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Actor Fluidity and Knowledge Persistence in Regional Inventor Networks

Michael Fritsch and Moritz Zoellner

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Abstract

The development of inventor networks is characterized by the addition of a significant number of new inventors, while a considerable number of incumbent inventors discontinue. We estimate the persistence of knowledge in regional inventor networks using alternative assumptions about knowledge transfer. Based on these estimates we analyze how the size and structure of a network may influence knowledge persistence over time. In a final step, we assess how persistent knowledge as well as the knowledge of new inventors effect the performance of regional innovation systems (RIS). The results suggest that the knowledge of new inventors is much more important for RIS performance than old knowledge that persists.

JEL-classification: O3, R1, D2, D8

Keywords: Innovation networks, knowledge, RandD cooperation, patents, persistence

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1. Fluidity of network actors and regional knowledge[1]

Well-functioning regional innovation systems (RIS) are characterized by a high level of knowledge transfer and division of innovative labor. This means that the relationships between actors within and outside a region can play a key role in the development of the regional knowledge base and the performance of RIS. The network of relationships among actors that are involved into innovation processes may, therefore, contribute to explaining the scope, nature, and efficiency of regional innovation activity (Ejermo and Karlsson 2006; Jackson 2008; Cantner and Graf 2011).

Innovation networks are not at all static, but may be characterized by rather high levels of newly emerging actors while many incumbent actors withdraw from regional innovation processes. A study by Fritsch and Zoellner (2017) of inventor networks in German regions over five three-year periods that was based on patent statistics, found that the majority of inventors are active in only one period and are not included in successive periods. On average, only about one third (32.34%) of the inventors that are present in a network in a certain period are also included in the previous period.[2] Hence, a majority of about two thirds of inventors in a regional inventor network occur in a certain sub-period for the first time. The degree of fluidity of links between actors may be even higher. Fritsch and Zoellner (2017) found that on average, only 9.7% of all links between inventors can still be found in the successive period. Looking at links between patent applicants, this share was only 8.4%. These figures clearly indicate that the majority of links among inventors and patent applicants are rather short term.

The consequences of this high level of actor-turnover or ‘fluidity’ for the network and the performance of the respective regional innovation system (RIS) are largely unexplored. In general, the high level of fluidity in inventor networks can be regarded as an indication that there are benefits

[1] We benefitted from the comments that we received at presentations of earlier versions of this paper. Special thanks go to Holger Graf and Muhamed Kudic.

[2] The share of patent applicants that occur in two successive three-year periods is on average 25.54%.

of switching cooperation partners despite considerable transaction costs. These transaction costs involve the effort of establishing new links as well as sunk costs related to abandoning an established link. One specific benefit may be access to new knowledge through newly established links.

The empirical analyses of the performance of inventor networks in German regions by Fritsch and Zoellner (2017) show mixed results for the relationship between the turnover of inventors with the performance of the respective RIS measured by the level and change of the number of patents per R&D employee (patent productivity). While there is a significantly positive relationship of the share of new inventors with RIS performance, the relationship of patent productivity with the share of discontinued actors was also positive, but showed a negative effect for the share of discontinued links (Fritsch and Zoellner 2017). A possible explanation for the positive relationship between RIS performance and the share of new actors is the additional knowledge that the new inventors add to the system. A reason for the non-negative relationship between the share of discontinued actors and RIS performance may be that the knowledge of discontinuing actors remains with their cooperation partners who continue in the network.

Based on the data used by Fritsch and Zoellner (2017) we investigate two potential sources of knowledge, namely persistent knowledge and the knowledge of inventors who newly enter inventor networks in nine German regions. We try to assess how much of the knowledge of those inventors that disappear from an inventor network may still be available because it has been passed on to continuing network inventors during their cooperation. For this purpose, we identify those inventors that cooperated with discontinuing inventors and determine if these co-inventors are included in the network in the subsequent period. We assume that at least part of the knowledge of a discontinued inventor is still available if co-inventors are still contained in the network. Based on alternative assumptions about the amount of knowledge transfer among co-inventors, we estimate the share of knowledge that is still available in the network and analyze the role of network characteristics that measure the frequency relationships and the integration of inventors in larger components for knowledge continuity. Our analyses suggest that there is a higher level of persistent knowledge in a network that is well-integrated and has a large average component and team size, with relatively high shares of inventors in the largest component, and low shares of isolates. Finally, we analyze the effect of persistent knowledge and the knowledge of new inventors on the performance of RIS. The results suggest that the knowledge of new inventors is much more important for RIS performance than old knowledge that persists.

In what follows, we first discuss the cost and the benefits of changing actors and relationships in innovation networks (Section 2). Section 3 introduces data and indicators, and in the following section we assess the effect of inventor fluidity on the continuity of knowledge in the network (Section 4). We then investigate to what extent the level of knowledge continuity is related to characteristics of the respective inventor network (Section 5). The effect of knowledge persistence on the performance of RIS is investigated in Section 6. The final section (Section 7) summarizes the results and concludes.

2. Actor turnover, knowledge persistence, network characteristics, and performance of the regional innovation system

Knowledge, especially non-codified tacit knowledge, is of fundamental importance for innovations and the performance of RIS (Wang and Wang 2012). Hence, the performance of RIS may suffer if an inventor discontinues his activity and is not part of the network anymore. However, if an inventor disappears from a network, his knowledge is not necessarily lost but may persist in the network because it has been transferred to co-inventors who are still part of the network during the period of their cooperation. Cooperative activities then not only lead to the generation of new knowledge, but they may also ensure that knowledge of discontinued inventors persists (Schilling and Phelps 2007). Keeping the knowledge of discontinuing inventors available may be an important way of how networks affect the performance of the respective RIS. If knowledge is transferred by co-inventorship, then the size of inventor teams should be important for the persistence of knowledge (see, Tang, Mu and MacLachlan 2008). The larger the inventor team the higher the propensity that one or more of the inventors from the original team who possess at least parts of the discontinued inventor's knowledge will be available in a successive period. Assuming that the knowledge of inventor teams may also be passed on to inventors who are linked to other inventors but not directly linked to a certain invention, this argument may be extended to the respective network component (see, Fronczak, Fronczak and Holyst 2004); those inventors who are directly and indirectly linked. Hence, RIS with larger inventor teams and larger network components should benefit from a higher intensity of knowledge exchange that may keep the knowledge of discontinuing inventors available. For this reason we expect:

Hypothesis I: The larger the size of inventor teams the more knowledge of discontinuing inventors can be stored in the network and is able to persist.

Hypothesis II: The larger the size of a network's components the more knowledge of discontinuing inventors can be stored in the network and is able to persist.

It may, however, not only be the size of a network's components, but also the density of relationships that define a network's level of cohesion that is important for the amount of knowledge that is transferred within a network (Ahuja 2000; Uzzi and Spiro 2005; Jackson 2008). Cohesion measures the clustering or density of a network (Burt 2001; Cowan and Jonard 2004; Fritsch and Kauffeld-Monz 2010), whereas range describes the average distance between inventors within a network. If a network shows a high level of clustering and a low range, this indicates small world properties. Since more ties between inventors should lead to increased knowledge transfer, knowledge of discontinuing inventors should more easily persist in dense networks.

Hypothesis III: The higher the cohesion of a network, the more knowledge of discontinuing inventors can persist and is available in later periods.

It is plausible to expect that the performance of a RIS will benefit if knowledge of discontinuing inventors persists and remains available.

Another important source of knowledge that should be important for RIS performance is the entry of new inventors that add new knowledge. Based on these considerations we expect:

Hypothesis IV: The more knowledge of discontinuing inventors remains available in a network the better the performance of the respective innovation system.

Hypothesis V: The larger the share of new inventors who enter the network and make their knowledge available the better the performance of the respective innovation system.

It is, however, an open question which of the two sources of knowledge—new knowledge or knowledge from previous periods that persists—has a more pronounced effect on RIS performance. We will try to answer this question in our empirical analysis.

3. Data and spatial framework

We analyze inventor networks based on patent application as documented in the DEPATISnet database (www.depatisnet.de) maintained by the German Patent and Trademark Office (*Deutsches Patent- und Markenamt)*. Compared to the OECD RegPat data, this source has several important advantages. First, since the patent identification number does not change over the different versions of the statistics, it avoids multiple counting of the same patent. Second, it is considerably more comprehensive since it also contains the complete set of patents that has only been filed at the German Patent Office and that is not included in the RegPat data.[3] Third, we spent a considerable amount of time correcting typing errors and identifying variant spellings of an inventor's name in order to maximize the reliability of the identification of inventors, an issue that is of key importance for the topic of our analysis.

The key assumption in constructing networks of inventors is that inventors who are named as inventors in the same patent document know

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[3] The number of patents that is recorded in RegPat (version March 2018) for the same regions and period of time is only about 53 % percent of the number of patents that we find in our data base. Quite remarkably, this share varies considerably across the regions of our sample.

each other and have worked together in generating the respective invention (Balconi, Breschi, and Lissoni 2004). Patents are assigned to regions based on the information about the residence of the inventor (Breschi and Lissoni 2001; Raffo and Lhuillery 2009). If some of the inventors named in a patent have residences in different regions, we divide the respective patent by the number of inventors involved and assign only that fraction to the region that corresponds to those inventors who have their residence in the region.[4]

As an alternative to inventor networks, one could analyze cooperative patenting activities between organizations (e.g., public research institutes and firms). This would be based on the assumption that the relevant knowledge is retained mainly in the researching organizations and not in the inventors. Such cooperative relationships between organizations can be identified in the patent statistics if the patent document names several organizations as applicants. There is, however, no information available in such cases that identifies the partner with which an individual inventor that is listed in the patent document is affiliated. The total number of patents that have several applicants (over all regions and time periods) in our data amounts to 2,748 cases. This is only a rather small share (0.57% percent) of all patent applications. This implies that the largest part of cooperative efforts by inventors occurs within the same organization. Given the small share of co-applications, we believe that an analysis of cooperative relationships at the level of inventors gives a much more comprehensive picture of knowledge flows in a RIS than investigating co-applications of organizations.[5] Such an

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[4] If, for example, a patent has three inventors and only two inventors have their residence in the region, we assign two third of the patent to the region. Hence, the number of regional patents may not always be a whole number.

[5] Another issue with identifying cooperative relationships between organizations is that some members of such organizations may file patent applications as private inventors. This is a particularly relevant scenario in Germany, because the professor’s privilege that allowed university researchers to file inventions for patenting on their own account was only abolished in the year 2002, while our period of analysis is 1994-2008. Moreover, even after this regulatory change university professors are still entitled to patent as private inventors if their university is not interested in the exploitation of their invention (von Proff, Buenstorf and Hummel 2012). A main reason why universities may not use their right to patent an invention is that they do not want to pay the patent fees. The share

analysis assumes that the relevant knowledge is represented by the inventors rather than by the organizations with which they are affiliated.

We construct the regional inventor networks in nine German planning regions for five three-year periods[6] over a time span of 15 years (1994 to 2008). Patents are assigned to time periods according to the year they were filed. Five of these regions are located in East Germany, the former socialist GDR, and four regions are in West Germany (see Figure 1). Planning regions are functional spatial units that are somewhat larger than labor market regions or travel-to-work areas. They normally comprise several NUTS3-level districts, namely, a core city and its surrounding area. While districts are administrative geographic units, planning regions are more often used for spatial analysis and policy development, particularly regarding public infrastructure planning.

We consider planning regions as more suitable than districts for an analysis of regional innovation systems (RIS) for two reasons. First, a single district, particularly a core city, is probably too small to include the most important inventors of innovation-related local interaction. The second reason is of a methodological nature: Since patents are assigned to the residence of the inventor, taking just a core city as a region would lead to an underestimation of patenting activity since many inventors who work in cities have their private residence in surrounding districts. Looking at the spatial structure of the co-inventor relationships we find that 73.4% of these interactions are with inventors located in the same planning region, and 16.8% are with inventors in adjacent planning regions. These figures clearly indicate that planning regions are a meaningful spatial category for the analysis of regional innovation processes.

The case study regions have been selected to fulfil primarily two purposes. First, they are supposed to serve as a comparison of regions with a relatively high or low innovation performance. Second, the sample

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of such cases is quite significant but can considerably differ between universities and time periods.

[6] These periods are 1994-96, 1997-99, 2000-02, 2003-05 and 2006-08. Using longer time-periods (e.g., five year periods) does not lead to substantially different results.

contains regions in East and West Germany that are similar in size and density. This allows us to make a meaningful comparison between the two parts of the country, even though this is not the focus of this paper. Aachen, Dresden, Jena and Karlsruhe have medium level population densities, and are characterized by RIS that have a relatively good performance. The other five regions, Halle, Kassel, Magdeburg, Rostock and Siegen have considerably lower levels of innovation activity. Rostock and Siegen are smaller cities located in rather low-density rural areas. Halle, Magdeburg and Kassel have larger populations than Rostock and Siegen, but they can hardly be regarded as densely populated. All regions are host to at least one university. Data on the regional number of employees in R&D are from the Establishment History File of the Institute for Employment Research (IAB, Nuremberg). Figure 1 shows the location of the nine case-study regions.

The nine regional inventor networks under inspection are quite heterogeneous with regard to the numbers of patents, inventors, ties, and components (see Table A1 in the Appendix). All regions, except Halle and Aachen, show a steady growth in the numbers of inventors (network size) and ties. In all regions, the number of components increases over the period of analysis. Except for Halle, all regions exhibit a total increase in the mean degree, indicating increasing interconnectedness of regional inventors (Table A1). The number of patents reaches its maximum in the 2000-02 period, followed by a decrease in the following period and an increase in the final period.

The share of co-patents increases over the observation period and makes up about 90 percent in the final sub-period (Table A4). These developments of the mean degree and the increasing importance of R&D

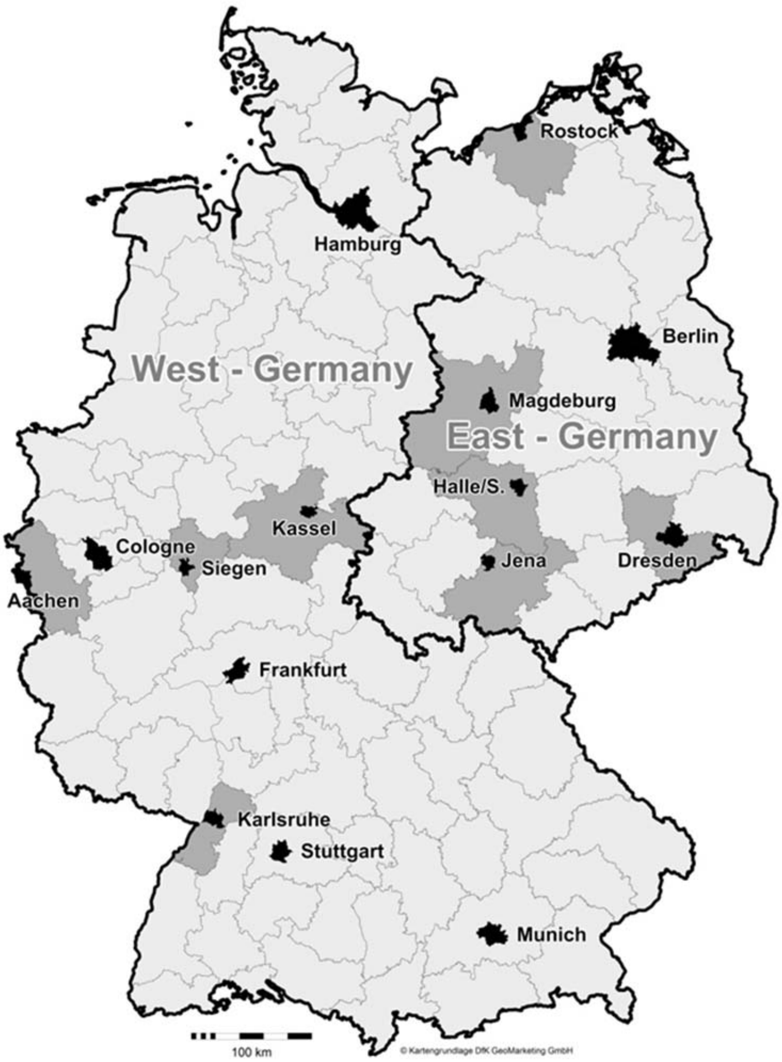

Figure 1: The regional framework of the analysis

collaborations are in line with overall trends reported in the literature (e.g. Wuchty et al. 2007; Jones et al. 2008) and indicate an increasing importance of research collaboration.[7]

We use two metrics for the performance of a network. The first is the number of patents per R&D employee and describes the productivity of a network in generating patentable inventions (patent productivity). The higher the level of patent productivity the better the performance of the

[7] Due to the increasing mean degree of the networks under inspection one might also expect a decrease of average path length. We find, however an increase of the average path length in most of the networks (Table A4) that can be explained by the growing number of actors and therefore, to an exponential increase of the number of potential cooperation partners. A further explanation could be the growing number of components (Table A1) that may also indicate increasing variety of knowledge fields within a region.

network in terms of generating new ideas (Fritsch 2002; Fritsch and Slavtchev 2011). The second performance indicator is the percent change of patent productivity. Table A3 in the Appendix provides descriptive statistics for the variables and Table A5 displays the correlations between variables.

4. Inventor turnover and continuity of knowledge

4.1 Inventor turnover in inventor networks

In contrast to the widespread assumption that inventors and ties in networks are persistent over time, our data shows a rather high level of inventor turnover between time periods. We find that more than 78 percent of all inventors are present only in one observation period, 14.51 percent are active in two periods and only about 7 percent appear in networks for more than two periods (Figure 2). On average, 32.34 percent of the inventors that are active in a network are carryovers from the previous period.[8] Hence, at least 60 percent of the inventors in a regional network appear in a sub-period for the first time, indicating that large amounts of new knowledge frequently enter the network from period to period.[9]

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[8] The shares of applicants that are present in two successive periods are in about the same range. Taking all applicants together, the average share is 25.54%. There are, however, rather pronounced differences in this respect between types of applicants. While the share of reappearing private persons that cannot be assigned to a certain organization is rather low (14.44%) the share for organizations (firms and public research organizations) is much higher (33.85%). For larger universities the share is close to 100%.

[9] Persistence of links among actors is even less pronounced. We find that 83.73 percent of the links exist only in one period, 13.06 percent last for two periods, 2.51 percent of the links can be found in three periods, 0.52 percent in four periods and only 0.17 percent of the links last over five periods. For the shares of discontinued actors and new actors in the different regions and time periods see Table A2 in the Appendix.

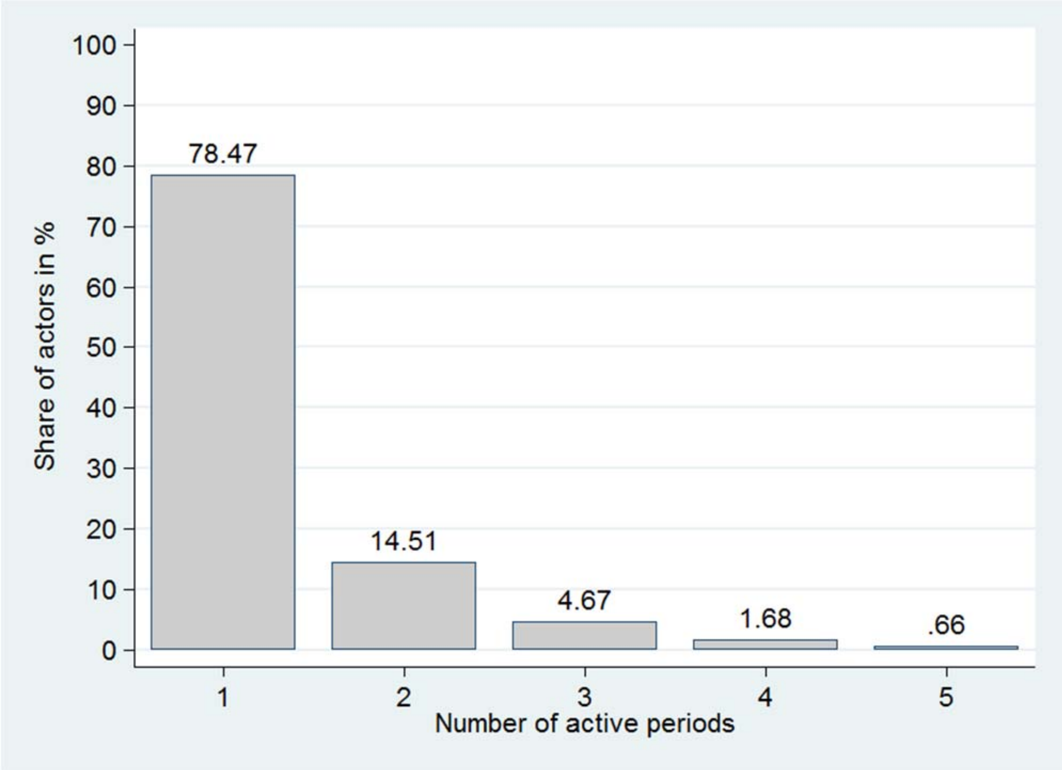

Figure 2: Share of inventors that are present in different numbers of time periods

The increasing share of co-patents (Table A4) indicates that networks are characterized by a growing tendency to cooperate. Figure 3 supports this assumption. Thus, around 93 percent of new inventors enter a network in a collaboration with other inventors, while only a minor share emerges as an isolate (7%). With regard to the largest component, the share of discontinuing inventors (7.4%) is more than compensated for by the share of new inventors (9%). In the group of isolates, the share of discontinued inventors is larger than the share of newly emerging ones. These developments clearly indicate a growing level of connectivity between network inventors.

Overall, we find that inventor networks are characterized by rapidly changing compositions of inventors and links, contradicting the transaction cost theory (Ejermo and Karlsson 2006), as well as the assumptions of

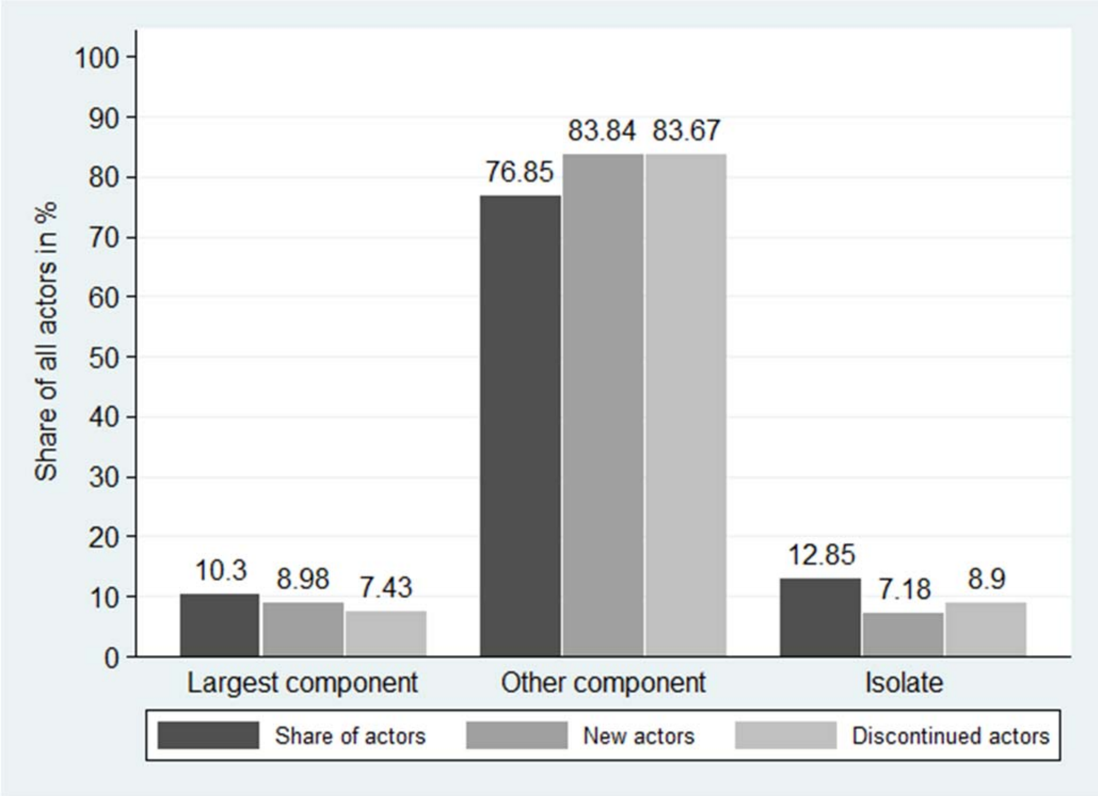

Figure 3: Positions of newly emerging and of discontinued inventors over the entire observation period

Barabási and Albert (1999, 2000). The networks of our sample show a tendency to grow continuously since the number of discontinued inventors is more than compensated for by new inventors that mainly enter with a cooperative relationship. Thus, the inventor networks under inspection show an increasing level of connectivity over time.

4.2 Assessing the share of persistent knowledge

We use several indicators to assess the amount of a discontinuing inventor's knowledge that may be still available because it has been passed on to his co-inventors in the previous period. For this purpose, we identify those co-inventors of a discontinued inventor that are still included in the network in the subsequent period. If a co-inventor of a discontinued inventor remains in the network we assume that at least certain parts of the patent-specific knowledge of the discontinued inventor is still available. If a discontinued inventor was involved in several co-patents, we assume that he only transfers that knowledge that is specific to the patented invention and not the knowledge that for relevant for his other patents.

In the baseline version we assume that the patent-specific knowledge of a discontinuing inventor is entirely transferred to each co-inventor during the time of collaboration. We then identify those inventors who remain active in the network in the subsequent period and the knowledge that they represent. Based on this information we finally determine the amount of persistent knowledge.

In detail, we proceed as follows:

- We generate a list of all patents that involve regional inventors that represents the knowledge stock of period t-0.
- If an inventor from period t-0 is still in the network in period t-1, we assign his patents from period t-0 to him.
- The share of knowledge that is transferred between period t-0 and t-1 is the number of patents in the list from period t-1 over the total number of patents in period t-0.[10]

As robustness checks, we also calculate the share of knowledge that is transferred across periods in two alternative ways.

- The first alternative method is based on the assumption that knowledge transfer among inventors is not complete but that inventors keep parts of their knowledge that is completely lost when they discontinue in the network. We assume that co-inventors transfer only 50 percent of their knowledge to each co-inventor.
- In a second alternative way of calculating the transferred knowledge we assume that the complete patent-specific knowledge is equally divided among all co-inventors. Hence, if there are, say, three (five) co-inventors of a patent, each co-inventor represents one third (one fifth) of the new knowledge that is behind the patent. In a next step, we check

[10] Since an inventor from period t-0 may not be present in t-1 but re-emerge in a later period t-2 or t-3, we run additional models to compare the list of patents between more distant time periods as a robustness check. However, the direction and significance of the coefficients remain the same.

which inventors remain active within a network in the next period. If only one inventor remains active in the subsequent period, then one third (one fifth) of the knowledge remains available. In case of two remaining inventors, two thirds (two fifths) of the knowledge is available. The rest of the procedure follows the previous model. The idea behind this second alternative way of estimating the amount of knowledge transfer is that there should be more specialization and division of labor in larger teams so that the knowledge of an inventor may not be completely transferred to all team members. Moreover, larger teams may be characterized by a rather pronounced division of labor between specialists with limited understanding that are only able to only absorb parts of the knowledge of their co-inventors.

Based on the first method of estimating the transfer of knowledge between periods that assumes that the knowledge of an inventor is completely transferred to all his co-inventors, we find that between 30.1% and 92.7% of the knowledge from one period remains in the network in the subsequent period despite high levels of fluidity (Table 1).[11] This share does, however, vary considerably across time periods and regions. If we assume an only 50% transfer of knowledge, the share of remaining knowledge ranges between 18.9% and 64.4%. Under the assumption that the share of transferred knowledge depends on the number of co-inventors the share of transferred knowledge is between 13.41% and 47.8%. These figures clearly suggest that the discontinuation of inventors leads to considerable losses of knowledge in the respective RIS even if it is assumed that inventor’s knowledge is completely transferred to all co-inventors during the cooperation.

[11] If we assume that knowledge remains in the network if the respective applicant is still present in the successive period then the share of persistent knowledge varies between 0.0% and 84% (average value 55.5%).

Table 1: Share of knowledge of previous period that remains in the network

Region		1997-1999	2000-2002	2003-2005	2006-2008	Average
Aachen	I	76.4	66.2	43.1	66.1	63.0
	II	37.2	34,1	31,0	45,3	36,9
	III	28.0	24,8	26,9	29,4	27,3
Dresden	I	92.7	68.6	73.2	88.4	80.7
	II	50.4	48,4	55,4	64,4	54,6
	III	32.3	40,8	45,6	47,8	41,6
Halle	I	72.1	37.4	27.9	30.1	41.9
	II	29.6	20,0	18,9	24,1	23,2
	III	23.9	20.0	19,1	20,0	20,7
Jena	I	90.8	59.6	73.8	81.2	76.4
	II	43.6	38,5	44,5	55,6	45,5
	III	25.0	30,0	27,2	37,6	30.0
Karlsruhe	I	57.6	60.4	51.9	68.8	59.7
	II	26.6	32,6	39,0	48,4	36,7
	III	13.4	22,4	30,1	35,7	25,4
Kassel	I	56.4	43.2	47.7	74.0	55.3
	II	24.9	22,9	29,1	45,2	30,5
	III	16.7	16,4	16,2	21,7	17,7
Magdeburg	I	48.8	47.2	44.4	41.1	45.4
	II	25.9	24,2	26,1	27,1	25,8
	III	18.0	15,7	16,2	16,0	16,5
Rostock	I	69.1	34.8	48.5	68.6	55.3
	II	27.2	25,2	36,9	44,6	33,5
	III	17.2	24,6	27,4	24,1	23,3
Siegen	I	65.4	55.4	60.2	74.9	64.0
	II	34.8	35,1	41,9	50,1	40,5
	III	23.8	26,7	30,0	30,3	27,7
All regions	I	66.5	62.9	57.8	71.7	64.7
	II	34.8	35,7	39,7	47,9	39,5
	III	23.5	25,9	28,0	31,7	27,3
Average values	I	69.9	52.5	52.3	65.9	60.15
	II	33.3	31,2	35,9	45,0	36,4
	III	22.0	24,6	26,5	29,2	25,6

Notes: The values in the first row are based in the assumption that the knowledge of an inventor is completely passed on to all his co-inventors. For the values in the second row it is assumed that only 50% of an inventor's knowledge is transferred to co-inventors. The third row contains the values based on the assumption that the knowledge of a patent is equally divided between all co-inventors.

5. What determines the persistence of knowledge in regional networks?

The previous sections showed that inventor networks are characterized by diverging shares of persistent knowledge. This raises the question of how far micro-level fluidity and a network's macro structure are related to the share of knowledge that is passed on to other members during their cooperation (knowledge persistence). To test for such effects, we estimate fixed-effect models with different independent variables, such as the share of reoccurring inventors from t-1, the share of discontinued inventors from t-1, and measures for the network structure (Table 2). Due to the relatively low number of observations and the considerable correlation between many of the measures for network characteristics, only one independent variable is included in a model.

Table 2: Inventor fluidity, network characteristics and the share of knowledge transfer over time

	Knowledge persistence—complete transfer								
	I	II	III	IV	V	VI	VII	VIII	IX
Share of discontinued inventors t-1	-2.175*** (0.361)	-	-	-	-	-	-	-	-
Share of new inventors t-0	-	-1.211* (0.830)	-	-	-	-	-	-	-
Average team size t-1	-	-	0.3849*** (0.0723)	-	-	-	-	-	-
Share of isolates t-1	-	-	-	-3.016*** (1.131)	-	-	-	-	-
Average component size t-1	-	-	-	-	0.220*** (0.060)	-	-	-	-
Share of the largest component t-1	-	-	-	-	-	1.267** (0.541)	-	-	-
Number of inventors in largest component t-1	-	-	-	-	-	-	0.0003*** (0.0002)	-	-
Mean degree t-1	-	-	-	-	-	-	-	0.0316 (0.0387)	-
Density t-1	-	-	-	-	-	-	-	-	-1.264 (1.097)
Constant	-0.0289 (0.114)	1.476*** (0.488)	-0.3139* (0.1711)	0.961*** (0.157)	-0.129 (0.208)	0.472*** (0.092)	0.559*** (0.0825)	0.453** (0.191)	0.569*** (0.0648)
Adjusted R²	0.864	0.624	0.7956	0.698	0.760	0.676	0.639	0.5872	0.5938

Notes: Fixed-effects panel regressions. Robust standard errors in parentheses. ***: statistically significant at the 1 % level; **: statistically significant at the 5 % level; *: statistically significant at the 10% level. The number of observations is 36 in all models (nine regions).

Table 2 *continued*

	Knowledge persistence—50% transfer								
	I	II	III	IV	V	VI	VII	VIII	IX
Share of discontinued inventors t-1	-0.606*** (0.136)	-	-	-	-	-	-	-	-
Share of new inventors t-0	-	-0.606* (0.321)	-	-	-	-	-	-	-
Average team size t-1	-	-	0.1924*** (0.0362)	-	-	-	-	-	-
Share of isolates t-1	-	-		-1.508*** (0.566)	-	-	-	-	-
Average component size t-1	-	-	-	-	0.110*** (0.0300)	-	-	-	-
Share of the largest component t-1	-	-	-	-	-	0.634** (0.270)	-	-	-
Number of inventors in largest component t-1	-	-	-	-	-	-	0.00002*** (0.0000)	-	-
Mean degree t-1	-	-	-	-	-	-	-	0.0173 (0.0205)	-
Density t-1	-	-	-	-	-	-	-	-	-0.407 (0.631)
Constant	0.581***	0.738***	-0.1570*	0.480***	-0.0647	0.236***	0.280***	0.347***	0.406***
	(0.071)	(0.244)	(0.0856)	(0.078)	(0.104)	(0.046)	(0.0413)	(0.101)	(0.0373)
Adjusted R^2	0.802	0.624	0.7956	0.698	0.760	0.676	0.639	0.7189	0.6811

	Knowledge persistence—weighted transfer								
	I	II	III	IV	V	VI	VII	VIII	IX
Share of discontinued inventors t-1	-0.386*** (0.0915)	-	-	-	-	-	-	-	-
Share of new inventors t-0	-	-0.575*** (0.202)	-	-	-	-	-	-	-
Average team size t-1	-	-	0.1380*** (0.0228)	-	-	-	-	-	-
Share of isolates t-1	-	-		-1.010*** (0.365)	-	-	-	-	-
Average component size t-1	-	-	-	-	0.0754*** (0.0187)	-	-	-	-
Share of the largest component t-1	-	-	-	-	-	0.376** (0.181)	-	-	-
Number of inventors in largest component t-1	-	-	-	-	-	-	0.0001* (0.0000)	-	-
Mean degree t-1	-	-	-	-	-	-	-	0.00841 (0.00910)	-
Density t-1	-	-	-	-	-	-	-	-	0.447 (0.415)
Constant	0.348***	-0.591***	-0.1576***	0.289***	-0.0817	0.130***	0.155***	0.253***	0.275***
	(0.0475)	(0.154)	(0.0534)	(0.0506)	(0.0649)	(0.0308)	(0.0269)	(0.0448)	(0.0245)
Adjusted R^2	0.775	0.615	0.7911	0.683	0.764	0.633	0.614	0.8971	0.7490

Notes: Fixed-effects panel regressions. Robust standard errors in parentheses. ***: statistically significant at the 1 % level; **: statistically significant at the 5 % level; *: statistically significant at the 10% level. The number of observations is 36 in all models (nine regions).

As expected, we find a highly significant negative relationship between the share of discontinued inventors of the previous period (t-1), the share of new inventors and the share of persistent knowledge of a network (Table 2, Models I and II). We use several measures for the size of a network and its components. Average team size measures the number of inventors who cooperate in a project and may directly exchange their knowledge. Average component size and the number of inventors in the largest component represent the inventors who are directly and indirectly connected by co-inventorship. The share of inventors in the largest component, as well as the share of isolates represent the level of (non-)integration of inventors in a RIS. The results indicate that larger inventor teams (Hypothesis I), as well as larger network's components enhance the share of persistent knowledge (Hypothesis II).

The positive relationship between the share of inventors in the largest component and our measure for knowledge persistence, as well as the negative relationship between knowledge persistence and the share of isolates shows that knowledge persistence is higher in well-integrated networks (Hypothesis II). However, relationships based on other measures of network cohesion, such as mean degree (Model VIII) or density (Model XI), or even using different types of clustering coefficients, were found to be statistically insignificant. This result contradicts our Hypothesis III. All in all, the results clearly suggest that the continuity of inventors, larger teams and components, and a high level of integration of inventors are important for keeping the knowledge of discontinued inventors available.

6. The effect of knowledge persistence on network performance

To investigate the effect of persistent knowledge and of new knowledge on the performance of the respective RIS we use patent productivity as a measure of performance. Patent productivity is defined as the number of patents filed by private sector innovators with at least one inventor residing in the respective region per 1,000 R&D employees. While this metric reflects the level of the efficiency of RIS (Fritsch 2002; Fritsch and Slavtchev 2011), we also use the percentage change of patent productivity to analyze the development of that level. An advantage of this second performance measure is that relating indicators for the dynamics of the composition and the structure of networks to changes of patent productivity may lead to a more robust identification of causal relationships.

All models include the share of manufacturing employees in establishments with less than 50 employees as a control variable. This variable accounts for the observation that the number of patents per unit of R&D input tends to be higher in smaller firms than in larger firms (for a theoretical explanation and discussion, see Cohen and Klepper 1996). Hence, we expect a negative sign for the estimated coefficient of this variable. In the models for the change of patent productivity, we also include the level of patent productivity in the previous period. The estimated coefficient of this variable should have a negative sign for two reasons. First, regions with an already relatively high level of patent productivity may have lower potentials for improvements than regions that are characterized by a comparatively low performance. Second, the level of patent productivity in the base year controls for a regression to the mean effect. This effect denotes the phenomenon that periods with relatively large changes in one direction may be followed by periods where the changes are relatively small, or even work in the opposite direction.

The estimation results presented in Table 3 provide empirical evidence for the positive connection between the performance of a network and the two potential sources of knowledge, namely new and persistent knowledge. Thus, we find a significantly positive relationship between a network’s patent productivity and the share of new inventors (Model I) as well as with the share of persistent knowledge (Models III and IV). The non-significance of the share of persistent knowledge in Model II that does not include the share of new knowledge may be caused by the relatively high correlation between the measures of these two knowledge sources (see Table A5 in the Appendix). The share of persistent

Table 3: The relation between the share of persistent knowledge, the share of new inventors, and patent productivity

	Patent productivity (ln)					Change of patent productivity (%)						
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Share of new inventors	2.714*** (0.892)	-	3.044*** (0.874)	3.044*** (0.874)	3.239*** (0.940)	2.290** (0.930)	-	-	-	2.345*** (0.861)	2.345*** (0.861)	2.676*** (0.925)
Share of persistent knowledge												
– complete transfer	-	0.293 (0.323)	0.494* (0.275)	-	-	-	0.610* (0.316)	-	-	0.631** (0.281)		
– 50% transfer	-	-	-	0.988* (0.549)	-	-	-	1.219* (0.633)	-		1.262** (0.562)	
– weighted transfer	-	-	-	-	1.370 (0.920)	-	-	-	0.890 (1.018)			1.548* (0.919)
Employment share of manufacturing establishments < 50 employees	0.518 (0.717)	2.498*** (0.839)	1.988*** (0.713)	1.988*** (0.713)	1.978*** (0.753)	0.950 (0.766)	1.946** (0.783)	1.946** (0.783)	1.840** (0.859)	1.816*** (0.697)	1.816*** (0.697)	1.874** (0.751)
Patent productivity in t-1 (ln)	-	-	-	-	-	-0.911*** (0.177)	-0.517*** (0.186)	-0.517*** (0.186)	-0.614*** (0.192)	-0.684*** (0.176)	-0.684*** (0.176)	-0.758*** (0.175)
Constant	-2.721*** (0.639)	-1.130*** (0.365)	-3.403*** (0.720)	-3.403*** (0.720)	-3.484*** (0.807)	-2.366*** (0.742)	-1.031*** (0.319)	-1.031*** (0.319	-0.824** (0.338)	-2.820*** (0.715)	-2.820*** (0.715)	-2.992*** (0.806)
Adjusted R^2	0.6615	0.551	0.5858	0.6183	0.6901	0.5347	0.495	0.495	0.435	0.7017	0.7017	0.5858

Notes: Fixed-effects panel regressions. Robust standard errors in parentheses. ***: statistically significant at the 1 % level; **: statistically significant at the 5 % level; *: statistically significant at the 10% level. The number of observations is 36 in all models (nine regions).

knowledge has, however, only a weakly significant effect if the change of patent productivity is taken as the dependent variable (Models VII and VIII). The insignificance of the coefficient of the weighted measure of knowledge transfer in Models V and IX may result from the fact that the construction of this measure is based on the assumption that only smaller amounts of the total knowledge are transferred so that the share of persistent knowledge is, perhaps, underestimated.

We also find statistically positive relationships for our measure of new knowledge in the models for the change of patent productivity (Models VI-XII). For two out of our three measures of knowledge persistence we also find a statistically significant relationship with the expected positive sign (Table 3, Models VII-IX). Again, the weighted knowledge transfer remains statistically insignificant in models that do not include the share of new inventors (Model IX). When we introduce the share of new inventors (Models X-XII), all three measures of knowledge persistence are statistically significant, supporting our earlier finding that both existing and new knowledge are extremely important to the process of enhancing the efficiency of a RIS.

All in all, these results indicate that the generation of inventions may benefit from both persistent knowledge and new sources of knowledge. This is consistent with our Hypotheses IV and V. The effect of our measure for new knowledge—the share of new inventors—is, however, considerably more robust at higher levels of statistical significance. This pattern suggests that new knowledge may be more important for the performance of RIS than old knowledge. We can, however, not exclude that the reason for the poor performance of our measure of persistent knowledge is due to its construction. If the interpretation is correct that new knowledge is more important for the performance of a RIS than older knowledge, this could also contribute to explaining the rather high levels of inventor fluidity in the networks under investigation. New ideas are mainly generated by new people, and inventors switch their cooperation partners because they believe that this may be more promising for producing newness than continuing to cooperate with their old partners or their former collaborators.

We have argued that new inventors who enter the network as part of a component create new opportunities of knowledge recombination by making their knowledge available to co-inventors (Section 2). Hence, they should have a stronger effect on the performance of a RIS than inventors who enter as an isolate. In order to test this assertion, we distinguish between new inventors who enter as part of a component and those who enter as isolates. Consistent with our expectations, we find that only those new inventors who are attached to a component have a significantly positive effect on the performance of the respective RIS (Models I, II, V and VI of Table 4). This result may also be regarded as confirmation of the result of Wuchty, Jones and Uzzi (2007) and Jones, Wuchty and Uzzi, (2008) that team inventions are of higher quality than inventions by single inventors.

In a final step of analysis, we compare the effects of new inventors who are attached to a component with at least one continuing inventor with new inventors who enter as part of a component that does not include any continuing inventor. The idea behind this approach is that combinations of old and new knowledge may be particularly important for the performance of the respective RIS. Hence, one might expect that new inventors who enter as part of a component that also includes a continuing inventor have a stronger effect on RIS performance. The results of Models III, IV, VII and VIII of Table 4 clearly suggest the opposite, i.e., components that entirely consist of new inventors have a strong effect on RIS while the effect of those newcomers who are attached to a component that also comprises at least one old inventor remains completely insignificant. This result underlines our findings of the relative effect of old and new knowledge (Table 3). It is new inventors who emerge as new components that drive the performance of RIS. In contrast, combinations of new knowledge and the knowledge of continuing inventors seem to be unimportant.

Table 4: The relationship between the share of persistent knowledge and patent productivity

	Patent productivity (ln)				Change of patent productivity (%)			
	I	II	III	IV	V	VI	VII	VIII
Share of new inventors attached to components	0.681*** (0.224)	-	-	-	0.595** (0.241)	-	-	-
Share of new inventors that are isolates	-	0.703 (2.265)	-	-	-	0.260 (2.128)	-	-
Share of new inventors attached to components with at least one old inventor	-	-	-2.954*** (1.033)	-	-	-	-2.448** (0.971)	-
Share of new inventors attached to a completely new component	-	-	-	2.323** (0.988)	-	-	-	1.992** (0.912)
Employment share of manufacturing establishments < 50 employees	-0.831 (1.151)	1.941** (0.897)	0.690 (0.804)	1.529** (0.704)	-0.461 (1.099)	1.526* (0.901)	0.485 (0.843)	1.048 (0.782)
Patent productivity in t-1 (ln)	-	-	-	-	-0.886*** (0.177)	-0.691*** (0.181)	-0.717*** (0.158)	-0.674*** (0.161)
Constant	-0.394 (0.240)	-0.831*** (0.235)	0.370 (0.469)	-2.312*** (0.648)	-0.419* (0.249)	-0.627** (0.266)	0.356 (0.456)	-1.866*** (0.613)
Adjusted R2	0.6611	0.5380	0.6505	0.6202	0.5352	0.4175	0.5392	0.5137

Notes: Fixed-effects panel regressions. Robust standard errors in parentheses. ***: statistically significant at the 1 % level; **: statistically significant at the 5 % level; *: statistically significant at the 10% level. The number of observations is 36 in all models (nine regions).

To sum up, our results indicate that it is the new knowledge of new people that drives the performance of RIS. The share of old knowledge that remains in a regional inventor network across subsequent time periods is of only minor importance.

7. Conclusion

If inventors are no longer active in innovation networks, their knowledge for the respective RIS may be lost. Assuming that inventors transfer at least parts of their knowledge during their cooperation with other inventors, we constructed indicators for the persistence of discontinuing inventors' knowledge. Based on these measures, we find that discontinuation of inventors can lead to large losses of knowledge, and that the share of these losses varies quite considerably across regions and time periods.

Using our measures for the persistence of knowledge, we analyzed the role of network characteristics in knowledge persistence. We found a positive relationship between the share of transferred knowledge and measures that indicate the connectedness of network members. According to our expectations, more knowledge is transferred and preserved over time in more densely connected network structures. We also find a positive relationship between knowledge persistence and the size of a network's components. Hence, the size of the components of a network and dense relationships among inventors are positively related with the persistence of knowledge across time.

In a next step, we estimated the effect of the share of persistent knowledge that is transferred between two subsequent time periods and the share of new knowledge that is introduced by new inventors on the performance of the respective RIS. RIS performance was measured by patent productivity and the change of patent productivity. The results of these analyses indicate that both old and new knowledge may make a positive contribution to RIS performance, but that the effect of new knowledge, measured by the share of new inventors, is considerably more important. Moreover, we find that only newcomers who are attached to a component that entirely consists of new inventors have a positive effect on the performance of the respective RIS. New inventors who are attached to a component with old inventors, as well as new inventors who enter are isolates have no significant effect.

In a nutshell, knowledge of discontinuing inventors may particularly remain in large and dense networks. Hence, one important way by which networks contribute to the performance of RIS is to make knowledge of discontinuing inventors available in later time periods. Both, new and persistent old knowledge contribute to the performance of RIS but the effect of new knowledge is much stronger. The significant role played by new knowledge in the generation of inventions may also explain why inventor teams are rather unstable.

Our analysis is not without limitations. Since patents cover only a part of total innovation activities in a region, our method of estimating the share of persistent knowledge could lead to an underestimation of that knowledge. For example, a patent-based analysis neglects inventions that cannot be patented (incremental inventions and results of basic research), as well as inventions that, for various reasons, are not filed for patenting (Hall et al. 2014; Walter, Schmidt, and Walter 2011). Moreover, inventors may exchange knowledge in many other, often rather informal ways. A further limitation of our empirical analysis is the relatively low number of observations (regions and time periods).

Further analyses should try to overcome these shortcomings by including other channels of knowledge transfer (see Fritsch, Piontek and Titze 2018), and by generating data sets with larger numbers of observations. In particular, further work in this field should test different indicators for knowledge persistence, as well as for the performance of RIS.

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Appendix

Table A1: Numbers of nodes, ties, components, and total patents in different time periods

	Aachen				*Dresden*			
	Number of				Number of			
	Inventors	Ties	Components	Patents	Inventors	Ties	Components	Patents
94-96	2,219	5,480	407	1,858	1,948	6,298	362	1,458
97-99	2,799	7,202	482	2,455	2,791	10,798	400	2,556
00-02	3643	13,944	141	2,866	3,121	13,274	421	2,295
03-05	3,283	13,208	546	1,873	3,306	14,578	416	2,062
06-08	3,135	11,840	506	1,900	3,707	17,430	446	2,522
	Halle				*Jena*			
	Number of				Number of			
	Inventors	Ties	Components	Patents	Inventors	Ties	Components	Patents
94-96	815	3,082	128	485	1,153	3,722	200	753
97-99	1,183	4,392	199	941	1,789	7,212	259	1,477
00-02	1,230	5,664	209	615	1,917	8,922	244	1,147
03-05	842	3,172	164	384	1,925	9,004	254	1,089
06-08	642	2,164	141	320	1,936	8,438	290	1,152
	Karlsruhe				*Kassel*			
	Number of				Number of			
	Inventors	Ties	Components	Patents	Inventors	Ties	Components	Patents
94-96	1,339	3544	290	2,313	739	1,838	159	509
97-99	2,745	10,256	475	4,327	1,118	3,212	238	740
00-02	4,849	22,520	688	3,932	1,107	3,354	260	677
03-05	4,657	22,212	649	3,073	1,115	3,860	221	726
06-08	4,972	23,420	622	3,924	1,326	4,332	254	828
	Magdeburg				*Rostock*			
	Number of				Number of			
	Inventors	Ties	Components	Patents	Inventors	Ties	Components	Patents
94-96	635	1,710	143	414	243	514	59	178
97-99	865	2,406	178	513	426	1,342	75	411
00-02	1008	3,504	208	577	412	1,592	68	235
03-05	977	3,048	206	526	371	1,568	56	188
06-08	909	2,880	196	518	466	1,842	78	256
	Siegen				*All regions*			
	Number of				Number of			
	Inventors	Ties	Components	Patents	Inventors	Ties	Components	Patents
94-96	754	1,776	152	662	9,845	27,964	1,900	8,630
97-99	1,051	3,024	192	820	14,767	49,844	2,498	14,240
00-02	1,095	3,698	200	759	15,394	63,856	2,439	13,103
03-05	1,007	3,482	188	742	17,483	74,132	2,700	10,663
06-08	1,231	4,586	194	928	18,324	76,932	2,727	12,348

Table A2: Shares of discontinued inventors and new inventors in the case study regions in different time periods

	Share of discontinued inventors	Share of new inventors	Share of discontinued inventors	Share of new inventors
	Aachen		Kassel	
1997-1999	0.7388	0,7388	0.8391	0,8399
2000-2002	0.7383	0,7736	0.8024	0,8464
2003-2005	0.6902	0,7548	0.7819	0,8502
2006-2008	0.6571	0,7544	0.7692	0,8363
	Dresden		Magdeburg	
1997-1999	0.7715	0,7101	0.8399	0,8428
2000-2002	0.6885	0,6405	0.8335	0,8621
2003-2005	0.6326	0,6071	0.7990	0,8628
2006-2008	0.6078	0,5967	0.7869	0,8680
	Halle		Rostock	
1997-1999	0.7903	0,7870	0.8416	0,8357
2000-2002	0.8016	0,8163	0.7372	0,7670
2003-2005	0.7672	0,8230	0.6873	0,7547
2006-2008	0.7274	0,8193	0.7082	0,7940
	Jena		Siegen	
1997-1999	0.7732	0,7719	0.7821	0,7821
2000-2002	0.6978	0,7366	0.7023	0,7543
2003-2005	0.7049	0,7787	0.6594	0,7319
2006-2008	0.6226	0,7004	0.6442	0,7474
	Karlsruhe			
1997-1999	0.8984	0,8984		
2000-2002	0.7862	0,8125		
2003-2005	0.7078	0,7505		
2006-2008	0.6378	0,7200		

Table A3: Descriptive statistics

	Mean	Median	Minimum	Maximum	Standard Deviation
Share of persistent knowledge	0.504	0.471	0.201	0.884	0.175
Share of discontinued inventors	0.740	0.739	0.608	0.898	0.072
Share of new inventors	0.777	0.776	0.597	0.898	0.070
Share of re-emerging inventors	0.260	0.261	0.102	0.392	0.072
Share of isolates	0.087	0.084	0.033	0.188	0.037
Share of the largest component	0.098	0.072	0.023	0.333	0.079
Average component size	4.102	3.936	2.774	6.073	0.975
Mean degree	5.355	5.565	3.225	7.260	1.165
Patent productivity (ln)	-0.368	-0.416	-0.785	0.547	0.259
Change in patent productivity (ln)	-0.038	-0.048	-0.486	0.337	0.188
Employment share of manufacturing establishments < 50 employees	0.350	0.331	0.187	0.560	0.106
Share of service employment	0.877	0.876	0.758	0.971	0.048
Number of links	6785	3860	514	23,420	5,982
Average team size	2.711	2.790	2.002	3.324	0.320

Table A4: Number of co-patents, single patents, mean degree (all regions)

	94-96	*97-99*	*00-02*	*03-05*	*06-08*	*94-08*
Total number of patents	8,63	14,24	13,10	10,66	12,35	58,98
Number of co-patents	7,37	12,60	11,85	9,50	11,14	52,46
Share of co-patents in %	85.45	88.46	90.42	89.07	90.20	88.93
Number of patents with single inventor	1,26	1,64	1,26	1,17	1,21	6,53
Number of inventors per patent	2.71	2.82	2.99	3.07	3.00	2.91
Number of inventors per co-patents	3.40	3.51	3.65	3.70	3.58	3.58
Mean degree	3.76	5.11	5.51	5.44	5.36	3.76
Average path lengths	2.22	3.57	3.85	3.77	3.83	3.45

Table A5: Correlation of variables

		1	2	3	4	6	7	8	9	10	11	12	13	14
1	Share of persistent knowledge	1.00												
2	Share of discontinued inventors	-0.66***	1.00											
3	Share of new inventors	-0.66***	0.84***	1.00										
4	Share of re-emerging inventors	0.66***	-1.00	-0.84***	1.00									
6	Share of isolates	-0.33	0.45***	0.40	-0.45***	1.00								
7	Share of the largest component	0.58***	-0.54***	-0.64***	0.54***	-0.34	1.00							
8	Average component size	0.55***	-61***	-0.64***	0.61***	-0.89***	0.62***	1.00						
9	Mean degree	0.45***	-0.36	-0.48***	0.36	-0.61***	0.54***	0.79***	1.00					
10	Patent productivity (ln)	0.32	0.11	-0.24	-0.11	0.21	0.24	0.02	0.31	1.00				
11	Change in patent productivity (ln)	0.26	0.03	0.03	-0.03	-0.01	-0.18	-0.07	0.06	0.29	1.00			
12	Employment share of manufacturing establishments < 50 employees	-0.29	0.23	0.06	-0.23	-0.08	0.07	0.02	0.01	-0.29	0.06	1.00		
13	Number of inventors	0.51***	-0.17	-0.51***	0.37	-0.44***	0.33	0.60***	0.53***	0.46***	-0.12	-0.54***	1.00	
14	Number of ties	0.50***	-0.42***	-0.3***	0.42***	-0.55***	0.38***	0.70	0.61***	0.40***	-0.14	-0.49***	0.98***	1.00
15	Average team size	0.24	-0.46***	-0.36	0.46***	-0.81***	0.38	0.77***	0.63	-0.38	-0.06	0.27	-0.18	0.20

Notes: Spearman rank correlation coefficients. ***: statistically significant at the 1 % level; **: statistically significant at the 5 % level; *: statistically significant at the 10% level. The number of observations is 45 and 36 respectively (nine regions).