Knowledge Interactions in Regional Innovation Networks: Comparing Data Sources

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Abstract

The value of social network analysis is critically dependent on a comprehensive and reliable identification of relationships between actors. In this regard we compare regional knowledge networks that are based on different types of data sources, namely co-patents, co-publications and collaborative R&D projects. Moreover, we construct a multi-layer network that combines all three data sources to provide a more complete picture of regional interactions. Comparing the networks based on the different data sources we address problems of coverage and selection bias. It is found that the networks differ considerably depending on the data source used. The use of only one data source leads to a severe underestimation of regional knowledge interactions, especially those of private sector firms and of independent researchers. The key role of universities is, however, identified in all three types of data.

Keywords: Knowledge interactions, social network analysis, regional innovation systems, data sources

JEL codes: O30, R12, R30

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1. Introduction

It is widely acknowledged that innovation plays a crucial role for (regional) economic development processes. Innovations are typically generated in interactive and systemic processes that involve various actors and particularly include the exchange of knowledge (Lundvall 1992; Nelson 1993; Edquist 1997). Geographical proximity of innovative actors may be an important prerequisite for successful innovation processes (Boschma 2005; Breschi and Lissoni 2009). Since knowledge tends to be geographically bounded, it is often interactions between local actors that trigger self-enforcing learning processes resulting in a region-specific knowledge base.

Participating in technological and innovative networks provides considerable advantages for actors. Being involved in these regional innovation systems (RIS) (e. g. Cooke 2004; Asheim and Gertler 2006; Graf 2006; Graf and Henning 2009; Fritsch and Graf 2011) may improve access to different knowledge sources of different actors within the network and can particularly foster the creation of new knowledge. The structure of the network determines the general availability of knowledge, the communication and the knowledge flows (Cowan and Jonard 2004; Fleming et al. 2007). Particularly public research institutions often hold central positions in RIS networks. Hence, well connected actors in a regional innovation network tend to benefit directly from the existence of public research institutions (e.g., Cantner and Graf 2004; Fritsch and Graf 2011; Graf 2006; Graf and Henning 2009).

A common approach to analyze such interaction processes is the construction of networks of relationships between actors. Information on the relationships may come from different sources such as patent statistics (see Graf 2006), publications and other forms by which research and knowledge may become manifest. Since each of such data sources is selective in the sense that it only records certain types of interaction and disregards others, analyses of a certain innovation system may show quite different results depending on the data source that is used.[1] As a consequence, actors that appear to be relatively important in a network that is constructed with a certain data source may appear to be unimportant or are even completely disregarded if a different source of data is used.

This paper compares three types of data bases and describes their comprehensiveness and selectivity. Moreover, we construct a multi-layer network that combines all three data sources to provide a more complete picture of regional interactions. Accounting for multiple types of interactions in the innovation process should particularly allow relatively deep insights into processes of knowledge generation and transfer.[2] This empirical exercise is performed for six German regions with different levels of density and levels of innovation activity. The analysis covers the period 2000-2010.

Our analyses show rather considerable differences between networks that are constructed from patent statistics, publication data and subsidized research collaborations. While a relatively high share of public research institutions (universities and other public research institutes) is involved in all three forms of interactions we observe many firms that only participate in one specific form of knowledge transfer. Hence, investigating only one specific type of data neglects a large share of factual interactions, especially relationships between private firms and public research institutions. This holds particularly for cooperative links of private sector firms that are underestimated when only patent statistics are used. Finally, our approach enables the quantification of the measurement bias if only one data source is used.

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[1] For example, patent data disregard cooperation for inventions that are not patented (e.g. Arundel and Kabla 1998).

[2] Empirical analyses that combine different data sources for the construction of networks do, however, hardly exist what is probably due to limited data availability and the more technical problems of combining different sources such as data matching. For first approaches see for example Schmoch (1999), Meyer (2002), Heinze (2006), and Youtie and Shapira (2008). A recent study by Lata et al. (2015) combines three different datasets (granted projects supported within EU framework programmes, co-patents and co-publications). Though, these datasets are merged at the regional level and not at the level of actors.

The paper is organized as follows. Section 2 describes the sources of data and introduces the case study regions. In Section 3 we compare the networks constructed with the different types of data. Moreover, we also provide a more comprehensive picture of the different networks for the Dresden region as an example. Section 4 summarizes and concludes.

2. Data and spatial framework

2.1 Data sources and matching procedures

The empirical literature commonly investigates innovative interactions on the basis of either co-patents (e. g. Hoekman et al. 2009)[3], co-publications (e. g. Ponds et al. 2007; Hoekman et al. 2009; Hoekman et al. 2010) or data on (granted) collaborative R&D projects (Scherngell and Barber 2011; Scherngell and Lata 2011; 2013; Barber and Scherngell 2013).

The study by Lata et al. (2015) goes one step further and takes into account overlapping channels of knowledge transfer. The authors join all three types of interactions mentioned, but at a regional level. Our analysis is an extension of Titze et al. (2013) by developing a multi-layer framework that allows the investigation of overlapping channels of knowledge transfer at the level of institutions. Since information on interactions in all three data bases does not rely on self-reported responses but represent officially documented spells they credibly reveal actual collaborations.

Data on (government funded) *R&D collaboration projects* are provided in the Subsidies Catalogue (*Foerderkatalog*), which is prepared by the Federal Ministry for Education and Research and the DLR[4] Project Management Agency (for a detailed description see Broekel and Graf 2012). It comprises data on more than one hundred thousands of current and completed research projects. There are a number of reasons why this data base may have an only limited scope. First, it does not contain

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[3] Fischer and Griffith (2008) as well as Fischer et al. (2006) use patent citations to depict innovative interactions with the help of the patent indicator.

[4] The abbreviation DLR stands for Deutsches Zentrum fuer Luft- und Raumfahrt, the national aeronautics and space research centre in Germany.

information on collaborative R&D projects that have been conducted without any public subsidies. Second, some public support schemes of the Federal States or the EU are not included in this database. Third, grants under analysis are addressed at institutions (universities, external research institutes, firms, etc.) but not at individual persons. As a consequence, this data base does not include the names of persons involved in a project. Ihree key variables from the Subsidies Catalogue are relevant for the purpose of our investigation: primary keys for the sub-project and the collaboration project[5], the name and location of the executing organization[6,7] and the funding period. Small and medium-sized enterprises, universities and extra-university public research institutes are generally eligible for public funding. We only account for public support schemes that involve at least two collaboration partners.

The database of the German Patent and Trade Mark Office (DPMA) provides data on *(co-)patents* with at least one German organization involved. Each record includes a unique patent identification number, the title of the patent, the patent classes (IPC) as well as names and locations of both the inventor(s) and the applicant(s). As we are interested in the actual knowledge flow we use the name and the regional information of the applicant. We consider patent applications with at least two applicants[8]. However, the use of the patent indicator is not free from (well-

[5] *n* subprojects are assigned to exactly 1 collaboration project.

[6] The database distinguishes between the recipient of the grant(s) and the organization that actually works on the project (executing organization). In most cases both actors are identical. Exceptions are typically large enterprises consisting of numerous subsidiaries and large publicly funded research organizations like the Fraunhofer Society. In case of the Fraunhofer Society the recipient of the grant is the headquarter in Munich, but the actual project is conducted in a specific Fraunhofer Institute that may be located elsewhere.

[7] The database also contains a variable indicating the type of the actor (private firm, university, extra-universtiy research institute and “others”).In principle this variable could be an appropriate indicator for measuring organizational proximity. Unfortunately, however, the raw data contains many incorrect assignments. Moreover, the spelling of the names has not been harmonized, and a unique identifier for organizations does not exist.

[8] Some studies also consider ‘mobility’ relations. A mobility link occurs if an inventor is named on two patent applications of different applicants. The idea behind is that knowledge flows if the inventor moves from institution A to institution B (Graf and Henning 2009). We include this specific form of knowledge transfer in the patent layer, but not in the remaining two layers (co-publications, collaborative R&D collaborations).

known) methodological problems (e. g. Griliches 1990; Schmoch 1999; Cohen et al. 2000; Mansfield et al. 1981; Blind et al. 2006). First, not all inventions are patented, e. g. due to secrecy issues, application cost, high efforts of demonstrating novelty, time span between patent filing and granting etc. Second, large companies like Siemens and extra-univeristy public research institutions such as the Fraunhofer Society have centralized patent offices that administer all patent applications. We follow the approach of Graf (2011) and solve the problem of headquarter applications by considering only patents where the majority of inventors have their residences in one of our case study regions. These patents are then assigned to the local subsidiary of the respective company or the local research institute of the research organization. Third, patent activities differ considerably across scientific disciplines – inventions in non-technological fields such as new methods of organization of management cannot be patented.

Finally, we rely on bibliometric data for the analysis of *co-publications* that is provided by the Thomson Reuters Web of Science (formerly ISI Web of Knowledge) database. The following packages were available for the analysis: Science Citation Index Expanded (SCI-EXPANDED), Arts & Humanities Citation Index (A&HCI), and the Social Sciences Citation Index (SSCI). We use the following information from this database: the primary key of the publication (the so-called "WOS" number), the name of the authors' affiliation, and the geographical locations listed in the authors' information record. We consider those co-publications that report at least two authors from different affiliations. However, the use of bibliometric data faces some difficulties that are well-known and discussed in the literature (e. g. Abramo et al. 2009). First, the Web of Science database is incomplete in the sense that it mainly contains articles published in peer-reviewed journals. Second, publication strategies differ considerably between scientific disciplines. Third, actual collaboration and publication of an article must not necessarily go "hand in

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The main reason is that the data on publicly funded collaborative R&D projects contains no information about the individual researchers involved. Hence, it is not possible to analyze whether a researcher moved from institution A to B.

hand”. Furthermore, it is difficult to identify interregional linkages (co-publication, scientist mobility) in the Web of Science database since affiliations are not standardized in this dataset.

The actors’ information (name and geographical code) taken from the mentioned three databases is subject to a harmonization procedure that consists of two steps[9]: a pre-cleaning routine (change of the spelling to uppercases, replacement of German umlauts, removal of double spaces etc.) and the record linkage in a narrow sense (using the software “Fuzzy Dupes”[10]). To receive further actor specific information (type of institution, number of employees, industry code, age etc.), we merge this dataset with the Amadeus and the Research Explorer database.

According to the limitations of each dataset and for harmonization purposes we investigate a subsample of the entire network that relies on intra-regional interactions between institutions, although the patent and publication data would in principle also allow an investigation of collaborations at the level of individual persons. The patent data and the data on publicly funded R&D collaboration would also allow to include inter-regional connections.

The *Amadeus data base* (provided by Bureau van Dijk) comprises information on companies in Europe. For Germany this data base includes about 3 million companies. Every company in this data set holds a unique identification number (BvD-ID) that is used to identify and link actors. The *Research Explorer dataset*[11] (provided by the German Research Foundation [DFG]) comprises about 23,000 German universities and publicly funded external research institutes. This data base complements the above mentioned Amadeus enterprise data base with regard to cooperation actors, since the Amadeus data usually does not include universities and external research institutes.

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[9] For the details on this procedure see Ehrenfeld 2015a and 2015b.

[10] See http://www.kroll-software.ch/products/fuzzydupes/ for details.

[11] See Research Explorer (2017) for details.

2.2 Spatial framework

We choose the level of planning regions (“Raumordnungsregionen”) as geographical unit of analysis. German planning regions typically comprise a core city (district-free city) and its neighboring regions (districts). This regional level of aggregation is considered as appropriate for regional network analyses for two reasons (Graf and Henning 2009). First, it takes into account that regional channels of knowledge transfer do not necessarily end at the boundaries of a district or a district-free city. Second, this aggregation level considers commuter flows. This aspect is particularly important for the analysis of patent applications as patents are assigned to the inventor’s place of residence that must not necessarily fit with his place of work.

As we are interested in the interactions between different channels of knowledge transfer we investigate three types of regions with respect to their settlement structure: two at either end of the scale (high and low agglomeration) and one in between (medium level of agglomeration). In order to be able to compare and analyze the role of academic research all of our case study regions host at least one university (Figure 1).

Figure 1 shows the spatial distribution of the case study regions. Two of the regions—Aachen and Dresden—represent smaller agglomerations.[12] Both regions host a large university that focused on engineering and natural sciences. Aachen and Dresden have a comparable number of inhabitants (about 1 Mio.), establishments (28,000) and employees (about 235,000) (see Table A1 in the Appendix for details). The number of population was relatively stable over the last decade. Both regions also match with respect to the qualification structure of the workforce (the share of natural scientists & engineers in the total number of employees is about 4.5 percent) and the size of the universities (number of professors: 600-800, total research & teaching staff: 4,700-4,900).

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[12] This definition is in line with the classification of the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). For details see BBSR (2015).

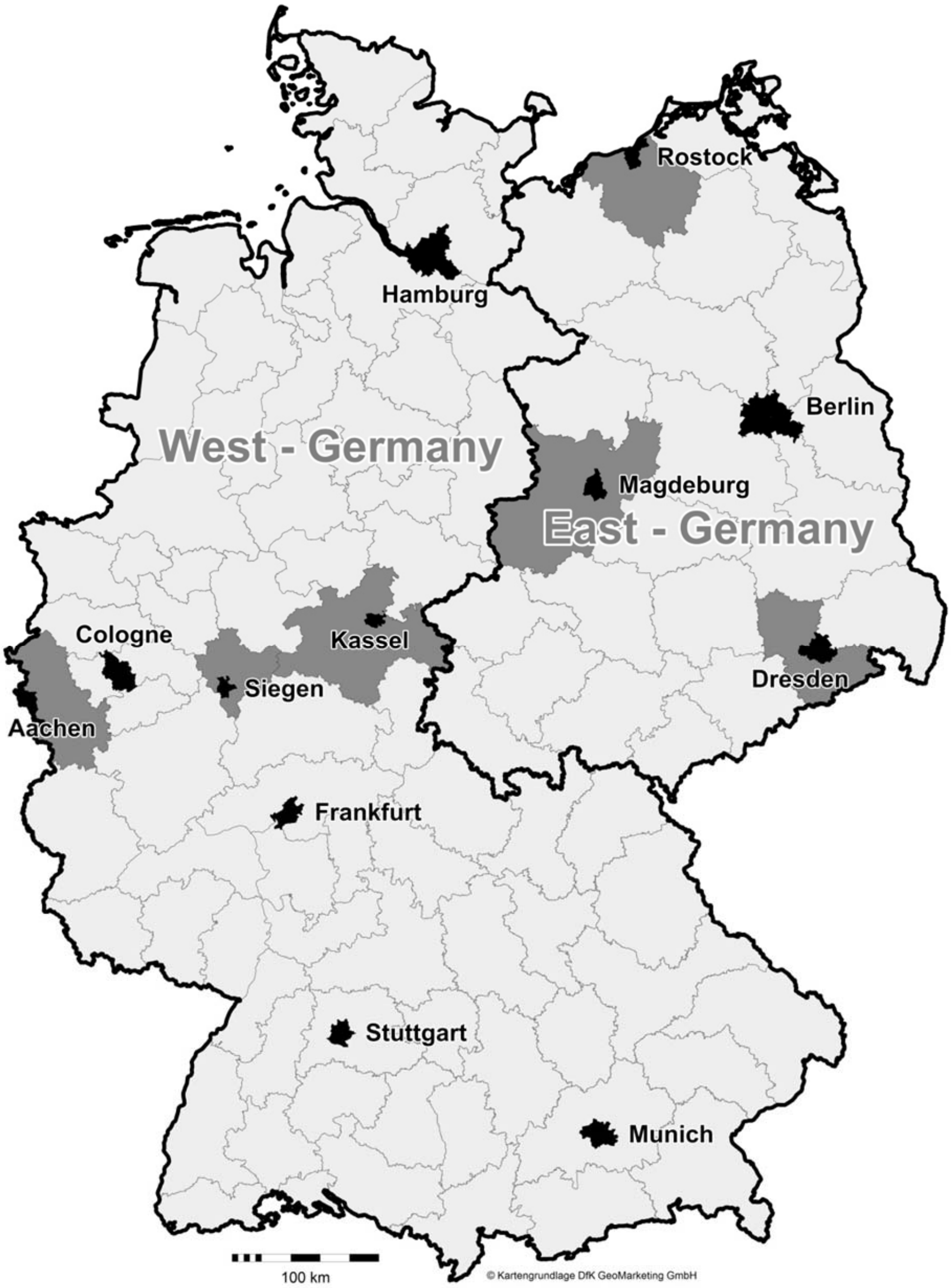


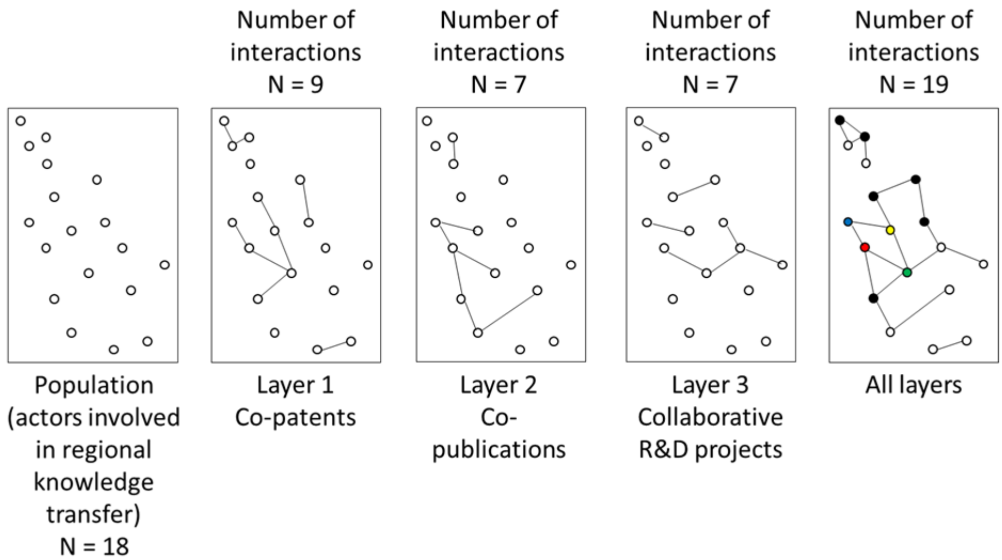
Figure 1: Case study regions in Germany (grey shaded areas)

The regions of Rostock and Siegen both represent smaller cities in a rather rural surrounding. Their population is about 430,000 each and was shrinking over the last decade in both regions. Kassel and Magdeburg are moderately congested region that host a population of about 1 Mio. that was slightly declining during the last decade.

3. Comparing regional innovation networks for different types of activities

3.1 Overlapping channels of knowledge transfer

Based on the three data sources described above we identified actors in the six regions under analysis involved in regional knowledge transfer. By "regional knowledge" transfer we mean that at least two actors must appear in at least one of the three types of interactions (either co-patents, co-publications, publicly funded collaborative R&D projects or a combination of them). Figure 2 illustrates how separate analyses of single channels of knowledge transfer might conceal interactions that occur in another layer. It also demonstrates that the total main component based on all three data sources or channels of knowledge transfer is larger than those of each single layer. According to this general methodological framework we then analyze interactions in the six case study regions.



Source: Own illustration.

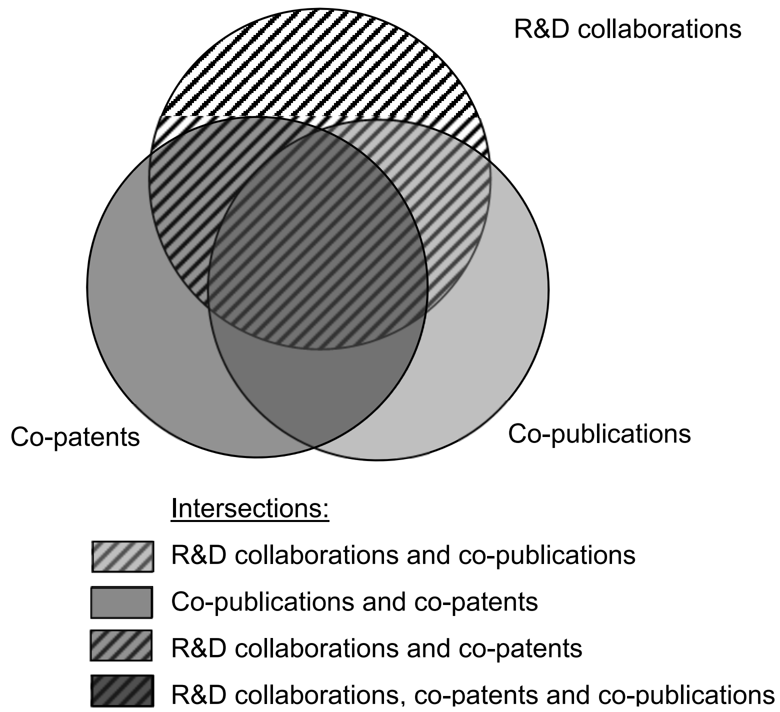
Figure 2: The principle of overlapping channels of knowledge transfer

In total, we identified 1,940 unique actors in the six case study regions and the three databases during the period 2000-2010[13]. 1,111 actors (57.2%) are identified as firms, 20 actors (1.0%) are universities,

[13] For the details on this assignment process see Ehrenfeld 2015a and 2015b.

and 115 actors (5.9%) are extra-university public research institutes. The remaining part (694 actors, 35.8%) mainly consists of individual inventors who could not be assigned to an institution (see also Section 2). 839 (43.3%) out of all 1,940 actors were identified either in the Amadeus or the Research Explorer database.

We now analyze how different actors are involved in different forms of knowledge transfer. For this purpose we form seven groups representing different forms of (regional) knowledge transfer.



Source: Own illustration.

Figure 3: Combinations of different forms of knowledge transfer

Table 1 presents the involvement of actors in different channels of knowledge transfer. In total, we find 27,434 interactions in all three layers in the six case study regions (column “All actors” in Table 1). If we differentiate these interactions by type, we find that 15,542 (56.7%) interactions between two institutions simultaneously appear as co-patents, co-publications and collaborative R&D projects. 3,729 (13.6%) are mere co-publications; 3,233 (11.8%) represent co-publications and joint R&D

projects; and 2,875 (10.5%) are pure co-patents. The bottom of Table 1 presents the total share of regional links that is captured by each type of interactions. It reveals that 69.4% of all regional interactions are analyzed by co-patents while 30.6% are not identified. The shares of the other two data sources are slightly higher. However, co-publications cover 83.1% of innovative links between actors; i.e. they disregards only 16.9% of all links that we have identified.

Table 1: Overlapping channels of knowledge transfer[b]

Channels of knowledge transfer (pooled 2000-2010)	All actors	Actors differentiated by type			
		Firms	Universities	Research institutes	Other[c]
	Number of interactions by type				
Co-patents only	2,875 (10.5)	1,312 (21.9)	2 (0.0)	252 (2.4)	1,309 (72.4)
Co-publications only	3,729 (13.6)	1,465 (24.5)	5 (0.1)	1,900 (18.3)	359 (19.9)
Collaborative R&D only	1,442 (5.3)	1,214 (20.3)	52 (0.6)	168 (1.6)	8 (0.4)
Co-publications and co-patents	304 (1.1)	192 (3.2)	0 (0.0)	79 (0.8)	33 (1.8)
Coll. R&D and co-patents	309 (1.1)	262 (4.4)	14 (0.2)	33 (0.3)	0 (0.0)
Coll. R&D and co-publications	3,233 (11.8)	681 (11.4)	16 (0.2)	2,438 (23.5)	98 (5.4)
All layers	15,542 (56.7)	860 (14.4)	9,157 (99.0)	5,525 (53,2)	0 (0.0)
Total	27,434 (100.0)	5,986 (100.0)	9,246 (100.0)	10,395 (100.0)	1,807 (100.0)
	Sum shares[a] (in %)				
Co-patents	69.4	43.9	99.2	56.7	74.3
Co-publications	83.1	53.4	99.3	95.6	27.1
R&D collaborations	74.8	50.4	99.9	78.5	5.9

Notes: [a]The respective number indicate, which share of regional knowledge transfer is captured by co-patents, co-publications and (granted) R&D collaboration projects. Due to overlap the figures sum up to more than 100.0%. – [b]Numbers in parentheses represent the share in %. – [c]This category represents actors (mainly individual inventors) which could not be assigned to an institution since patent statistics do not list inventors' affiliations in some cases.

Source: Own calculation.

The results change dramatically if we distinguish between the different types of actors. Firms are rather involved in only one facet of knowledge transfer, namely co-publications (24.5%), co-patents (21.9%) or collaborative R&D projects (20.3%). Firms tend to not use simultaneous channels of knowledge transfer—an exception is the combination of collaborative R&D projects and co-publications. Co-patents display only 43.9% of all intra-regional links of firms. Hence, investigating only co-patents neglects a large share of actual innovative relationships of firms. Co-publications and collaborative R&D projects capture about 50% of inter-regional knowledge transfer of firms.

These findings are completely different from the results obtained for universities. About 99% of knowledge links of universities occurs in all three layers. A considerably lower share applies to the “pure” forms of knowledge transfer (co-patents, co-publications and publicly funded collaborative R&D projects). Knowledge transfer of universities are reliably represented by all of the three indicators – their share is above 99%. The findings for firms and universities represent the lower respectively upper bounds. The results for extra-university public research institutes are in between these two.

Table 1 presents another remarkable finding, namely the importance of public research for regional knowledge transfer. 19,641 (10,395 + 9,246) out of 27,434 interactions (71.6%) under analysis take place with participation of either universities or extra-university public research institutes.

3.2 Actors involved in different types of innovative interactions

So far, we focused on the intensity of (regional) knowledge transfer differentiated by type of interaction(s) and type of actors. We now turn to the question how many actors (involved in regional innovative knowledge transfer) are captured by each of the three data sources under analysis. Table 2 presents our findings.

As mentioned above, our dataset contains 1,940 unique actors. The lion’s share is involved in only one type of innovative knowledge transfer, either co-patenting (50.5%), co-publication (17.1%) or collaborative R&D activities (22.0%). A negligible share of actors is part of multi-level activities. Having a closer look at the structure of this distribution reveals that this finding is mainly driven by the large share of "Other" actors representing patent applicants that could not be assigned to an institution.

This general pattern holds particularly true for firms. Table 2 indicates that firms mainly select one specific type of regional knowledge transfer. This finding again supports our hypothesis that the use of only one data source underestimates regional innovative knowledge transfer. The bottom of Table 2 shows that only 39.4% of all firms in our data are captured by co-patents. In other words, 60.6% of firms involved in regional knowledge transfer are neglected by this data source. The same applies to co-publications and publicly funded collaborative R&D activities. This finding emphasizes the need for an integrated and comprehensive approach to study regional innovative knowledge transfer.

Table 2: Actors in overlapping channels of knowledge transfer[b]

Channels of knowledge transfer (pooled 2000-2010)	Actors differentiated by type				
	All actors	Firms	Universities	Research institutes	Other[c]
	Number of actors by type				
Co-patents only	979 (50.5)	350 (31.5)	2 (10.0)	18 (15.7)	609 (87.8)
Co-publications only	331 (17.1)	230 (20.7)	1 (5.0)	28 (24.3)	72 (10.4)
Collaborative R&D only	427 (22.0)	391 (35.2)	6 (30.0)	24 (20.9)	6 (0.9)
Co-publications and co-patents	25 (1.3)	19 (1.7)	0 (0.0)	4 (3.5)	2 (0.03)
Coll. R&D and co-patents	46 (2.4)	42 (3.8)	1 (5.0)	3 (2.6)	0 (0.0)
Coll. R&D and co-publications	86 (4.4)	52 (4.7)	1 (5.0)	28 (24.3)	5 (0.7)
All layers	46 (2.4)	27 (2.4)	9 (45.0)	10 (8.7)	0 (0.0)
Total	1,940 (100.0)	1,111 (100.0)	20 (100.0)	115 (100.0)	694 (100.0)
	Sum shares[a] (in %)				
Co-patents	56.5	39.4	60.0	30.4	88.0
Co-publications	25.2	29.5	55.0	60.9	11.4
R&D collaborations	31.2	46.1	85.0	56.5	1.6

Notes: a) The respective number indicate, which share of actors is captured by co-patents, co-publications and (granted) R&D collaboration projects. Due to overlap the figures sum up to more than 100.0%. – b) Numbers in parentheses represent the share in %. – c) This category represents actors (mainly individual inventors) which could not be assigned to an institution since patent statistics do not list inventors' affiliations in some cases.

Source: Own calculations.

The results change considerably if we turn to universities and extra-university public research institutes. Table 1 and Table 2 show that a small number of universities is responsible for a large number of interactions highlighting the central role of universities for regional knowledge transfer. Furthermore, a large share of universities is involved in multiple channels – 9 out of 20 (45.0%) are part of all three types of collaborations under analysis. The bottom of Table 2 reveals that publicly funded R&D collaborations are an appropriate measure to identify universities as part of regional knowledge transfer. It captures 85.0% of actors belonging to the group of universities.

While firms and universities represent the lower and upper bound of the spectrum we find that extra-university public research institutes are in between the two. A considerable share of actors is involved in co-publication and publicly funded collaborative R&D activities. As a consequence of this 60.9% respectively 56.5% of all extra-univeresity public research institutes are covered by co-publications or publicly funded collaborative R&D projects.

3.3 Network descriptives

The previous two sections have shown that regional interactions differ considerably across different types of data sources and activities. We now describe how actors are involved in these (sub)networks. Table 3 presents network descriptives for the six case study regions. Here, the entire network including all layers works as scenario referece for the sub-networks that are constructed on only one of the three data sources. We focus on some basis network measures; connectedness, density, mean degree and binary mean degree.

The first row (All layers, Nodes) contains the number of actors involved in regional knowledge transfer in at least one of the three data sources under consideration. Since these figures correlate with regional

Table 3: Network descriptives

	average	Aachen	Dresden	Kassel	Magde-burg	Siegen	Rostock
All layers (base line scenario)							
Nodes[b]	323.3 (100.0)	581 (100.0)	588 (100.0)	145 (100.0)	278 (100.0)	103 (100.0)	245 (100.0)
Main Component[a,c]	185.5 (100.0)	319 (100.0)	405 (100.0)	44 (100.0)	176 (100.0)	24 (100.0)	145 (100.0)
Connectedness	0.50	0.549	0.689	0.303	0.633	0.233	0.592
Density	0.195	0.221	0.225	0.033	0.288	0.038	0.366
Mean degree	72.96	128.25	131.85	4.72	79.71	3.88	89.32
Mean degree (binary)	2.53	2.43	3.20	1.53	2.98	1.42	3.59
Collaborative R&D projects							
Nodes[b]	100.5 (31.1)	158 (27.2)	206 (35.0)	18 (12.4)	122 (43.9)	12 (11.7)	87 (35.5)
Main Component	85.2 (45.9)	144 (45.1)	171 (42.2)	12 (27.3)	96 (54.5)	10 (41.7)	78 (12.4)
Connectedness	152.50	0.911	0.830	0.667	0.787	0.833	0.897
Density	0.008	0.020	0.003	0.002	0.008	0.002	0.012
Density frag.[d]	0.081	0.027	0.023	0.144	0.040	0.167	0.086
Mean degree	1.35	1.14	1.62	0.30	2.11	0.21	2.74
Mean degree frag.[d]	4.24	4.19	4.61	2.44	4.80	1.83	7.55
Mean degree (binary)	1.03	0.84	1.23	0.28	1.68	0.21	1.91
Mean degree (binary) frag.	3.29	3.09	3.52	2.22	3.82	1.83	5.26
Co-publications							
Nodes[b]	81.5 (25.2)	176 (30.3)	154 (26.4)	21 (14.5)	67 (24.1)	10 (9.7)	60 (24.5)
Main Component	78.5 (42.3)	165 (51.7)	154 (38.0)	21 (47.7)	65 (36.9)	8 (33.3)	58 (40.0)
Connectedness	167.44	0.938	1.000	1.000	0.970	0.800	0.967
Density	0.020	0.025	0.022	0.006	0.030	0.004	0.035
Density frag.[d]	0.408	0.277	0.322	0.281	0.527	0.444	0.595
Mean degree	7.62	14.66	12.90	0.81	8.38	0.39	8.60
Mean degree frag.[d]	29.53	48.40	49.25	5.62	34.78	4.00	35.10
Mean degree (binary)	0.63	0.88	1.03	0.28	0.66	0.16	0.76
Mean degree (binary) frag.	2.70	2.90	3.95	1.90	2.72	1.60	3.10
Co-patents							
Nodes[b]	184.7 (57.1)	320 (55.1)	335 (57.0)	113 (77.9)	134 (48.2)	85 (82.5)	121 (49.4)
Main Component	46.7 (25.2)	60 (18.8)	158 (39.0)	15 (34.1)	24 (13.6)	6 (25.0)	17 (11.7)
Connectedness	0.20	0.188	0.472	0.133	0.179	0.071	0.140
Density	0.008	0.003	0.006	0.009	0.005	0.018	0.005
Density frag.[d]	0.019	0.008	0.018	0.015	0.022	0.026	0.022
Mean degree	1.74	1.44	3.25	1.31	1.32	1.86	1.26
Mean degree frag.[d]	2.96	2.63	5.76	1.70	2.85	2.23	2.57
Mean degree (binary)	1.02	0.99	1.20	1.02	0.79	1.07	1.05
Mean degree (binary) frag.	1.71	1.64	2.14	1.32	1.71	1.28	2.15

Notes: a) In each case study region, universities belong to the largest component. An exception is Siegen where the university is not part of the regional network of co-patents. – b) Numbers in parantheses represent the relation to the number of nodes in the base line scenario in percent. Please, note that the numbers do not sum up to 100% since some institutions are involved in several layers. – c) Numbers in parantheses represent the relation to the number of nodes in the main component in the base line scenario in percent. Please, note that the numbers do not sum up to 100% since some institutions are involved in several layers. – d) Fragmented (frag.) network measures only include actors, which are active within this layer whereas non-fragmented network measures include all identified actors in the region (= nodes from the base line scenario).

characteristics we do not interpret absolute but relative numbers. At first glance, the largest share of actors involved in regional knowledge transfer acts in the co-patent layer. This finding is certainly affected by the data preparation process since a large number of inventors could not be assigned to an affiliation which works as unit of analysis in our study.

However, notably are the high values in the regions Kassel and Siegen. These regions show a relative low number of actors that are involved in the other two forms of regional knowledge transfer. The share of actors participating in regional collaborative R&D networks and co-publications ranges between 24.1 and 43.9% in Aachen, Dresden, Magdeburg and Rostock. Again, the share in these two types of regional knowledge transfer in Siegen and Kassel is remarkably low (range: 9.7-14.5%).

Regarding the number of actors in the main component involved in different types of regional knowledge transfer we find that a large share is active in the publication layer (range: 33.3-51.7%). The other two layers under consideration show smaller values and a higher deviations. The connectedness measure represents the number of actors in the main component relative to the total number of actors participating in a specific type of regional knowledge transfer. In comparison with the baseline scenario the connectedness for regional knowledge transfer in the case study regions is higher for publicly funded collaborative R&D projects (except Rostock) and co-publications but lower for interactions that are based on co-patents.

It is not surprising that density increases when all layers are put together. This result holds for all regions. In other words, the intensity of interaction is underestimated if only one type of innovative connection is analyzed. Graf and Henning (2009) point out that the sole use of this measure might produce biased results since the growth of possible interactions exceeds the actual growth of links which would lead to low densities in large networks. Indeed, we find that Magdeburg and Rostock show higher densities than Aachen and Dresden although they have smaller numbers of nodes. Surprisingly, this finding does not hold for

Kassel and Siegen. This bias becomes apparent, when the density and the fragmented density measures are compared. The fragmented density only considers active actors within this layer, whereas the density considers all actors in this region. Differences can be rather small (e.g. publicly funded collaborative R&D projects in Aachen: 0.020 and 0.027) or large (e.g. co-publications in Siegen: 0.004 and 0.444).

Similar to the result for the density measure we find that mean degree (and binary mean degree) is highest in the combined layer in all regions of our sample. If we analyze each single layer we observe that the mean degree in the co-publication layer is higher than for collaborative R&D project and co-patent networks. Remarkably, we find high (fragmented) mean degree values for the co-publication networks except for Kassel and Siegen). It seems that there are fewer obstacles for co-publications than for co-patents and publicly funded collaborative R&D projects.

3.4 In-depth analysis of multi-layer networks: The example of Dresden

So far, we analyzed networks in different fields of activity from a “macro-perspective”. We now turn to an in-depth analysis of networks in co-patenting, co-publications and publicly funded R&D projects. Due to space limitations we focus on the Dresden region as it has the largest number of actors and the largest main component.[14]

Figure 3 depicts the main components of the different network layers for the Dresden region. Red circles represent private sector firms, green rectangles universities, and yellow diamonds identify extra-univeristy public research institutes. The remaining category of actors (blue

[14] We provide network graphs for all case study regions in an online appendix.

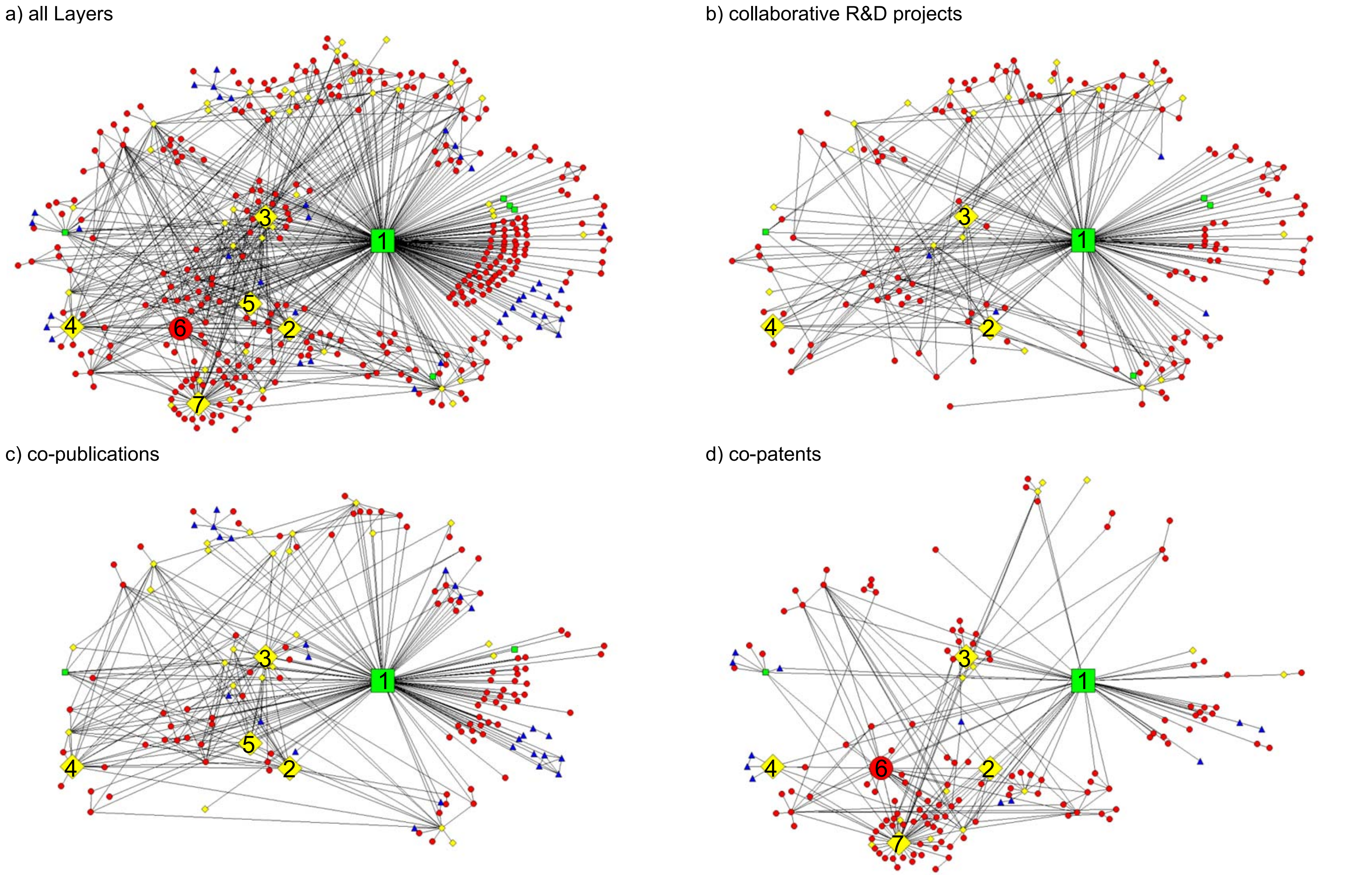


Figure 3: Networks of the Dresden region (largest component, period 2000-2010)

Source: Authors' own illustration.

Legend:

Private Sector (firms) University Research Institute Other actors

Legend actors with central positions:

1: TU Dresden 2: Leibniz Institute for Solid State and Materials Research 3: Helmholtz-Zentrum Dresden-Rossendorf
4: Leibniz Institute for Polymer Research 5: Max Planck Institute for Chemical Physics of Solids 6: Infineon 7: Fraunhofer Society

triangles) captures those individuals that could not be assigned to an organization in the record-linkage procedure. Cooperative relationships between actors (linkages) are represented by light grey edges.[15]

We find tremendous differences between the networks that are based on only one of the three data sources. These differences clearly demonstrate that each of these networks covers only a specific part of the overall knowledge transfer. The most complete picture of the relationships in the Dresden region is provided by a combination of all three data sources. Around two thirds of all actors in Dresden (405 of 588) are present in the main component of the comprehensive network (Figure 3 a). The picture also clearly shows the central position of the Technical of University Dresden..

Graphical representations of networks for Dresden—based on patents—are often characterized as bipolar where two dominant institutions hold gatekeeper positions (Graf and Henning 2009; Graf 2011; Fritsch and Graf 2011). In our case, the publication and the subsidized research project networks are strongly cross-linked (Figures 3 b and c). The dominating actor in this network is the Technical University of Dresden. Several othe public research institutes are responsible for the highly interwoven structure of the network. The most central actors in the entire multi-layer network (Figure 3 a) are identified as actors 1 to 5. The first four are active in all three channels of knowledge interactions under consideration. Most of them also assume a broker role for the network.[16]

Public research institutes are not only connected to universities but also among each other. This cobweb offers manifold links for firms to cooperate. Many of these research institutes (Figure 3 a) are surrounded or at least connected to a high number of firms. This finding shows that the research conducted in these institutes is of importance for regional

[15] The position of nodes was produced using the spring embedding method (see Brandes 2001). For the sake of clarity, we do not attempt to represent the strength of a link or the number of patents, publications and R&D projects of an actor by the thickness of an edge or the size of a node.

[16] The five actors with the highest betweenness centrality are the Technical Universityof Dresden, the Fraunhofer Society, the Helmholtz-Zentrum Dresden-Rossendorf, the Institute of Air Handling and Refrigeration and the Leibniz Institute for Polymer Research.

firms and that it is transferred into the regional economy. Research institutes can be taken as fixtures in the networks in Figure 3 to compare the actors. The co-publication and collaborative R&D networks (Figure 3 b and c) look similar, but only a small fraction of actors is active in both fields of knowledge transfer.

Linkages between actors in one network do not necessarily occur in other networks (i.e. actors 2 and 3). Only a small number of actors, like the Technical University of Dresden and the Helmholtz Zentrum Dresden-Rossendorf cooperate in all three networks.

The patent network (Figure 3 d) differs strongly from the previous with respect to the size and composition of actors. The before mentioned bipolar character for patent networks can also be identified here. The two dominating actors are the Fraunhofer Society (actor number 7) and the Technical University of Dresden. The fact, that the Fraunhofer Society does not appear in network 2 and 3 is due to the differences in the used datasets. Graf and Henning (2009) discuss the problem that the Fraunhofer Society files all patents centrally at the headquarter in Munich. It was not possible to assign patents to one of the twelve Fraunhofer Institutes located in Dresden. We know, that all twelve institutes take part in the knowledge transfer process as we have identified them in Figure 3 b and c.

If it would be possible to split the patents among the institutes the similarity between Figure 3 b, c and d would be morepronounced. The circumstance that in network 3a all twelve Fraunhofer Institutes and the Fraunhofer Society are included somewhat distorts the graphical presentation.

In Dresden the share of actors within the largest component of the patent network is 47.2%. The shares in Figure 3 b and c are 83% and 100%, respectively. This means, all 154 co-publishing actors are connected through the main component and 171 out of 206 actors with a collaborative R&D project. Not connected to the main component were 33 firms, one “other” actor and one extra-university public research institute.

Other actors are mainly active in the patent layer (see Tables 1 and 2). Only twelve of them are connected to the main component in Dresden. There are 115 “other” actors, who are not part of the main component whereas only three public research institutes and 59 firms are not connected.

4. Discussion and conclusions

4.1 Research contributions

We have constructed regional innovation networks based on different types of data: patents, publications, and publicly subsidized R&D collaborations. Applying comprehensive record-linking techniques we merged these three databases at the level of institutions. We find that this combined network provides a much more comprehensive picture of regional innovation activities than networks that are constructed by using only one or two of these data sources.

Since each data source has a certain bias, a combination of these datasets provides more credible insights into the nature and structure of regional innovative interactions. A comparison of the networks based on the different sources of data also allows to assess the bias of each of the single data sources in capturing cooperative relationships. We find that universities tend to be well-represented in all three types of data while private sector firms are particularly included in publicly subsidized R&D collaboration. Our analyses suggest that patent statistics—the most frequently used data base for constructing innovation networks—tend to underestimate links of private sector firms. An obvious reason for this pattern is that patents tend to particularly represent activities in the field of knowledge exploration which is the domain of universities while R&D collaboration of private firms represent more activities that can be characterized as knowledge exploitation. Data on co-publications add a considerable number of links that are not identified in patent statistics and in data in publicly subsidized R&D collaborations. The main reason for this observation is probably that patents and publicly subsidized R&D

collaborations represent mainly links that focus on the development of technologies while co-publications cover a much wider spectrum of knowledge fields.

Our comparisons make very clear that the results of social network analyses can be considerably shaped by the characteristics of the respective data base and that one should be well aware of such biases when interpreting the respective results. Clearly, combining different sources of data has considerable merits in providing a more complete picture of regional innovation activities.

Despite such biases and incomplete representations, our analyses demonstrate the importance of R&D cooperation and division of innovative labor for innovation processes. In particular, the key role of universities and other public research organizations as a broker that links many actors and ‘organizes’ regional innovation networks becomes very obvious on the basis of all three types of data. Moreover, our analyses reveal immense differences across the regions of our sample with regard to the intensity of networking. Such differences in the levels of cooperative relationships reflect divergent levels of division of innovative labor that can have important consequences for the efficiency of innovation processes at the level of individual actors as well as for the respective regional innovation system as a whole.

4.2 Limitations and avenues for further research

Although we have provided some new empirical evidence on regional innovation systems, the analyses also have shortcomings that could represent starting points for further research. One main limitation of our analyses is that we have only considered formal links and do not capture informal relationships. Moreover, we have identified only intra-regional links, the ‘local buzz’ (Bathelt, et al. 2004; Storper and Venables 2004). In order to complement this picture, further work should include and analyze differences of the data bases in capturing inter-regional links, the ‘global pipelines’. This would particularly allow identifying and analyzing the role of gatekeepers in a RIS that are well connected to other actors inside and outside a region (Graf 2011).

Since our data did not allow us to identify those actors within private firms that are involved in an R&D project, we were unable to merge the data at the level of persons but had to choose the level of institutions—firms, universities, other public research institutions—as the smallest unit of observation. A main advantage of data at the level of individual persons would be the possibility to include mobility across institutions as a link (Graf 2006).

The considerable differences of the levels of R&D cooperation as well as the structures of the innovation networks that we found deserve explanation. Given the strong role of universities in regional innovation networks, the number and size of the regional universities as well as their fields of knowledge may provide such an explanation. The fields of knowledge should particularly play a role for being included in a certain type of data base. For example, there is good reason to expect that university researchers in natural sciences and engineering have a much higher propensity to apply for a patent than researchers in the social and administrative sciences (Arundel and Kabla 1998; Fritsch and Aamoucke 2017). Moreover, private sector firms may find more interesting opportunities for R&D cooperation with the technologically oriented departments of a university than with humanities. A further important factor may be correspondence of the knowledge fields in public and private research in that high levels of correspondence lead to high levels of cooperation (Fritsch and Slavtchev 2011; Schmoch et al. 2003).

Since two of the three types of data that we used in our analyses are more or less entirely limited to analytical and synthetic types of knowledge, we cannot exclude the possibility that the links that we have identified represent mainly transfer of such kinds of knowledge while transfer of symbolic knowledge may only be included in links that are identified by co-publications.[17]

4.3 Implications for theory development

Furthermore, our approach may contribute to theory development in the sense that it enables the identification different forms of knowledge transfer during different stages of the innovation process. Some authors claim that certain actors have a particularly pronounced role in different stages of the innovation process. A common assumption in this regard is that universities are mainly involved in knowledge exploration while the activities of private firms is more in the field of knowledge exploitation, i.e., transferring knowledge into commercial application. So far, it was not possible to identify different forms of knowledge transfer along the innovation process. However, a further promising step of future research could be to create longer time-series and perform longitudinal analyses.

4.4 Policy implications

The rather pronounced role of public research institutions, particularly of universities in regional innovation networks that we have found qualify them as an important starting points for policy measures that aim at stimulating knowledge transfer and division of innovative labor in RIS. Hence, our analyses corroborate that policies aiming at stimulating links between public research and private sector firms in order to improve knowledge transfer in RIS are on a right track.

By identifying actors in RIS we provide evidence on absorptive capacities for innovative knowledge which are crucial for the design of effective and efficient regional support schemes in the future.

Independent private researchers can be particularly identified in patent data. This finding demonstrates the important role that these types of actors play in regional innovation activity. Moreover, it indicates that

[17] For a detailed chracterization of the three types of knowledge base see Asheim, et al. (2007).

links of universities and other public research institutes are considerably more likely to be included in a certain data base than private sector firms.

Network descriptions reveal that connectedness in regional collaborative R&D projects and co-publications is rather high in comparison with co-patents. Intensity of interaction (network density) considerably increases when all different types of interactions analyzed are put together indicating that intensity of interaction is underestimated when types of knowledge transfer are analyzed separately. This finding is supported by the analysis of mean degrees in the case study regions under analysis. Particularly, the co-publication networks are characterized by high intensities of knowledge transfer according to this measure.

Appendix

Table A1: Case study regions at a glance

Planning Region	*Aachen*	*Dresden*	*Siegen*	*Rostock*	*Kassel*	*Magdeburg*
Macro-region in Germany	West	East	West	East	West	East
Population 2000	1,282,164	1,022,527	431,845	424,191	902,491	993,891
Annual change 2000-2010 (%)	0.2	-0.0	-0.4	-0.3	-0.4	-0.9
Private sector 2000						
Number of establishments[b]	28,753	27,868	9,952	11,386	21,213	24,714
Annual change 2000-2008 (%)	-0.6	-1.0	-0.9	-1.3	-0.7	-1.4
Number of employees 2000	239,343	231,352	113,680	83,781	185,882	194,111
Annual growth 2000-2010 (%)	-0.6	-0.1	-0.3	-0.6	-0.6	-0.6
Share of R&D employees 2000 (%)[c]	4.7	4.5	2.0	2.6	2.4	2.2
Annual change 2000-2008 (%)	0.0	0.1	0.0	-0.0	0.1	-0.0
Research sector (2000)						
Number of research institutes[a]	21	38	0	14	7	19
Number of universities[ad]	3	10	1	2	3	4
Total research teaching staff[d]	4,898	4,715	837	1,958	1,389	1,988
Annual change 2000-2010 (%)	4.1	4.3	4.7	2.2	8.4	0.8
Share of research and teaching staff in natural sciences & engineering (%)[de]	61.7	53.0	50.6	38.5	50.4	37.6
Annual change 2000-2010 (%)	-0.1	0.3	-0.7	0.2	-0.6	0.3
Number of professors[d]	649	820	231	299	318	392
Annual change 2000-2010 (%)	0.6	-0.4	0.4	-0.5	2.9	0.4
Share of professors in natural sciences and engineering (%)[d]	64.9	54.6	48.3	43.3	47.1	42.5
Annual change 2000-2010 (%)	-0.4	-0.1	-0.8	-0.9	-0.8	0.2

Notes: [a]These figures are reported for the year 2013. – [b] Includes all establishments with at least one employee. – [c] Employees with tertiary education in natural science or engineering. - [d] Includes research universities and technical colleges (‘Fachhochschulen’). – [e] Includes three groups of scientific disciplines: natural sciences, agricultural and nutritional sciences, and engineering. Excludes medical sciences, cultural and social sciences, law and economics, and arts. – [f] Total of private and public sector.

Sources: German Statistical Office (population, university staff), establishment file of the German Social Insurance Statistics (establishments, employees), DFG Research Explorer (number of universities and research institutes).

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