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Abstract

We investigate the stability of cooperative relationships between inventors and consequences for the characteristics and patent productivity of the respective regional innovation systems (RIS). The empirical analysis is for nine German regions over a period of 15 years. We find a rather high level of 'fluidity', i.e., entry and exit of actors, as well as instability of their relationships over time. The aggregate characteristics of the regional networks are, however, quite robust even with high levels of micro-level fluidity. There are both significantly positive and negative relationships between micro-level fluidity and the performance of the respective RIS.

JEL-classification: O3, R1, D2, D8

Keywords: Innovation networks, R&D cooperation, division of innovative labor, patents

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1. Division of innovative labor, innovation networks, and regional performance[1]

Innovation processes are increasingly characterized by a pronounced division of labor among actors, such as private firms and public institutions of education and research (Jones et al. 2008; Wuchty et al. 2007). This division of innovative labor has become an important topic of innovation research. A main focus of this research is on the networks of relationships among actors. It is a basic conjecture of this type of research that embeddedness in networks and the structure of these networks leads to more highly effective innovation processes and higher levels of innovation.[2] The analysis of innovation networks plays a particularly prominent role in attempts to explain the performance of regions (Ejermo & Karlsson 2006; Fleming, King & Juda 2007).

Although research on regional networks has produced many interesting results concerning network structures and the role of certain types of actors (for an overview, see Cantner & Graf 2011), still little is known about the dynamic characteristics and development of network structures over time. In fact, empirical studies on the stability of network structures and of the underlying relationships hardly exist. Many scholars claim that cooperative relationships between actors should be long lasting because the effort of establishing and maintaining a trusting relationship would be sunk if the link is abandoned (Gilsing & Nooteboom 2005; Ejermo & Karlsson 2006; Storper &

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[1] We are indebted to Holger Graf and Muhamed Kudic for helpful comments on an earlier version of this paper.

[2] There are two main reasons why embeddedness in networks may have a positive effect on the performance of actors. First, interaction with others may be an important channel for transferring (tacit) knowledge (Owen-Smith & Powell 2004; Storper & Venables 2004). Particularly, face-to-face contact promotes the development of personal trust that can be regarded as an important precondition for fruitful R&D cooperation. Second, the formation of links in R&D networks implies a process of screening and selection. Assuming that actors choose cooperation partners according to their abilities, actors included in a network have been positively evaluated. This positive selection of relatively able cooperation partners should have a positive effect on the probability of success (Granovetter 1995; Storper & Venables 2004; Wilhelmsson 2009).

Venables 2004). Stability of network ties is a key assumption of Barabási & Albert's (1999, 2000) well-known model of network development.[3] Quite remarkably, some researchers even exclude unstable relationships from their empirical analysis because they regard them as outliers (e.g., Balland et al. 2013).

This paper seeks to shed some light on the dynamics of innovation networks. We describe and analyze the disappearance of actors and links, as well as the emergence of new actors and links, and the consequences for network structure and performance. Our data is patent information on co-inventorship for nine German regions over a time span of 15 years. The starting point of our analyses are hypotheses about the stability of cooperative relationships in R&D. Testing the assumption of stable network relationships with these data we find a surprisingly high level of instability. Our analysis shows that inventors that appear to be well embedded within a network in one period are unlikely to re-occur in the following (three year) period. As a result, links between nodes of the networks tend to be highly unstable. Hence, in contrast to a widespread assumption, regional innovation networks are characterized by a rather high level of fluidity with quickly changing relationships between actors over time. However, we find that when we relate the measures of actor fluidity to the structure of a network, these structures remain rather stable. There are both significantly positive and negative relationships between the micro-level fluidity of actors and links with the performance of the respective regional innovation system (RIS) in terms of patent productivity. Based on these results we draw conclusions for theory and for further research.

In what follows, we first review the reasons offered for the stability of R&D cooperation and implications for network development (Section 2).

[3] Barabási & Albert (1999) investigate two generic mechanisms for large networks: (i) networks grow over time by entry of new actors, and (ii) the new actors tend to collaborate with already well embedded actors (preferential attachment).

Section 3 introduces the spatial framework, data, indicators and modelling of our analysis, followed by a brief overview on the development of networks over time (Section 4). We then describe the magnitude of the fluidity phenomenon and perform micro-level analyses in order to identify determinants of the reoccurrence of actors in subsequent time periods (Section 5). Section 6 analyzes the relationship between micro-level fluidity and the macro structure, as well as the performance of the specific networks we exam. Finally, we discuss the results and draw conclusions for theory and further research (Section 7).

2. The nature and the stability of cooperative Research and Development

Cooperation in Research and Development (R&D) is characterized by considerable levels of uncertainty and asymmetric information. The uncertainty follows from the very nature of R&D as a discovery procedure. Since the result of this discovery procedure is unknown ex ante, it cannot be completely specified in an R&D contract, leaving room for opportunistic behavior of cooperation partners. Asymmetric information arises when there is incomplete knowledge about the abilities and future behavior of a potential cooperation partner. Because R&D involves asymmetric information and the danger of opportunistic behavior by a cooperation partner, successful cooperation requires trust (Gilsing & Noteboom 2005; Noteboom 2002). Another reason why trust is a critical component of any cooperative R&D effort is the considerable transfer of information and knowledge between partners that may be regarded sensitive. When engaging in cooperative R&D, actors need to trust that their partners will not use this information in an undesirable way. The development of trust between actors is often based on past experiences of frequent and intensive collaborations and an actor's reputation (Gilsing & Nooteboom 2005; Tomkins 2001).

The R&D problems of uncertainty and asymmetric information are reflected in the transaction costs of establishing a cooperative relationship. There are costs involved in identifying a suitable cooperation partner, in negotiating the terms of the cooperation and in establishing a well-working and trust-based relationship that may require frequent face-to-face contacts (Ejermo & Karlsson 2006; Storper & Venables 2004; Gilsing & Nooteboom 2005). Particularly, the generation of trust involves a partner-specific effort that is irreversible and is sunk if a relationship is abandoned. Sunk costs of terminating cooperative R&D relationship may also occur if the relationship requires specific skills and equipment (e.g., Powell et al. 2005). The sunk costs of abandoning an R&D cooperation create an incentive for actors to maintain the relationship over longer periods of time, unless maintaining the relationship is more costly than establishing a new relationship with a different actor. Based on these arguments we expect:

Hypothesis I: Cooperative relationships between actors in R&D are long-lasting. Hence, actors remain in the network for longer periods of time so that the level of 'fluidity' is rather low.

The model of Barabási & Albert (1999) assumes that network relationships are stable over time so that all actors that are part of a network at a certain point in time remain in the network in subsequent periods. Based on this stability assumption, Barabási & Albert investigate a certain mode of tie formation, "preferential attachment". According to the preferential attachment mode of tie formation, new actors are especially attracted to and try to link with already well embedded actors. Barabási & Albert (1999) run simulations of network dynamics based on the preferential attachment mode. The resulting networks show properties such as a scale-free or fat-tailed degree distribution[4] that fit quite well with the characteristics of large and heterogeneous real world networks (Powell et al. 2005). They then examine

[4] Scale-free networks are characterized by a highly heterogeneous degree distribution that includes some nodes with many degrees and a long tail of nodes with very few connections.

the structural robustness of the simulated networks if network actors are randomly omitted.

Barabási & Albert (1999, 2000) use the average length of the shortest path between any two nodes in the network as the indicator for the robustness of a network. They argue that this measure can be regarded as an indicator for the ease of transferring information and knowledge within a network. The smaller the length of the average shortest path, the lower the frictions created when there is an exchange between actors, and the better the interconnectivity of a network. Based on their simulations, Barabási & Albert (1999, 2000) conclude that the disappearance of actors has a rather minor effect on average path length. Their results suggest that large scale-free networks (Powell et al. 2005) are highly robust against randomly removed nodes.

The high level of macro-level stability of networks found by Barabási & Albert (1999, 2000) in their simulations, despite the disruption of randomly removed nodes, raises the question about the relationship between micro-level stability and the robustness of a network from a macro-level perspective. Does high fluidity of actors and links, in fact, lead to unstable network structures? To what extent does micro-level stability, in terms of persistence of actors and links, constitute a precondition for stability at the macro-level? Following Albert, Jeong & Barabási (2000), the performance of large scale-free networks is highly stable with regard to fluctuations of actors and links for two reasons. First, since most actors in such type of network have only a few links (Albert, Jeong & Barabási 2000), the probability that a randomly removed actor has a central position in the network is rather low. Second, assuming that new actors tend to gravitate to well-embedded actors (‘preferential attachment’) there is a high probability that these new actors are at least as well connected in the network as the discontinued actors. Based on these considerations we expect:

Hypothesis II: Macro-level robustness and performance of scale-free networks does not require high levels of stability of actors and their links at the micro-level.

Dynamic innovation processes require some fluidity of actors and links, yet abandoning cooperative relationships and establishing new links may imply considerable sunk costs and significant effort. It is rather unclear how the fluidity of actors and links might impact the performance of a RIS. Due to this ambiguity, we abstain from setting up a concrete hypothesis about the expected relationship between RIS performance and the fluidity of actors and their links.

3. Data and indicators

3.1 Data

We analyze inventor networks based on data from the DEPATISnet database (www.depatisnet.de) maintained by the German Patent and Trademark Office (*Deutsches Patent- und Markenamt)*. Analysis of inventor networks is based on the assumption that actors who are named as inventors on the same patent document[5] know each other and have worked together (Balconi, Breschi & Lissoni 2004). Patents are assigned to regions based on the information about the residence of the inventor. We are well aware that patents reflect only a part of the diverse types of formal and informal relationships among innovating actors.[6] It is, however, plausible to assume that documented co-inventorship implies other forms of cooperation, such as co-publications and informal knowledge exchange. A comprehensive data

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[5] By harmonizing the data, we corrected for misspellings and compared the obtaining individuals regarding their first name, second name and ZIP code. If all of these three criteria were identical, we assumed that the individuals are identical.

[6] A comparison of regional innovation networks constructed with different data sources (Fritsch, Titze & Piontek 2017) finds that patent data tend to underestimate links of private sector firms, while universities and other public research institutions are well-represented in patent data.

source that accounts for the variety of relationships between innovating actors does not exist.

We construct the regional inventor networks in nine German planning regions for five, three-year periods[7] over a time span of 15 years (1994 to 2008). 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 tend to be 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 to be more suitable 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 actors of innovation-related local interaction. The second reason is of a methodological nature; since patents are assigned to the residence of the inventor, taking simply 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.

The case study regions have been selected to fulfill two primary purposes. First, these regions allow us to compare regions that have a relatively high innovation performance with low innovation performance regions. Second, although this is not the principal thrust of our paper, the sample contains regions in East and West Germany that are similar in size and density, allowing for a meaningful comparison of the two parts of the country. Aachen, Dresden, Jena and Karlsruhe have a medium level population density and are characterized by a relatively good RIS

[7] These periods are 1994-96, 1997-99, 2000-02, 2003-05 and 2006-08.

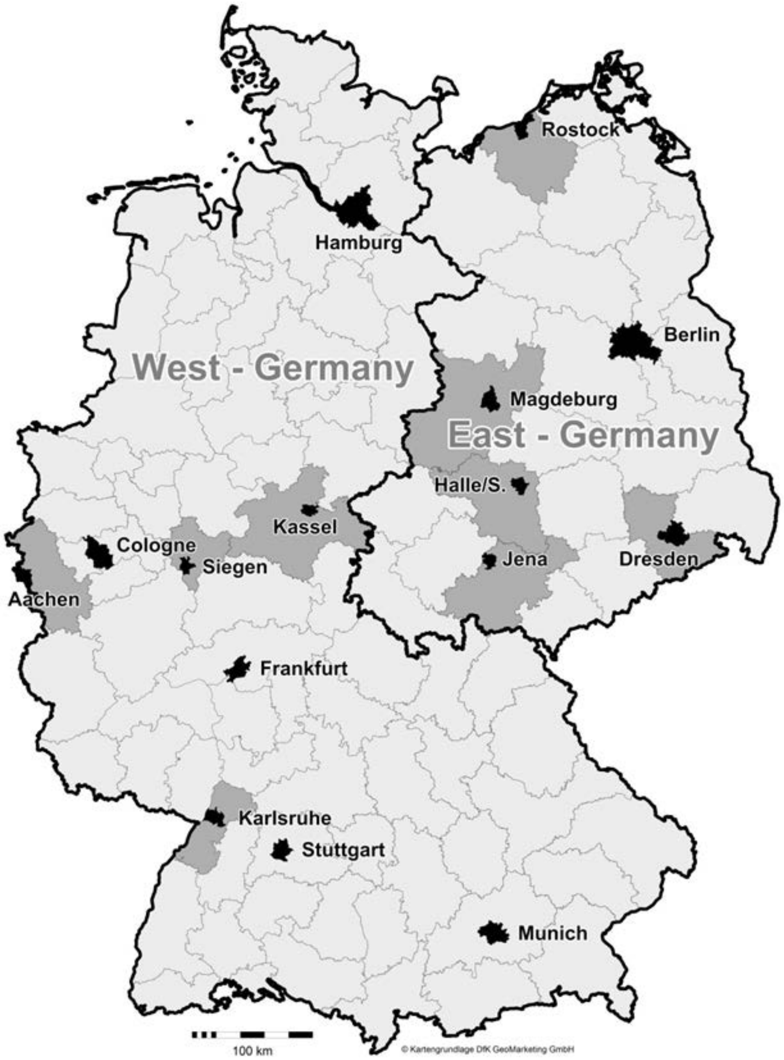

Figure 1: The regional framework of the analysis

performance. The other four regions, Halle, Kassel, Magdeburg, Rostock and Siegen, have a relatively low innovation activity performance. Rostock and Siegen are smaller cities located in rather low-density rural areas. Halle, Magdeburg and Kassel are larger urban areas, but they can hardly be considered as densely populated (see Table A1). Each region hosts 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.

3.2 Indicators

The following measures are used to investigate the fluctuation of actors at the micro-level. The dependent variable is the presence of an actor in the network, i.e., if he or she has contributed to a patent in a previous period. This variable has the value 1 if the actor was present in any previous period and it is 0 otherwise. We measure the amount of an actor's innovative output by the number of patents filed in a certain period that mention him or her as an inventor. The intensity of an actor's involvement in a network is measured by three variables:

- the number of links that an actor maintains with other actors in the network during a certain period of time (degree);
- the presence of an actor in the largest component (1 = yes; 0 = no);
- being an isolate (degree = 0) with no links to other actors.

Characteristics of a network are measured by variables, such as the mean degree, the share of the largest component, the share of isolates, the overall clustering coefficient, and the patent productivity. The mean degree is the average number of links an actor maintains, constituting a precondition of knowledge and information transfers (Jackson 2008). Average path length is defined as the average shortest path between two nodes within a network (Albert et al. 2000; Wassermann & Faust 2007). Patent productivity is the number of patents per R&D employee, and describes the performance of a network. The higher the level of patent productivity the better the performance, in terms of generating new ideas (Fritsch & Slavtchev 2011). Table A2 in the Appendix provides descriptive statistics for the variables and Table A3 displays the correlations between variables.

The distribution of the number of patents per actor is highly skewed (Figure A1 in the Appendix). While over 60 percent of all actors have just one patent, less than 20 percent have two patents, and the share of actors with larger numbers of patents is rather small. The degree distribution of the networks (Figure A2 in the Appendix) corresponds to a scale-free distribution, i.e., there are only a few actors with relatively numerous network links, while most actors have very few or no relationships. As mentioned in Section 2, this type of network should be better able to compensate for discontinued nodes than a network where all actors have about the same number of links (Albert et al. 2000; Barabási & Albert 1999; Jackson 2008; Khokhlova & Kipnis 2013).

4. The development of the regional networks over time

The nine regional inventor networks we exam show quite diverse characteristics with regard to the numbers of patents, actors, ties, and components. All regions, except Halle and Aachen, show steady growth in the numbers of actors (network size) and ties (Table A4). 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 actors (Table A5). The number of patents varies slightly over time but does not exhibit any clear trend. It reaches its maximum in the 1997-99 period, followed by a decrease in the following two period, and an increase in the final period (Table A6).

The share of co-patents increases over the observation period, accounting for about 90 percent in the final sub-period. We also find a growing number of inventors per patent (Table A6). These developments of the mean degree and the increasing importance of R&D collaborations are in line with overall trends reported in the literature (e.g., Jones et al. 2008; Wuchty et al. 2007) and indicate an increasing importance of research collaboration. The steady growth of nearly all networks, together with an increasing mean degree over time, is consistent with Barabási & Albert's (1999) preferential attachment hypothesis claiming that new actors are more likely to link with relatively well-embedded actors.

Due to the increasing mean degree of the networks over time, one might also expect a decrease of average path length. We find, however, that the average path length increases in most of the networks (Table A5). The increasing path length can be explained by an exponential increase in the number of potential cooperation partners created by the growing number of actors, a higher share of actors in the largest component of a network and a larger average component size.[8] An additional explanation could be that the growing number of components (Table A4) may also indicate greater variety of knowledge fields within a region. As a consequence of the rather pronounced effects of changes in the number of actors on average path length, we refrain from using average path length as an indicator for network performance, in contrast to Albert, Jeong & Barabási (2000).

5. Fluidity of actors at the micro level

5.1 General observations

This section analyzes the fluidity of actors at the micro level over time. What determines the re-emergence of actors in a subsequent time period, and how do actor's positions within a network change over time?

In contrast to the widespread assumption that actors and ties in networks are rather persistent (Section 2), our data shows a rather high level of actor turnover. We find that more than 78 percent of all actors 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 actors that are active in a network are carryovers from the previous period. Hence, at least 60 percent of the

[8] Isolates are not included in the calculation of the average component size.

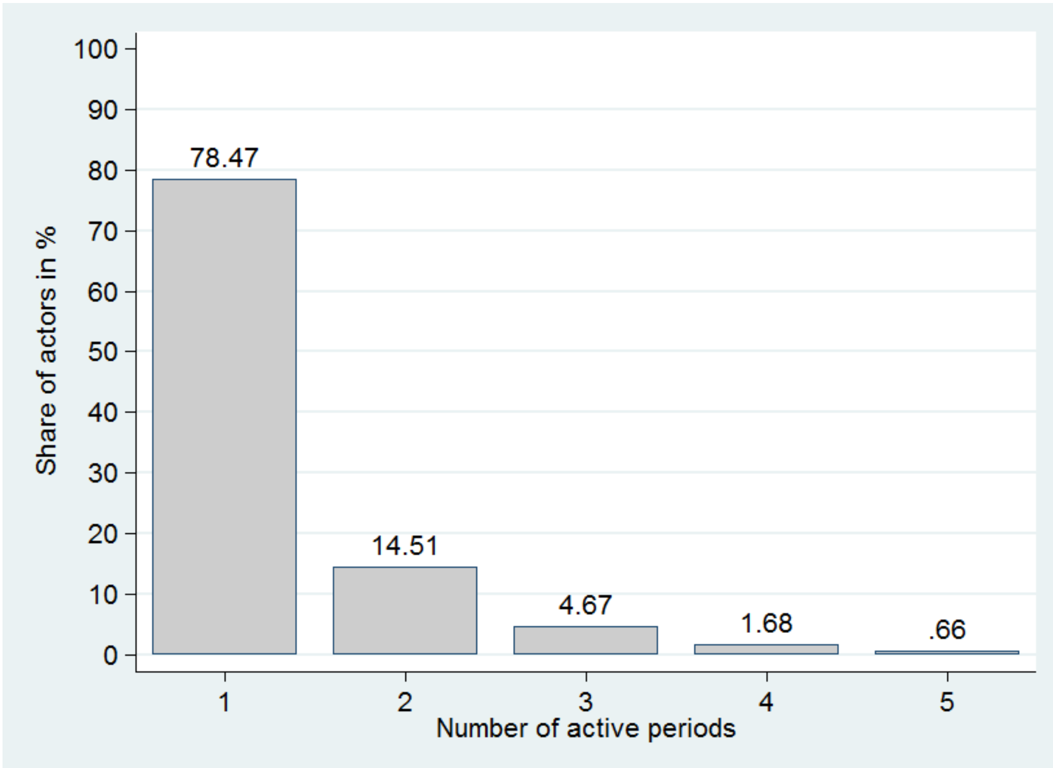

Figure 2: Share of actors that are present in different numbers of time periods

inventors in a regional network appear in a sub-period for the first time. Based on these figures, we clearly have to reject our Hypothesis I about the persistence of actors at the micro-level.[9]

Table 1 shows rank correlations between the shares of discontinued and newly occurring actors and links. Looking at the statistical relationships between the different measures for the fluidity of actors we find a remarkably strong relationship between the share of discontinued actors and the share of new actors indicating that the number of exits from the network is more or less completely substituted by about the same number of newcomers. As to

[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.

Table 1: Correlations between fluidity of actors and links

		1	2	3	4	5
1	Share of discontinued actors from t-1	1				
2	Share of new actors	0.948***	1			
3	Net change of actors: share of new actors minus share of discontinued actors	-0.961***	0.840***	1		
4	Share of discontinued links from t-1	0.138	0.314*	0.025	1	
5	Share of new links	0.677***	0.638***	-0.668*	0.424***	1
6	Net change of links: share of new links minus share of terminated links	0.327*	0.090	-0.494***	-0.692***	0.259

Notes: Spearman rank correlation coefficients. ***: statistically significant at the 1 % level; *: statistically significant at the 10 % level.

be expected there are considerable correlations between the fluidity of actors and of links. However, correlations between the fluidity of actors and links and the measures for the different types of link changes are considerably less pronounced than those between the measures for the fluidity of actors. Most interestingly, the correlations between the net change of the number of actors with the share of new links as well as with the net change of the number of links are significantly negative. This suggests that an increasing number of actors does not necessarily lead to a larger number of connections within the regional innovation system.

There is a pronounced tendency of new actors to occur as part of a collaboration. Nearly 93 percent of the new actors are part of a component (around 9 percent are part of the largest component) while only 7 percent occur first as an isolate. These shares closely correspond to the overall shares of co-patents or isolates respectively (Table A6). The largest components of the networks grow over time (see Table A5) as they have a larger inflow of new actors as compared to the loss due to discontinued actors. With regard to the isolates, we can see the opposite development, i.e., there are more discontinued than new actors. For the other components (excluding the

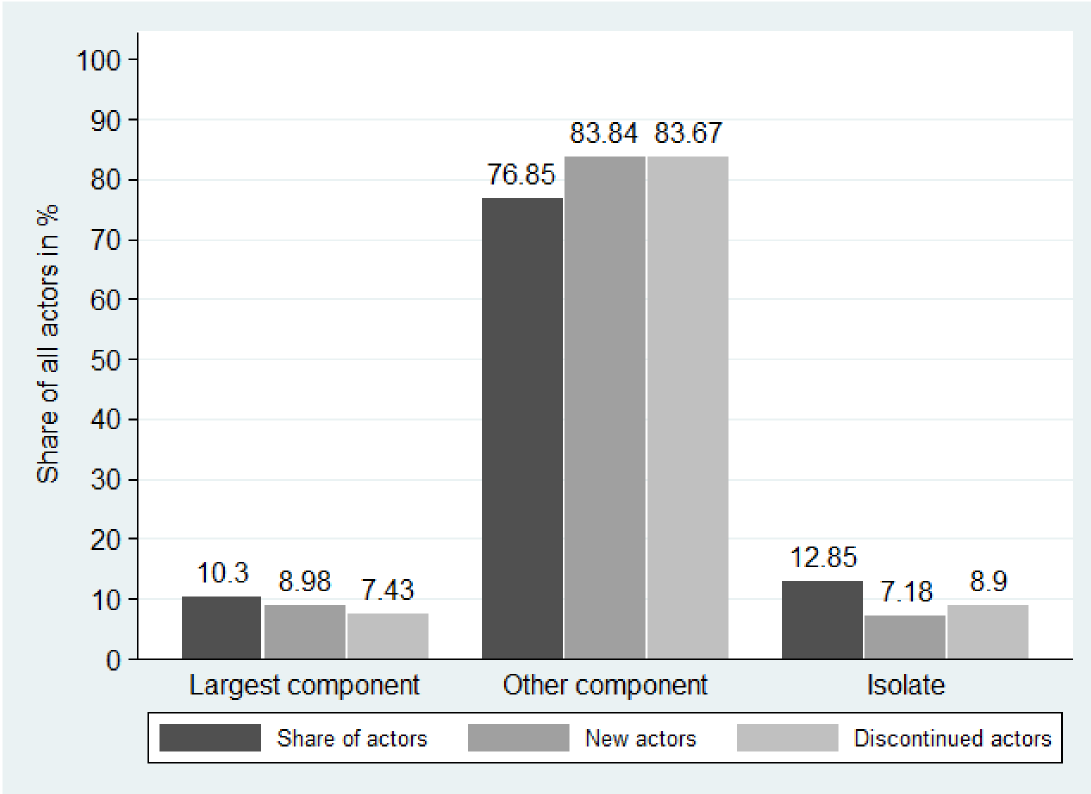

Figure 3: Positions of newly emerging and of discontinued actors over the entire observation period

largest component) the inflow of new actors and the number of discontinued actors are of about the same magnitude (Figure 3). Only about 53 percent of the newcomers are attached to an actor that has already been present in the previous period.[10]

Summing up, regional innovation networks are characterized by a rather high level of fluidity with rapidly changing relationships between actors over time. In contrast to a basic assumption of Barabási & Albert (1999), most actors that are in a network in one period are not included in this network in

[10] If the networks are constructed for a period of five years, the share of actors in the largest component is considerably larger (28.35%) than in the case of a three year period (Figure 3) and the share of isolates comes out to be smaller (8.39%). As a consequence, a larger share of the newly emerging actors become part of the largest component (30.08%). The share of discontinued actors from the largest component in the case of five-year networks is 19.66%; 72.56% are from other components and 7.78% are isolates.

the subsequent time period. However, the number of exits from the network is more or less completely compensated for by an equal number of newcomers. This results in a rather small net change in the number of actors. There is a tendency for new actors to collaborate with already active nodes within a network leading to a decreasing share of isolates. However, in contrast to the preferential attachment hypothesis, not all of the new actors collaborate with actors that are already established in the network, about 10 percent of the newcomers enter the network as isolates. All in all, an increasing number of actors does not lead to a larger number of links. On the contrary, the statistical relationship between the net change of the number of actors and the number of links is significantly negative.

5.2 What determines the reoccurrence of actors?

We estimate several multivariate models in order to assess the probability of an actor reoccurring in a network. The dependent variable is 1 if an inventor is included in the network in the period 2006-08 and it is 0 otherwise. The independent variables are the presence of an actor in a previous period (yes = 1, no = 0), if the actor has been part of the largest component in a previous period (yes = 1, no = 0), the number of patents held by an actor, and the number of an actor's links (degree) (Table 2).[11] We present a separate model for each variable because of some quite significant correlations between these variables (see Table A3 in the Appendix). All models include dummy variables for the regions that are always highly significant.

The marginal effect of having been present in the previous period (t-1) on reoccurrence in the present period is 26.4 percent. Not surprisingly, the estimated coefficients for periods t-2, t-3 and t-4 clearly indicate that this effect decreases with the time distance. The effect of the position of an actor

[11] For the coefficients, see Table A6 in the Appendix.

Table 2: Marginal effects of the binominal logistic regression models

	Reoccurrence of a node in the period 2006-2008			
Variables	I	II	III	IV
Actor present in				
t-1	0.264***	-	-	-
	(0.0044)			
t-2	0.087***	-	-	-
	(0.0033)			
t-3	0.056***	-	-	-
	(0.0038)			
t-4	0.043***	-	-	-
	(0.0046)			
Actor was part of largest component in				
t-1	-	0.276***	-	-
		(0.011)		
t-2	-	0.039***	-	-
		(0.0078)		
t-3	-	0.052***	-	-
		(0.0108)		
t-4	-	0.058***	-	-
		(0.0182)		
Number of actor's patents in				
t-1	-	-	0.065***	-
			(0.0018)	
t-2	-	-	0.008***	-
			(0.0012)	
t-3	-	-	0.006***	-
			(0.009)	
t-4	-	-	0.005***	-
			(0.0013)	
Number of an actor's links in				
t-1	-	-	-	0.009***
				(0.0006)
t-2	-	-	-	0.002***
				(0.0002)
t-3	-	-	-	0.001***
				(0.0003)
t-4	-	-	-	0.001***
				(0.0005)
Log likelihood	-15011.173	-17118.235	-15049.471	-16785.956
Pseudo R^2	0.170	0.054	0.168	0.072
McFadden's R2	0.170	0.053	0.167	0.072
Number of observations	46,827	46,872	46,872	46,872

Notes: All models include dummy variables for regions that are statistically significant at the 1% level (the reference region is Siegen). Robust standard errors in parentheses. ***: statistically significant at the 1% level; **: statistically significant at the 5% level; *: statistically significant at the 10% level.

in the largest component in one of the previous periods does not differ much from that of an actor's previous presence. The number of patents held by an actor in a sub-period also has a highly significant effect on the probability of continuing in the final sub-period. However, the marginal effect for the number of patents in period t-1 on reoccurrence of an actor in the present period is only 6.52 percent, whereas the remaining sub-periods exhibit only a rather small effect of less than 1 percent. An actor's number of links (degree) in a previous period also has a positive effect on his probability of being present in a subsequent period. This result suggests that comparatively well connected inventors tend to be active over a longer time span and, thus, have a higher probability of being involved in future projects. The marginal effect of this variable for all sub-periods is, however, less than 1 percent, and decreases with the time distance. Thus, an actor's embeddedness must not be a major factor in explaining his or her or reemergence in a later period. These surprising results for an actor's number of patents and an actor's degree are in accordance with the observation that slightly less that 40 percent of the inventors generate two or more patents (see Figure A1 in the Appendix), and that about half of all actors do not have more than three links (Figure A2 in the Appendix).

Putting all the results of the empirical models together, we can conclude that the pure presence of an actor and his position in the largest component of a network are more important for reoccurrence in a subsequent period than a high individual performance as represented by the individual's degree and the absolute number of patents. Having been part of the largest component in t-1 has the strongest impact on the reoccurrence of a node in the final sub-period. The number of an actor's patents as well as his or her number of links has only a minor impact on subsequent network presence.

6. The effect of fluidity on network structure and performance

The previous section showed that networks are characterized by a high level of actor fluidity at the micro-level. This raises the question about the relationship between micro-level fluidity of a network and its macro structure. According to our Hypothesis II the macro structure of a network should be unaffected by the fluctuation of actors. To investigate the effect of actor fluctuation on network structure we run fixed effects regressions with three fluidity measures as independent variables: the share of discontinued actors from period t-1, the share of new actors, and the net change in the number of actors. Table 3 shows the results for the dependent variables share of the largest component, share of isolates, and mean degree.[12]

Table 3: The relationship between the shares of discontinued actors, shares of new actors and network structure

Variables	Share of largest component			Share of isolates			Mean degree		
Share of discontinued actors from t-1	-0.356** (0.146)	-	-	0.230*** (0.067)	-	-	-1.810 (2.558)	-	-
Share of new actors	-	-0.691*** (0.232)	-	-	0.118 (0.132)	-	-	-2.226 (4.259)	-
Net change number of actors	-	-	0.240 (0.219)	-	-	-0.414*** (0.062)	-	-	3.586 (4.266)
Constant	0.339*** (0.104)	0.612*** (0.176)	0.077*** (0.024)	-0.047 (0.048)	0.025 (0.100)	0.137*** (0.007)	5.957*** (1.829)	6.373** (3.237)	4.491*** (0.473)
Adjusted R^2	0.740	0.761	0.728	0.744	0.639	0.642	0.631	0.628	0.629

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

We find that the share of discontinued actors from the previous period is significantly related to a smaller share of actors in the largest component and a higher share of isolates. The mean degree seems to be, however,

[12] See Tables A8 and A9 for descriptive statistics and correlations between the variables.

unaffected by the fluidity of actors. A higher share of new actors is related to a smaller share of actors in the largest component, and a higher net change of the number of actors is related to a lower share of isolates. The non-significance of a relationship between the share of new actors and the share of isolates is consistent with the observation that the vast majority of new actors do not enter as an isolate, but connect with a component (Section 5.1). It is quite remarkable that the relationship between the three fluidity indicators and the mean degree is not statistically significant. This result suggests that the number of new links created by new actors is not significantly smaller than the number of links that are disrupted because of actors exiting the network. This corresponds to our earlier finding that the share of actors who attach themselves to a network component is larger among newcomers than among those who exit (Section 5.1). Relationships with other measures of network structure such as average component size, network centralization and overall clustering coefficient were found to be not statistically significant.[13] All in all, we can conclude from the results of these regressions that fluidity of actors leads to some fragmentation of a network, but does not affect the average number of relationships. Besides these observations, network structures appear to be rather robust with regards to entry and exit of actors, supporting our Hypothesis II.

For investigating the effect of fluidity of actors on the performance of the respective regional innovation system we use patent productivity as the measure of performance. Patent productivity is 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 a RIS (Fritsch 2002; Fritsch & Slavtchev 2011), we also take the percent change of the patent productivity to analyze the development of that level. Two control variables are included in all models. The first of these

[13] The squared form of the fluidity measures is never statistically significant, indicating absence of non-linear relationships.

variables is the share of service sector employment, this accounts for the observation that the propensity of actors in this sector to apply for a patent is comparatively low (Bode 2004; Fritsch & Slavtchev 2011). Hence, we expect a negative sign for the respective coefficient because regions with higher shares of service employment should have lower numbers of patents. The second control variable is the share of manufacturing employees in establishments with less than 50 employees. This control 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 & Klepper 1996) so that we expect a negative sign for this variable.

Table 4: The relationship between the shares of discontinued actors, new actors and patent productivity

	Patent productivity (ln)			Change of patent productivity (%)		
Share of discontinued actors from t-1	1.501*** (0.417)	-	-	1.387*** (0.434)	-	
Share of new actors in t0	-	2.647*** (0.934)	-	-	2.299** (0.954)	
Net change number of actors	-	-	-2.999*** (0.726)	-	-	-2.870*** (0.756)
Share of service employment	-0.768 (1.762)	0.560 (1.787)	-1.935 (1.773)	-1.228 (1.744)	-0.192 (1.818)	-2.267 (1.717)
Employment share of manufacturing establishments < 50 employees	0.638 (0.779)	1.280 (0.791)	0.048 (0.791)	0.950 (0.766)	1.463* (0.799)	0.416 (0.761)
Patent productivity in t-1 (ln)	-	-	-	-0.911*** (0.177)	-0.848*** (0.186)	-.951*** (0.168)
Constant	-0.425 (1.521)	-3.163** (1.554)	2.415 (1.777)	0.003 (1.568)	-2.199 (1.759)	2.607 (1.714)
Adjusted R^2	0.636	0.663	0.737	0.497	0.535	0.677

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).

In the model with the percent change of patent productivity as the dependent variable, we also include the level of patent productivity in the base year. 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 denotes the phenomenon that periods of relatively large changes into one direction may be followed by periods where the changes are relatively small or even in the opposite direction.

Table 5: The relationship between the shares of ceased and new links with patent productivity

	Patent productivity (ln)			Change of patent productivity (%)		
Share of discontinued links from t-1	-4.810** (1.919)	-	-	-5.117*** (1.715)	-	-
Share of new links	-	6.135*** (2.118)	-	-	5.638*** (2.140)	-
Net change number of links	-	-	6.579*** (1.187)	-	-	6.236*** (1.069)
Share of service employment	1.088 (1.807)	1.166 (1.741)	0.256 (1.357)	-0.743 (1.750)	0.368 (1.778)	-0.756 (1.298)
Employment share of manufacturing establishments < 50 employees	0.463 (0.932)	1.203 (0.791)	-0.460 (0.708)	0.170 (0.887)	1.398* (0.785)	-0.289 (0.649)
Patent productivity in t-1 (ln)	-	-	-	-0.629*** (0.168)	-0.863*** (0.183)	-0.803*** (0.126)
Constant	2.886 (2.618)	-7.376*** (2.303)	-0.560 (1.213)	5.064** (2.523)	-6.179** (2.610)	0.409 (1.200)
Adjusted R^2	0.643	0.667	0.803	0.580	0.552	0.765

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

Generally, the relationship between the indicators for the fluidity of actors and our measures of network performance are highly statistically significant (Table 4). The significantly positive signs of the estimated coefficient for both, the share of discontinued actors and the share of new actors, suggests that replacement of ‘old’ actors by new ones may be conducive for the performance of the respective regional innovation system. We find, however, a significantly negative relationship between patent productivity and the net change of the number of actors. This result could be caused by the trend towards an increasing number of inventors per patent (see Table A6 in the Appendix), so that the number of inventors grows stronger than the number of patents.

There are also highly significant relationships between the fluidity of links and network performance, but the directions of the effects are quite different from the estimations for fluidity of actors (Table 5). The negative effect of the share of ceased links may indicate negative effects of dissolving R&D cooperation on the division of innovative labor. In contrast, the pronounced positive coefficients for the share of new links and the net change of the number of links suggest that newly established relationships, as well as increasing numbers of relationships, are conducive to the performance of RIS. These results clearly support the notion that the connectedness of actors resulting in an intense transfer of knowledge along with the division of innovative labor are both important determinants of the performance of regional innovation systems (Fritsch & Slavtchev 2011). The results for the control variables remain the same as in the analysis of the fluidity of actors (Table 4).

7. Discussion: What does this mean and what do we need to know?

We investigated the stability of cooperative relationships within regional inventor networks, focusing our analysis on the effect of the fluidity of actors and their links for the structural stability of networks and the performance of the respective regional innovation system. The analysis was performed for nine German planning regions over a period of 15 years (1994-2008). At the micro-level of individual inventors, we observed rather high levels of fluctuation of actors across time periods. This finding challenges considerations that suggest longer-term stability of R&D cooperation because of transaction costs, as well as the assumptions of the well-established Barabási & Albert (1999, 2000, 2002) model. We find that the pure presence of an actor and an actor's position in the largest component have a higher impact on the probability of his or her reemergence in a subsequent period than an inventors' performance in terms of the number of patents or links.

Our analyses show some statistically significant relationships between fluidity at the micro-level and stability of network structure. Higher fluidity of actors leads to more fragmentation, as indicated by a lower share of the largest component and a higher share of isolates. However, there is no statistically significant relationship with the mean degree and other conventional measures of network structure. This result suggests that abandoned ties due to actors leaving the network are, more or less, completely replaced by newly established relationships. We found pronounced statistically significant relationships between the fluidity of actors and patent productivity as a measure for the performance of the respective regional innovation system. This result suggests that the termination of cooperative relationships due to fluidity of actors is not generally harmful for regional innovation activities. However, the net change in the number of actors is negatively related to the performance of the respective regional innovation system. In contrast, an increase in the number of links among actors is positively related to network performance. This is consistent with the notion that the intensity of knowledge transfer and division of innovative labor are important determinants of the performance of regional innovation systems (Fritsch & Slavtchev 2011).

We conclude from our analysis that the efficiency of a RIS does not depend on actors remaining in an innovation network for long periods of time. On the contrary, since dynamic innovation processes require a permanent inflow of new actors with new knowledge and ideas, at least a certain degree of fluctuation of the actors in an innovation network can be regarded as essential for its effective performance. The negative relationship between the net change of actors and the performance of the respective regional innovation system requires further investigation. Our analyses suggest that increasing the connectedness within a network is more decisive for the effective performance of an innovation system than the fluidity of actors.

The high level of actor fluidity revealed by our analyses clearly indicates that the notion that transaction costs motivate long-term persistent cooperative relationships in R&D ignores other more important factors that influence the stability of cooperative relationships. One important influence could be the dynamics of innovative processes that require frequent changes in the combination of knowledge fields and, hence, of cooperative relationships among actors. Further research should seek to identify these influences in order to enable a more comprehensive understanding of the factors that determine the choice of cooperation partners and the duration of the relationship. How and why do actors select certain partners for R&D cooperation? Why do they decide to discontinue a once-established relationship? The preferential attachment mechanism proposed by Barabási & Albert (1999, 2000) is obviously inappropriate when discussing innovation networks, because, at best, it only explain a small part of an actor’s behavior.

Another interesting consequence of fluidity in networks worthy of further investigation is how it effects the knowledge content of a network and on knowledge diffusion. While the inclusion of new actors in a network implies an inflow of additional knowledge, it is unclear if the knowledge transferred by an actor who leaves a network continues to be used by those cooperation partners who remain in the network. The effect of this type of knowledge transfer should depend on number of links held by the non-continuing actor, and on the structure of the network. Hence, the effect of a well-connected member belonging to the largest component of a network should be much more significant than that of an isolate or of someone in a small component. Moreover, the structure of the network should play a role here. Does a larger and denser network lead to higher robustness against missing nodes?

A principal shortcoming of our analysis may follow from the fact that our data, drawn from patent statistics, covers only a certain aspect of innovation activities, i.e., research that leads to a patent application. Actors may pursue other types of collaborative innovation that do not lead to a patent application, e.g., basic research, that are not recorded in patent data. Hence, it could well be that data sources with a more comprehensive coverage of innovation activity would show higher levels of long-lasting R&D cooperation.

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Appendix

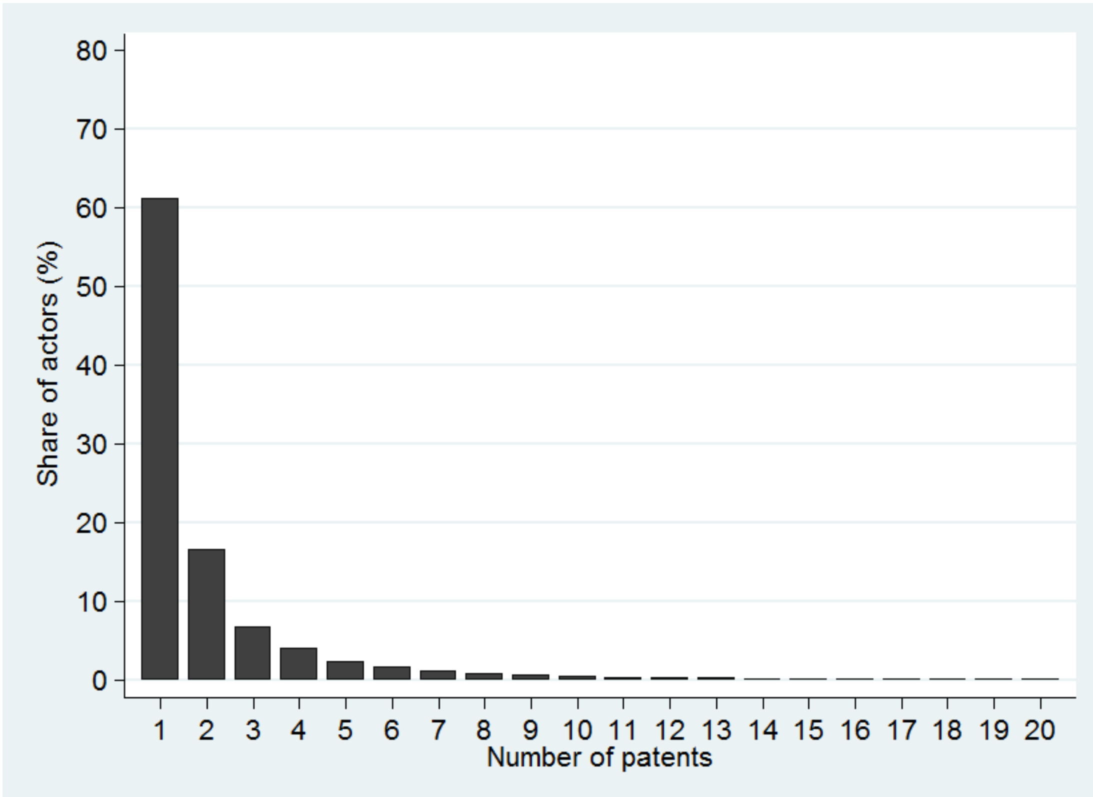

Figure A1: Shares of actors by number of patents (all periods)

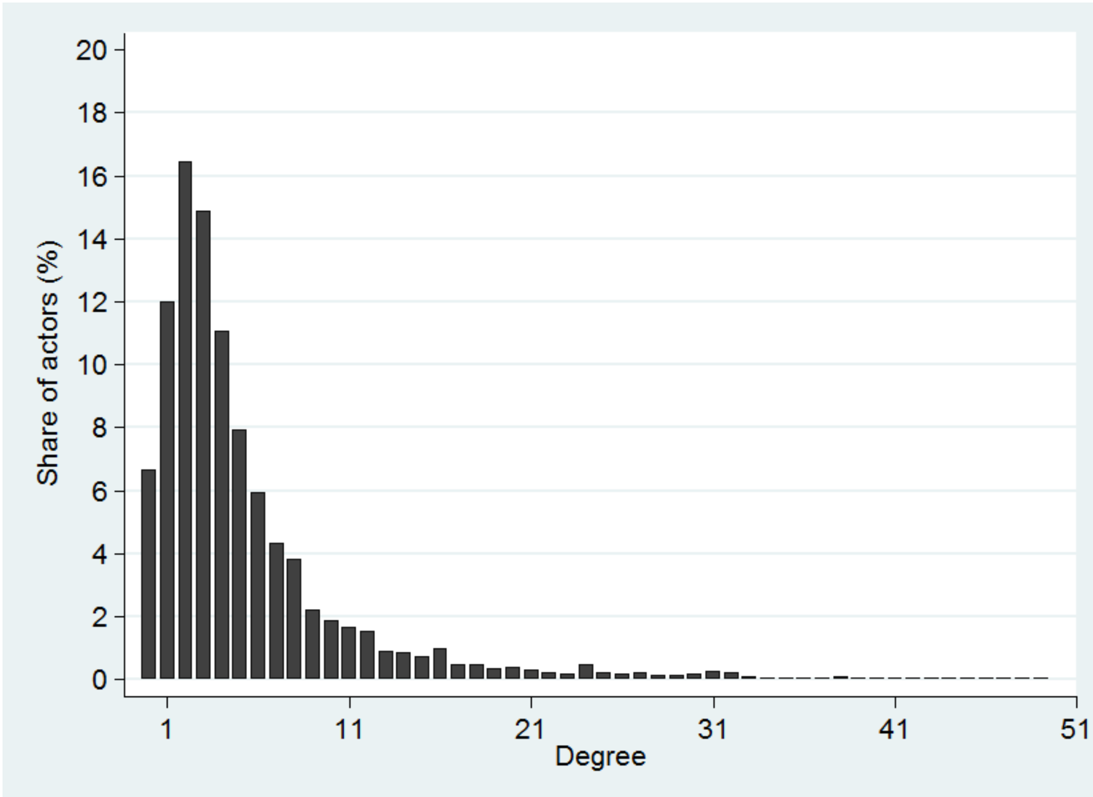

Figure A2: Shares of actors by number of degrees (all periods)

Table A2: Descriptive statistics of variables (all regions and all periods)

	Mean	Median	Minimum	Maximum	Standard deviation
Average path length	3.502	2.644	1.313	17.033	2.443
Share of continuing actors in successive periods	0.211	0.224	0.102	0.3	0.0544
Number of degrees	1.347	0	0	201	4.856
Actor was part of the largest component in previous period	0.0265	0	0	1	0.161
Actor appears in network for the first time	0.242	0	0	1	0.428
Actor's number of patens	3.634	2	2	135	3.525

Table A3: Correlations between variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Number of patents t-0	1																		
2	Number of patents t-1	0.46	1																	
3	Number of patents t-2	0.26	0.41	1																
4	Number of patents t-3	0.11	0.18	0.37	1															
5	Number of patents t-4	0.07	0.12	0.19	0.37	1														
6	Actor present t-0	0.57	0.13	0.03	-0.04	-0.05	1													
7	Actor present t-1	0.12	0.53	0.09	-0.02	-0.05	0.06	1												
8	Actor present t-2	0.02	0.09	0.5	0.07	-0.02	-0.08	-0.02	1											
9	Actor present t-3	-0.02	0.02	0.11	0.6	0.11	-0.13	-0.13	-0.06	1										
10	Actor resent t-4	-0.05	-0.03	0.01	0.12	0.53	-0.16	-0.18	-0.17	-0.02	1									
11	Actor’s degree t-0	0.79	0.34	0.17	0.06	0.03	0.54	0.1	0	-0.04	-0.06	1								
12	Actor’s degree t-1	0.31	0.75	0.27	0.1	0.05	0.11	0.5	0.06	-0.02	-0.06	0.34	1							
13	Actor’s degree t-2	0.14	0.26	0.76	0.23	0.09	0.00	0.07	0.48	0.05	-0.03	0.12	0.27	1						
14	Actor’s degree t-3	0.04	0.09	0.24	0.76	0.21	-0.05	-0.04	0.04	0.47	0.05	0.02	0.06	0.2	1					
15	Actor’s degree t-4	0.01	0.06	0.12	0.27	0.81	-0.07	-0.07	-0.04	0.07	0.5	0.01	0.03	0.07	0.21	1				
16	In largest component t-0	0.24	0.13	0.07	0.03	0.02	0.19	0.04	0.00	-0.01	-0.02	0.26	0.11	0.04	0.01	0.01	1			
17	In largest component t-1	0.09	0.25	0.1	0.05	0.03	0.05	0.24	0.03	0.00	-0.02	0.08	0.25	0.12	0.04	0.02	0.06	1		
18	In largest component t-2	0.02	0.1	0.23	0.12	0.04	-0.02	0.03	0.26	0.07	-0.01	0.01	0.11	0.27	0.11	0.04	0.02	0.11	1	
19	In largest component t-3	0.02	0.07	0.14	0.32	0.16	-0.03	-0.01	0.05	0.29	0.06	0.02	0.06	0.13	0.28	0.13	0.03	0.05	0.23	1
20	In largest component t-4	0.04	0.06	0.06	0.12	0.27	-0.02	-0.02	-0.01	0.04	0.29	0.05	0.06	0.05	0.08	0.29	0.08	0.07	0.08	0.18

Table A4: Numbers of nodes, ties, components, and total patents in different time periods

Time period	Number of Actors	Ties	Compo-nents	Patents
94-96	9,845	27,964	1,900	8,630
97-99	14,767	49,844	2,498	14,240
00-02	15,394	63,856	2,439	13,103
03-05	17,483	74,132	2,700	10,663
06-08	18,324	76,932	2,727	12,348

Table A5: Mean degree and average path length in different time periods

	94-96	*97-99*	*00-02*	*03-05*	*06-08*
Mean degree	3.76	5.11	5.51	5.44	5.36
Average path length	2.216	3.569	3.847	3.773	3.831
Share of largest component	0.05	0.07	0.10	0.12	0.10
Average component size	4.42	5.14	5.09	5.72	5.78

Table A6: Number of co-patents and single patents (all regions)

	94-96	*97-99*	*00-02*	*03-05*	*06-08*	*94-08*
Total number of patents	8,630	14,240	13,103	10,663	12,348	58,984
Number of co-patents	7,374	12,597	11,848	9,498	11,138	52,455
Share of co-patents in %	85.45	88.46	90.42	89.07	90.20	88.93
Number of patents with single inventor	1,256	1,643	1,255	1,165	1,210	6,529
Number of inventors per patent	2.708	2.819	2.987	3.071	2.955	2.914
Number of inventors per co-patents	3.400	3.512	3.652	3.698	3.582	3.577

Table A7: Logistic regressions

	Reoccurrence of a node in the period 2006-2008			
Variables	I	II	III	IV
Actor present in t-1				
t-1	2.34***	-	-	-
	(0.0344)			
t-2	0.95***	-	-	-
	(0.0317)			
t-3	0.63***	-	-	-
	(0.03641)			
t-4	0.47***	-	-	-
	(0.0439)			
Actor was part of largest component in				
t-1	-	1.625***	-	-
		(0.047)		
t-2	-	0.332***	-	-
		(0.059)		
t-3	-	0.430***	-	-
		(0.076)		
t-4	-	0.470***	-	-
		(0.126)		
Number of actor's patents in				
t-1	-	-	0.682***	-
			(0.018)	
t-2	-	-	0.092***	-
			(0.0121)	
t-3	-	-	0.068***	-
			(0.009)	
t-4	-	-	0.047***	-
			(0.014)	
Number of an actor's links in				
t-1	-	-	-	0.091***
				(0.006)
t-2	-	-	-	0.017***
				(0.002)
t-3	-	-	-	0.012***
				(0.0026)
t-4	-	-	-	0.007*
				(0.0046)
Regional dummies	Yes***	Yes***	Yes***	Yes***
	-4.07***	-1.876***	-2.437***	-2.017***
Constant	(0.0692)	(0.0528)	(0.0578)	(0.0548)
Log likelihood	-15011.173	-17118.235	-15049.471	-16785.956
Pseudo R²	0.1702	0.054	0.168	0.072
McFadden's R2	0.170	0.053	0.167	0.072
Number of observations	46,827	46,872	46,872	46,872

Notes: Coefficients; robust standard errors in parentheses. ***: statistically significant at the 1 % level; **: statistically significant at the 5 % level; *: statistically significant at the 10 % level.

Table A8: Descriptive statistics for measures of fluidity, network structure and network performance

	Mean	Median	Minimum	Maximum	Standard deviation
Share of discontinued actors from t-1	0 .7404	0.7386	0.6078	0.8984	0.0716
Share of new actors	0.7768	0.7762	0.5967	0.8984	0.0702
Net change number of actors	0.0364	0.0407	-0.0614	0.1032	0.0420
Share of discontinued links from t-1	0.9030	0.9034	0.8288	0.9640	0.0290
Share of new links	0.9206	0. 9205	0.8724	0.9541	0.0195
Net change of the number of links	0.0176	0.0173	-0.0364	0.1052	0.0267
Share of largest component	0.0982	0 .0716	0.0226	0.3333	0.0792
Share of isolates	0.0870	0 .0837	0.0327	0.1876	0.0366
Mean degree	5.3552	5.5645	3.225	7.26	1.1647
Patent productivity (ln)	-0.3677	-0.4157	-0.7851	0.5466	0.2589
Change of patent productivity (%)	-0.0384	-0.0477	-0.4856	0.3367	0.1882
Share of service employment	0.8773	0.8762	0.7579	0.9706	0.0483
Employment share of manufacturing establishments < 50 employees	0.3496	0.3307	0.1872	0.5603	0.1059

Table A9: Rank correlations between measures of fluidity, network structure and network performance

		1	2	3	4	5	6	7	8	9	10	11	12
1	Share of discontinued actors from t-1	1											
2	Share of new actors	0.840***	1										
3	Net change number of actors	-0.356**	0.107	1									
4	Share of discontinues links from t-1	-0.025	0.314*	0.503***	1								
5	Share of new links	0.668***	0.638***	-0.190	0.424***	1							
6	Net change number of links	0.494***	0.090	-0.682***	-0.692***	0.259	1						
7	Share of largest component	-0.538***	-0.641***	-0.196	-0.542***	-0.532***	0.098	1					
8	Share of isolates	0.445***	0.399**	-0.041	-0.117	0.267	0.354**	-0.337**	1				
9	Mean degree	-0.355**	-0.480***	-0.150	-0.393**	-0.380**	0.138	0.541***	-0.606***	1			
10	Patent productivity (ln)	-0.060	-0.241	-0.503***	-0.505***	0.121	0.661***	0.237	0.210	0.307*	1		
11	Change of patent productivity (%)	0.030	0.031	0.116	-0.074	0.106	0.083	-0.181	-0.014	0.058	0.286*	1	
12	Share of service employment	0.149	0.085	-0.077	-0.004	0.226	0.168	-0.043	0.150	-0.288*	-0.124	-0.059	1
13	Employment share of manufacturing establishments < 50 employees	0.158	0.055	-0.341**	-0.370**	-0.039	0.263	0.073	-0.076	0.008	-0.287*	0.060	0.436***

Notes: Spearman rank correlation coefficients. ***: statistically significant at the 1 % level; **: statistically significant at the 5 % level; *: statistically significant at the 10 % level.