries does



not follow a pure random pattern, since industries cannot settle anywhere in a country. It is obvious that natural barriers (lakes, rivers, mountains) or political restriction (nature reserves, residential areas) limit the location choice of entrepreneurs (Duranton and Overman 2005). The procedure of drawing random firm locations is repeated 1000 times, storing the  $\hat{K}(d)$  values of each iteration. For each estimated distance interval  $d$ , the 5<sup>th</sup> and the 95<sup>th</sup> percentile are selected and are used to provide us with the lower (5<sup>th</sup> percentile) and a upper (95<sup>th</sup> percentile) confidence band. Whenever the  $\hat{K}(d)$  value of an observed point pattern hits the upper/lower confidence band, the pattern has significantly more/less neighborhoods at the respective distance than expected from a random distribution of firm locations.

In our case,  $\hat{K}(d)$  is a useful tool to check whether R&D collaborations are significantly concentrated at short distances, as supposed by the concept of *local buzz*. However,  $\hat{K}(d)$  computes distances between all possible pairs of firms and therefore neglects the network topology. Thus we rewrite it as  $\hat{K}_n(d)$  and consider distances between firm  $i$  and  $j$  only if an edge  $e(ij)$  exists. Thus the formula reads:

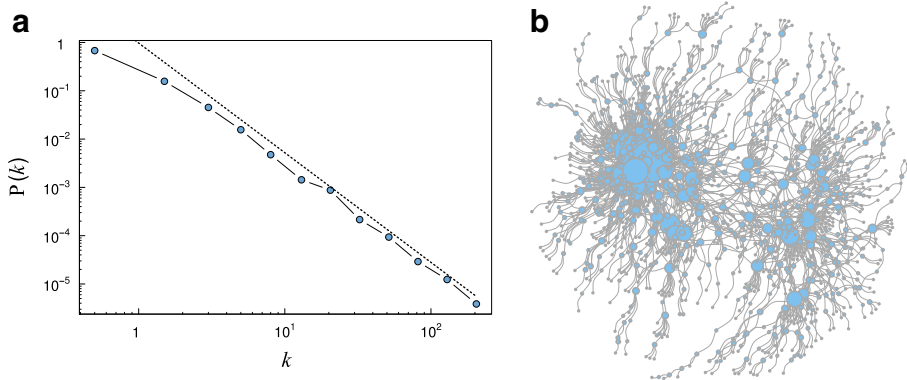
$$\hat{K}_n(d) = \frac{1}{Eh} \sum_{i=1}^n \sum_{j, e(ij) \in E}^n f\left(\frac{d - d_{i,j}}{h}\right) \tag{4}$$

where  $E$  is the number of edges.

Besides, also the calculation of confidence bands has to be adopted to the case of a network: By simply selecting random firm locations worldwide, results might be skewed by the fact that the locations of firms involved in R&D activities are actually highly restricted (see Fig. 3). By constructing random networks using the null model as described above, we keep all main properties of the network (number of edges and nodes, degree distribution) unchanged, except for the length of the edges. Furthermore, we ensure that the locations of the nodes are that of firms with an R&D activity. Analogous to the procedure of calculating  $\hat{K}(d)$ , we generate 1000 random networks and store the  $\hat{K}_n(d)$  values of each iteration. This provides us with the lower (5<sup>th</sup> percentile) and a upper (95<sup>th</sup> percentile) confidence band. Whenever the  $\hat{K}_n(d)$  curve of the observed R&D network hits the upper/lower confidence band, the network has significantly more/less edges at the respective distance than expected from a random distribution of edges at a 5% confidence level.

## 5 Empirical analysis

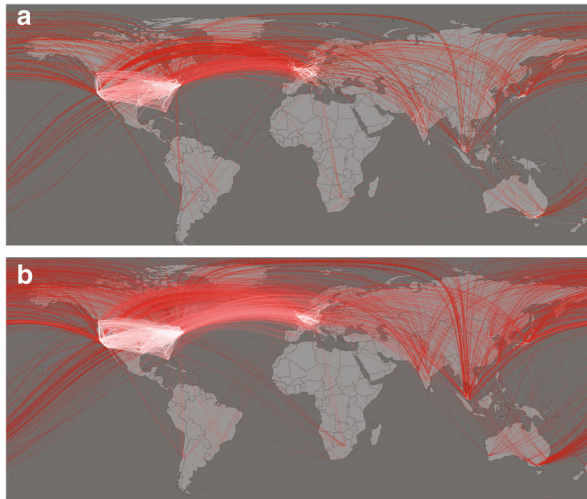
We start with the description of the topological features of the network. As shown in Fig. 2, the degree distribution of the R&D network follows a power law with exponent  $\gamma = 2.27$ , obtained using the maximum likelihood method as described in Clauset et al. (2009). Such degree distributions characterize a class of networks that are called *scale-free*, which includes biological networks, social networks, economic networks, technological networks, etc. A large empirical analysis of the dataset used here has already been performed by Tomasello et al. (2013). This analysis showed the existence of broad degree distributions together with other network properties like *core-periphery structure*, *nested organization*, and *small world topology*. We should



**Fig. 2** Topology of the observed R&D network. Left: The degree distribution; the dashed line shows a plot of a power law function with exponent  $\gamma = 2.27$ , i.e. equal to the exponent that describes the real network. The null hypothesis of the KS-test (both samples were drawn from the same distribution) can not be rejected ( $p = 0.99999$ ). Right: The largest connected component of the R&D network in an abstract space using the Fruchterman-Reingold Algorithm. The size of the nodes is relative to their degree  $k$

note that in most cases such properties depend on each-other, and the existence of one usually implies the existence of the others. For example, broad degree distributions imply small network diameter which is associated with small world properties (see Cohen and Havlin (2003)), and these properties play an important role for innovation networks and knowledge flows (Boschma and Martin 2010). In their analysis (Tomasello et al. 2013) showed that most network properties are invariant across pooled and sectoral networks, but they do change their value across time following a non-monotonic trend. However, in this empirical work the authors did not consider the *role of geography*, which is the topic of the current analysis.

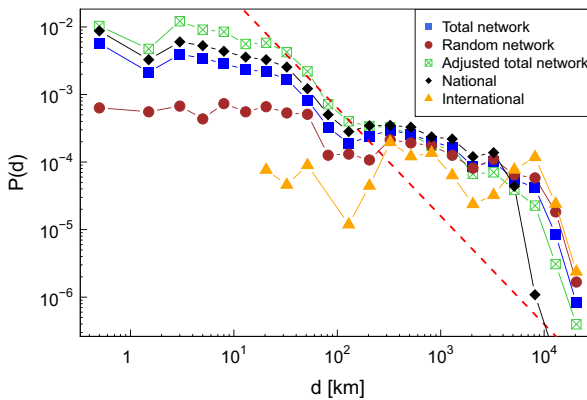
Thus, hereafter we focus on the spatial dimension of the R&D network, i.e. the location of nodes and the edge lengths. Figure 3 plots the nodes and edges of all observed collaborations from 1984 to 2009. For the observed network (Fig. 3a), we find a strong presence of edges between nodes (firms) located inside the US and between firms located in the US and the EU. There are less edges to firms in Asia (Japan, India, China), while in huge parts of the world (mainly in Southern America, Russia and Africa) only a few or not even one single node of the R&D network are located. Focusing on short distance collaborations only (lighter colored edges), we verify that the locations of their corresponding nodes are even more restricted and exclusive. There is strong concentration of such nodes at the US East and West-Coast, at the great lakes area, while in Europe high concentration is observed in Great Britain, France, and Germany. The plot of the random network as obtained from our null model is shown in Fig. 3b. From this figure, even visually we can observe that swapping the connections of the network, as discussed in the methods section, leads an over-representation of long distance collaborations. This is manifested by an increase in the number of intercontinental links of the random network with respect to the plot of the observed network. Actually, the arithmetic mean of the distances of



**Fig. 3** The global R&D network from 1984 to 2009. Nodes represent firms, edges represent R&D alliances. Edges are colored according to the orthodromic distance of their respective nodes. Top: Observed network. Bottom: Random network calculated according to the null model

the random network (4979 km) is about 42% larger than that of the observed network (3503 km).

To explore further the spatial allocation of collaborations, in Fig. 4 we plot the distribution of edge lengths for the observed and the randomized network. It is clear that the probability of finding collaborations at a short distance is much higher for the observed network with respect to the randomized one, even though the distances in both networks are broadly distributed. However, as shown in Fig. 4, the distribution



**Fig. 4** Distribution of edge lengths for the observed full network (blue ■), the random network (brown ●), the adjusted observed full network (green ☒), national collaboration (black ◆) and international collaboration (orange ▲). The dashed red line shows a power law distribution with  $\gamma = 1.6$ , as reported by Brockmann et al. (2006)

of edge lengths in the R&D network is significantly different from the distribution of edge lengths in scientific collaboration (Hennemann et al. 2012) or human mobility (Brockmann et al. 2006). In the R&D case the power-law hypothesis has to be rejected ( $p < 0.001$ ) due to the strong presence of transnational collaborations in the observed network. Since we know the exact address of each node, we can easily compute the share of edges where both nodes originate from different countries (35%). In comparison to scientific collaborations where the level of national collaborations exceeds the international level by a factor of 10-50 (Hennemann et al. 2012), R&D activities are thus clearly more international. When plotting the distribution of edge lengths of national and international collaborations separately, we observe a similar outcome as described by Hennemann et al. (2012): Distance has only an influence at the national level but is irrelevant for international R&D activities.

Since power-law distributed distances have been reported for many networks, here we discuss further why this is not the case for the observed R&D network. As noted above, in the R&D network a strong presence of transnational collaborations is observed. The most intuitive explanation is that this outcome reflects the nature of R&D collaborations in which the costs of long-distance collaboration are negligible compared to the importance of accessing complementary knowledge. However, we also have to bear in mind that the data collection of the SDC platinum database might be biased toward R&D activities of large US/EU firms. Since the SDC database contains only publicly announced R&D alliances, it is possible that many R&D activities of smaller firms were not monitored, and these alliances are mostly local ones.

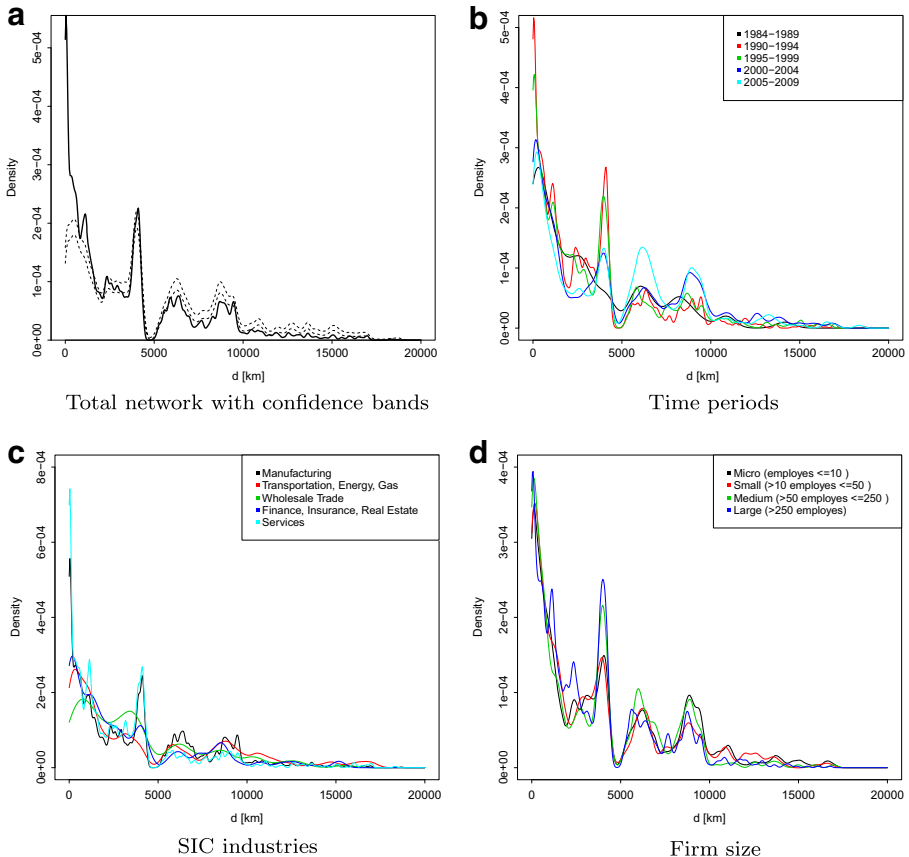
The third aspect could be the influence of the earth's topography. As shown in Fig. 3, the location of firms with R&D activity is highly restricted to only a few global hot spots. Thus, the distribution of distances could be skewed because of the topography between these hot spots. In particular, we assumed that the size of the Atlantic Ocean should have a notable influence since we observe a strong presence of edges between firms located at the US East Coast and firms located in the EU. To test for this possible influence, we adjusted the observed distances using the probability of finding an edge of a certain distance by the calculated  $\hat{K}_n(d)$  values. For each estimated bin  $b$ , the normalization factor  $N_b$  is the fraction of the  $\hat{K}_n(d)$  value of the observed network and the density of the 50<sup>th</sup> percentile of the random simulations:

$$N_b = \frac{\hat{K}_n(d)_b}{\hat{K}_n(d)_b^{50^{th}}}. \quad (5)$$

Thus,  $N_b$  shows how strongly the observed  $\hat{K}_n(d)$  value deviates from a median outcome. For each bin, the number of entries are then adjusted to the calculated  $N_b$ . As an example, consider that the first bin has 382 entries and its  $N_b$  value is 3.55. We randomly pick an entry and append it to the existing ones until there are  $382 \cdot 3.55 = 13561$  entries. For bins with  $N_b < 1$ , entries are randomly deleted until their number matches the normalized number. However, also this adjustment did not change the outcome either: As shown in Fig. 4, all different distributions (adjusted and not) deviate from what would be expected by a power law, but remain broad with heavy tails.

Of course, failing to observe a power law for the aggregated distances does not mean that the distance distribution does not contain any information. In Fig. 5 we plot the  $\hat{K}_n(d)$  values of the observed distances for a) the full R&D network, b) its decomposition into different time periods, c) its decomposition into industrial sectors, and d) its decomposition into firm sizes. In all these plots, we observe a peak at the 4000 km level which stands for the strong East Coast–West Coast collaboration network. The peak at 6,000 km represents East Coast-EU collaborations while the peak at the distance between 7,000 and 9,000 stands for collaborations between EU and East Coast firms and to firms located in Asia.

More interesting, however, is the peak around the 0 km interval. Almost 6% of the collaborations in the full network take place at a very narrow scale below 20 km, and 12% are located at a distance between 0 and 100 km. This shows, that despite globalization and communication technologies, the direct surrounding area is a very important place for firms to find R&D collaborators.



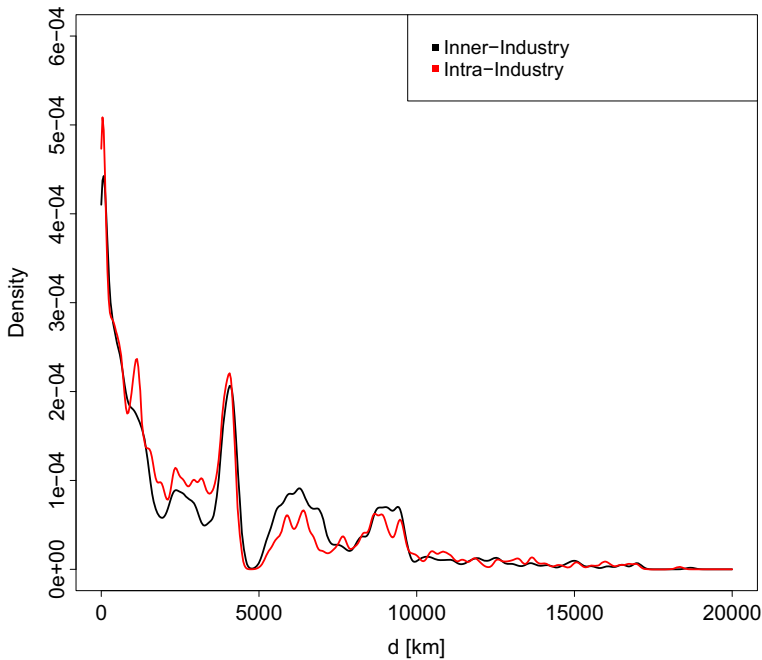
**Fig. 5**  $\hat{K}_n(d)$  values for different R&D networks. Networks in sub-figure c are only plotted for number of edges  $E > 100$

The confidence bands in Fig. 5a show that these peaks deviate from the random case. In particular, the probability of finding collaborations at a short distance is much higher than expected from a random network. For the distance between zero and 1300 km, the  $\hat{K}_n(d)$  values of the observed network exceed the upper confidence band. The distances of the East Coast-West Coast collaboration network lie within the confidence bands while we observe less collaborations at larger distances than expected from a random network. The observation of a high probability for local and East Coast-West Coast collaborations is very robust.

As discussed above, literature suggests a shift toward international R&D collaborations as the effect of globalization. This shift should be observed in our analysis, given that we can analyze changes in the collaboration activity between 1984 and 2009. By studying the network separately during consecutive time periods (4 year intervals between 1984 and 2009), a clear tendency toward larger distances in later time periods can indeed be observed in Fig. 5b. The rising of Asia displays in a higher peak at the 10,000 km level, at the expense of short distance and East Coast-West Coast collaborations. Furthermore, the last time period from 2005 to 2009 is characterized by a strong focus on transatlantic collaborations. While it might be assumed that this is the outcome of pre-crisis collaborations of the finance industry, actually more than 70% of these realizations origin from manufacturing firms. The first time period, 1984-1989, deviates form the described tendency toward larger distances in later time periods as it shows the lowest  $\hat{K}_n(d)$  values at short distances of all observed five periods and does not show a peak at the 4,000 km level. However, the first time period contains data for only 79 collaborations, so this result should be interpreted carefully. In order to test for differences between the  $\hat{K}_n(d)$  values of the five periods and the total network we applied the two sided Kolmogorov-Smirnov tests (KS-test). Except for the time periods of 1995-1999 and 1984-1989, all the pairwise two sided KS-tests are not significant at a 5% significance level, indicating that the distribution of distances for these time periods differs from the distribution of the total network.

On the firm specific level, the scope of business matters more than the firm size. Figure 5c shows that  $\hat{K}_n(d)$  values differ between different SIC codes. On the one hand, collaborations of the two SIC industries Transportation, Energy, Gas, and Wholesale, Trade are relatively equally distributed in space. This results from the fact that the location choice of companies within the first industry is often spatially bounded to the location of natural resources, while the location of firms in the latter industry follows the location of urban agglomeration. On the other hand, collaborations of service firms show the highest probability for short distances. This highlights the importance of spatial proximity in R&D activities of service firms (Muller and Doloreux 2009). The two sided KS-test is not significant for all investigated SIC codes except for the Finance, Insurance and Real Estate industry (5% significance level).

Since it is plausible to assume that the detected deviations between the industries result from their different tendency toward intra-industry collaboration, we calculated the  $\hat{K}_n(d)$  values separately for collaboration where the two partners have the same SIC code and a different SIC code, respectively. But, the differences between intra- and inner-industry collaborations are less pronounced than expected (Fig. 6). The



**Fig. 6**  $\hat{K}_n(d)$  values for inner-industry and intra-industry collaborations

KS-tests detect a deviation from the total network only for inner-industry collaborations. Testing for deviations from the total network using the Mann-Whitney test is negative for both cases (5% significance level).

With respect to the firm size, we do not observe a distinctive difference for short distance collaborations in comparison to the other time periods and SIC codes. Only at the 4000 km level, large and medium sized firms show a higher probability in comparison to micro and small sized firms. Concerning the KS-test, only micro and large sized significantly deviate from the total network (5% significance level).

To summarize, all of the aforementioned results highlight the ambiguity of distance in economic collaboration. The distribution of distances is multi-modal and differs between different industries and between different time periods, but it is comparatively similar for different classes of firm sizes.

In what follows, we are going to test the applicability of the *local buzz and global pipelines* hypothesis to the observed R&D network. Despite the absence of a power-law distribution of distances, it is possible that the R&D network follows a *local buzz and global pipelines* structure, but with more emphasis on global pipelines. As discussed in Section 2, *local buzz and global pipelines* properties can be measured by means of three network characteristics: Significant concentration of collaborations at short distances, heavy-tailed distribution of  $b_c(e)$  values and correlations between distances and  $b_c(e)$  values.

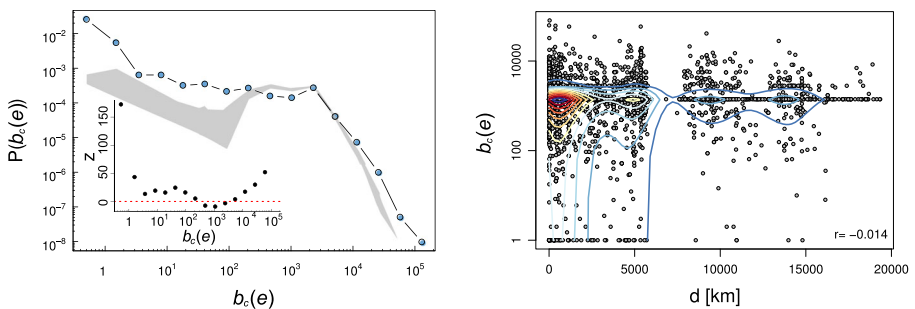
Starting with the first characteristic that represents the *local buzz* properties, the discussed outcome of the  $\hat{K}_n(d)$  plot in Fig. 5a has shown that the observed R&D

network clearly fulfills this specification: Edges with short lengths have a significant higher probability than expected from a random outcome, while edges with larger lengths do not exceed the confidence bands. All these are consistent with the existence of *local buzz*.

But what about the pipelines? Do they exist, and if so how global are they? As shown in Fig. 7, the distribution of  $b_c(e)$  values is, indeed, heavy tailed. In order to assess its significance, we compare it to the  $b_c(e)$  distribution we would obtain from a set of random networks. We repeat this step 1000 times, and for every bin  $i$  of the distribution we calculate the z-score defined as  $z_i = (b_c(e)_i - \langle b_c(e)_i^* \rangle) / \sigma_{b_c(e)_i^*}$ , where  $\langle b_c(e)_i^* \rangle$  is the average value of the  $b_c(e)$  for the ensemble of random networks, and  $\sigma_{b_c(e)_i^*}$  the standard deviation. The z-score plot shows high positive deviations for both very small and very large  $b_c(e)$  values. The deviation toward large values indicates that the tails are, indeed, “heavier” than expected by a random topology. In sum, this indicates that the R&D network contains central edges that act as pipelines, bridging separated clusters. But, this alone does not mean that global pipelines do exist, since it contains no information of how “global” the edges with high  $b_c(e)$  values are.

While the observed R&D network fulfills the first two properties of the *local buzz and global pipelines* model, we do not find any significant correlation between the  $b_c(e)$  values and the length of edges. The large deviation for small  $b_c(e)$  values points toward areas with many more local edges with high  $b_c(e)$  values than what would be predicted by a random topology. These could just be isolated components in the global network, and their presence may only create some unwanted bias in the overall statistics.

Therefore, in order to correct for this, from the empirical R&D network we extract the largest connected component, and we study whether any correlation exists between the  $b_c(e)$  values and the length of the edges. However, even after this correction the overall pattern remained the same, while the Pearson correlation coefficient between these two link properties is just  $r = -0.014$ , and as can be even visually



**Fig. 7** Global pipeline properties. Left: Distribution of the  $b_c(e)$  values for the empirical R&D network (dots) and for the ensemble of randomly generated networks (shaded area). Inset: z-score of the deviation between these two distributions. Right: Scatter plot of the  $b_c(e)$  values of all edges in the largest connected component of the R&D network versus their length. The contour lines highlight regions with high concentration of points



seen in Fig. 7 there is no traceable correlation. So, we conclude that the global R&D network is *not* characterized by *local buzz and global pipelines* but by *local buzz and gloCal pipelines*: Both local buzz and pipelines exist, but the pipelines do not only bridge clusters at a global scale, they are *simultaneously important at all levels* or, in other words, at a gloCal level.

However, similar to our discussion about the distribution of distances, this finding might be influenced by our dataset which is biased toward R&D activities of large US/EU firms. In addition, because we study R&D collaborations using a quantitative network approach, and in our analysis we do not consider the *value* of a collaboration for the firms involved, we cannot exclude that collaborations at larger distances are more important for knowledge creation and exchange than the local ones. But, this is something we cannot test with our data and further quantitative and qualitative work is necessary to check for this possible influence.

## 6 Conclusions

This paper studies the spatial component of global R&D collaborations by means of a complex network approach. Our empirical results provide evidence for the ambiguity of distance in economic collaboration which is also suggested by the existing literature. By pushing the geographic scale of our analysis to a micro geographic level, we are able to observe this ambiguity at all spatial scales, simultaneously. This approach allows for new insights into the spatial component of global R&D collaborations and leads to both well described and surprising outcomes.

One of the expected outcomes is the strong presence of collaborations at short distances. 12% of all R&D collaborations take place at a distance between 0 and 100 km and 6% are even located at a very narrow scale below 20 km. Our results support the idea that spatial proximity favors R&D collaborations between firms as it eases the buildup of trust and reduces the costs for communication. The high importance of short-distance collaboration is observable for all decompositions of the R&D network into different time periods, industrial sectors and classes of firm sizes. By means of these decompositions, we can also observe other expected outcomes: As suggested by literature, R&D collaborations of service firms are, in comparison to other industries, even more concentrated at short distances. Furthermore, the R&D network shows a tendency toward larger distances over time which can be seen as an effect of globalization.

On the other hand, we also find results that deviate from what is reported in literature. First, we do not find any evidence for a power-law distribution of distances in R&D collaborations. While such a distribution has been reported for many other similar networks (e.g. scientific collaboration, human mobility, ownership-networks), R&D collaborations at large distances are much more frequent than expected from a power-law distribution. By contrast, even after normalizing the possible influence of the earth's topography, the regional level is less pronounced in comparison to similar networks. Comparing the share of international collaboration, we find out that notwithstanding the high importance of the local level, R&D collaboration is a more international orientated process in comparison to scientific collaboration.

The observed co-existence of local and global collaborations has been described theoretically in the model of *local buzz and global pipelines* by Bathelt et al. (2004). The present paper has discussed how this model can be tested quantitatively by means of three network characteristics. The studied R&D network shows both a significance of collaborations at short distances and a heavy-tailed distribution of their edge betweenness centrality values. This supports the idea of the model of Bathelt et al. that local routines lead to a higher collaboration at the local level and that some firms are important for building bridges of collaboration between clusters of firms. However, we do not observe any correlation between the geographical length and the betweenness centrality of an edge. Although the regional level is less pronounced in the distribution of distances according to what would be expected by a power-law distribution, it is equally important for connecting local clusters of firms. Thus, from the observed statistical results we conclude that the R&D network is characterized by *local buzz and gloCal pipelines*.

In sum, the spatial component of R&D networks seems to be more heterogeneous than reported for similar networks of collaboration. While the existing literature provides different theories that support parts of our findings other results seem rather puzzling. As discussed, publications in the field of R&D research and innovation studies generally focus on one specific geographical level but do not provide an empirically substantiated theory for the coexistence of R&D alliances at different spatial scales. In addition, the literature does not offer a theoretical model for the higher probability of R&D collaborations at large distances in comparison to other networks about economic activities or international collaborations. Thus, we foresee a large demand for both observing further R&D networks from a micro-geographic perspective and for building theories that can explain the observed outcomes.

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#### Compliance with ethical standards

**Conflict of interests** The authors declare that they have no conflict of interest.

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