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The Network of Innovators in Jena: An Application of Social Network Analysis

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Abstract

We apply social network analysis methods to describe the evolution of the innovator network of Jena, Germany in the period from 1995 to 2001. We find this evolution to be directed towards an increasing focus on core competencies of the local innovation system. Further we analyze the network resulting from R&D cooperations and explain - by means of network regression techniques - that the job mobility of scientists and the technological overlap between the actors, rather than past cooperations, can best predict the resulting structure. We also observe an increasing importance of the university while the former "Kombinate" begin to lose their prominent role.

Keywords: Innovator Networks; Network Regression; Local Innovation Systems; R&D Cooperation; Research University

JEL Classification: O31; L14; R11

1 Introduction

In large parts of the economy the process of innovation is characterized by interaction between different actors. The fundamental idea behind this notion is collective invention which is very idealistic in Allen's (1983) pure and original sense but when interpreted less strictly describes well what is at the core of the idea of local innovation systems (LIS). In the literature we also find studies on user-producer relationships (Lundvall 1992), university-industry relationships (Owen-Smith, Riccaboni, Pammolli, and Powell 2002), and cooperative agreements between firms that belong to the same sector (von Hippel 1987). Interaction within the process of innovation is held responsible for a large part of new knowledge created by the actors as the mutual exchange

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of knowledge provides the most efficient way of learning and cross-fertilization. The probability of interaction should be increasing in proximity between the actors. Proximity might be defined in geographical as well as technological space. What both types of proximity actually imply is social proximity, that is the probability to know who might be a promising partner for mutual exchange and creation of knowledge.

We study the LIS of Jena, which stands out of the mass of communities in the eastern part of Germany as a technologically and economically successful region (OECD 2001, Cantner, Helm, and Meckl 2003). We thereby restrict the analysis to geographical proximity between the actors as being most relevant to foster interaction and thereby learning. Within this LIS, we focus on the different role of technological and social proximity.

Another focus of our work is on the determinants of the cooperative linkages. We analyze the network resulting from R&D cooperation and explain - by means of network regression techniques - that the job mobility of scientists and the technological overlap between the actors, rather than past cooperation, can best explain the resulting structure.

The paper proceeds as follows. In the next section we give a short introduction to the methodology and the data used for the empirical analysis. In section 3 we apply social network analysis methods and visualizations to describe the evolution of the innovator network of Jena in the period from 1995 to 2001. Besides the overall structure of the network we also investigate the change in relative positions of the core network members. Section 4 concentrates on the explanation of cooperative linkages between the actors. Finally, section 5 concludes the paper by summarizing and pointing towards further research required.

2 Research methodology and data

2.1 Social network analysis

Social network analysis is a interdisciplinary methodology developed mainly by sociologists and researchers in social psychology, further developed in collaboration with mathematics, statistics, and computing that led to a rapid development of formal analyzing techniques which made it an attractive tool for other disciplines like economics, marketing or industrial engineering.

> *"[...] social network analysis is based on an assumption of the importance of relationships among interacting units.[...] relations defined by linkages among units are a fundamental component of network theories."*(Wassermann and Faust 1994, p. 4)

There is a wide range of topics in economics, that employ methods of social network analysis. Some recent examples include the work of Cowan and Jonard, who evaluate the impact of the network structure on its performance by means of simulation (Cowan and Jonard 2003a, Cowan and Jonard 2003b). Owen-Smith, Riccaboni, Pammolli, and Powell (2002) compare the organization and structure of scientific research in the United States and Europe by building networks of R&D cooperation. Breschi and Lissoni (2003) as well as Singh (2003) expand the study of Jaffe, Trajtenberg, and Henderson (1993) and find that social proximity has the stronger relevance for the degree of knowledge spillovers than geographical proximity.[1]

2.2 Data

The following example should provide the reader with a short introduction to the methodology and our data setup. For more details, please refer to the widely cited book by Wassermann and Faust (1994). Since we use patent data it is natural to use a small number of patents as the raw data for our example given in table 1. On each patent you find information about the assignee(s), let us call them innovator, which is usually a firm or public research laboratory, but might also be an individual. You also find the actual inventor(s), i.e. the people who generated the knowledge that has been patented as well as the technological classification of the patent.

If one wishes to build a network of innovators where a linkage between the assignees A_1 and A_2 result from people having worked for both of them, one has to generate the incidence matrix I, where the rows are the assignees and the columns represent the

[1]Another example is the work of Potts (2000), who places the existence and generation of linkages between actors at the center of his evolutionary microeconomic theory.

Table 1: Example raw data

Patent	Innovator	Inventor	Class
P1	A_1	I_1, I_4	1
P2	A_2	I_2	2
P3	A_3	I_3, I_4	2
P4	A_4	I_1, I_4	1
P5	A_4	I_2, I_3	2
P6	A_4	I_5	2

inventors. Inventors are then the common "events" of the innovators.

$$I = \begin{pmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \end{pmatrix}$$

The square matrix that indicates the number of linkages a_{ij} between A_i and A_j, is called the adjacency matrix A, which is computed as the product of I with its transposed.

$$A = II' = \begin{pmatrix} - & 0 & 1 & 2 \\ 0 & - & 0 & 1 \\ 1 & 0 & - & 2 \\ 2 & 1 & 2 & - \end{pmatrix}$$

Since I_4 has worked both for $A_1(i_{14} = 1)$ and $A_3(i_{34} = 1)$, there is a linkage between A_1 and A_3, indicated by $a_{13} = 1$. The graphical or network representation of A is then given in figure 1.

We use data on patents that were applied for at the German Patent Office and were disclosed between 1995 and 2001. To include all patents that are relevant for Jena as an innovation system we filtered out all patents where at least one of the inventors named on the patent had their residence in Jena at the time of application. Altogether we could identify 368 distinct assignees holding 1181 patents in 29 out of the 30 technologies[2], employing 1888 inventors (1113 of which resided in Jena). To investigate the dynamics of the networks we split the sample into two periods of equal

[2]For the technological aggregation, patents have been classified according to a technology-oriented

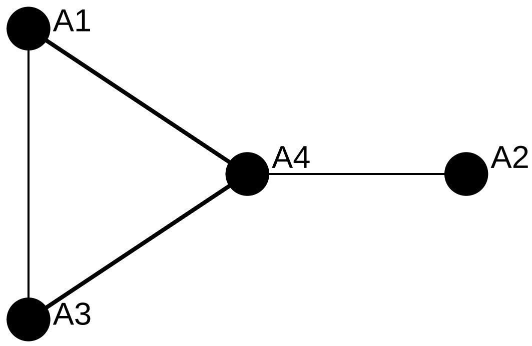


Figure 1: Example network

length, i.e. the first period includes all patents disclosed between 1995 and 1997 while the second period covers the years 1999 through 2001. By dropping the year 1998 from the sample we lose 42 innovators. The rest can be divided into 173 innovating entrants, 117 innovators that exit, and 36 permanent innovators, which make up the core of the system that is analyzed in more detail in section 4.

3 Innovator networks

According to the outline of our paper given in the introduction we now proceed to map the actors that build up the innovation system of Jena. We pursue two different paths in building innovator networks with our data. The first path to build such an assignee-network is to link the assignees by the kind of technological knowledge they have created. The more fields of research the innovators have in common, the closer they are related (technological overlap). The second possibility is related to the notion of knowledge transfer through workers mobility (e.g. Saxenian 1994, Almeida and Kogut 1999). The main idea is that organizations, i.e. firms or research institutes are closely related if scientists move from one organization to the other or know each other through working on joint projects.

Based on our data we analyze three different types of networks, all of which are

classification that distinguishes 5 industries and 30 technologies based on the International Patent classification (IPC). This classification has been elaborated jointly by the Fraunhofer-Institut für Systemtechnik und Innovationsforschung (FhG-ISI), the Observatoire de Sciences et des Techniques (OST), and the Science and Technology Research Policy Unit of the University of Sussex (SPRU).

built for the two consecutive periods (1995-1997 and 1999-2001):

Technological overlap: Linkages between assignees are formed whenever they patent in the same technological class. This network can be interpreted as the potential for cooperation.

Cooperation: When there is more than one assignee mentioned on a patent, there are linkages between all co-assignees.

Scientist mobility: In our database, the inventors who actually generated the knowledge for the patent are mentioned. Whenever a specific inventor is mentioned on (non cooperative) patents assigned by distinct assignees a link between those assignees is formed, since the inventor has worked for both.

3.1 The innovator network based on technological overlap

Innovators can be specialized in a certain field of knowledge or instead be diversified. Building a network where innovators are connected by the overlap in technological interest we would expect diversified actors forming the center of the network, whereas the specialized innovators are positioned in the periphery. This exercise serves three purposes. First, it gives us a picture of the structure of the innovation system in different time periods. Are the innovators all focussing on the same technologies or do we see several specialized groups of firms that form clusters in the periphery of the network? Second, we can identify the innovators in the center and the periphery, thereby investigating the roles of particular actors. Third, this type of network can be viewed as the potential for innovators to cooperate since the connected firms share a common knowledge base, a topic that will be addressed in section 4.

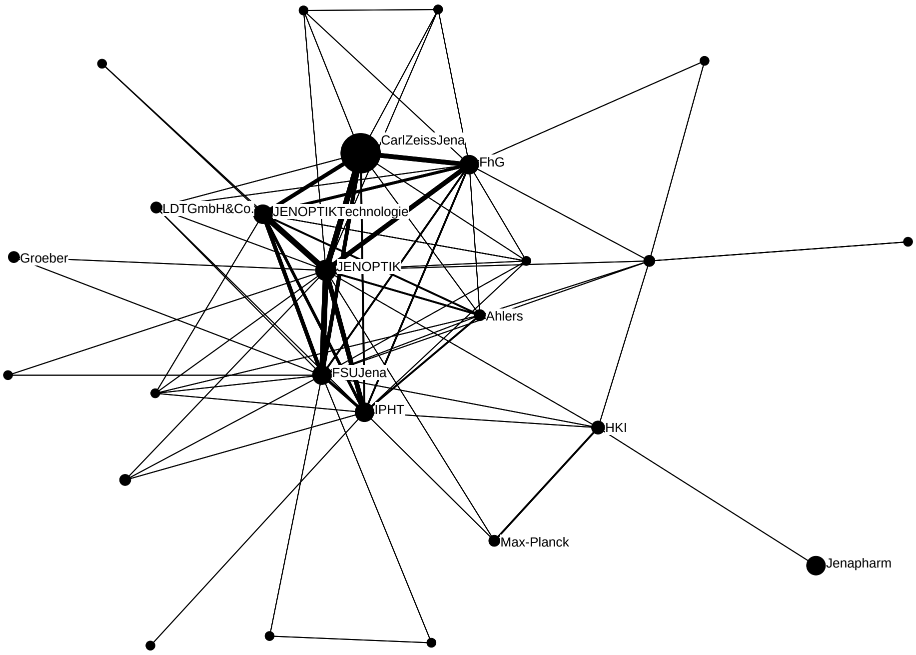
Figure 2 visualizes the Jena network of innovators, where nodes are patent assignees and edges result from an overlap in at least two technologies[3].[4]

It comes as no surprise, that the larger innovators form the center of these networks. Jenapharm is the only exception, being a specialized firm in pharmaceuticals. Carl Zeiss

[3]This restriction is only used for visualization of the network.

[4]The network visualization for this and the following figures was performed using NetDraw as implemented in UCINET 6 software and multidimensional scaling with node repulsion and equal edge length bias as layout.

Technological overlap 1995-1997



Technological overlap 1999-2001

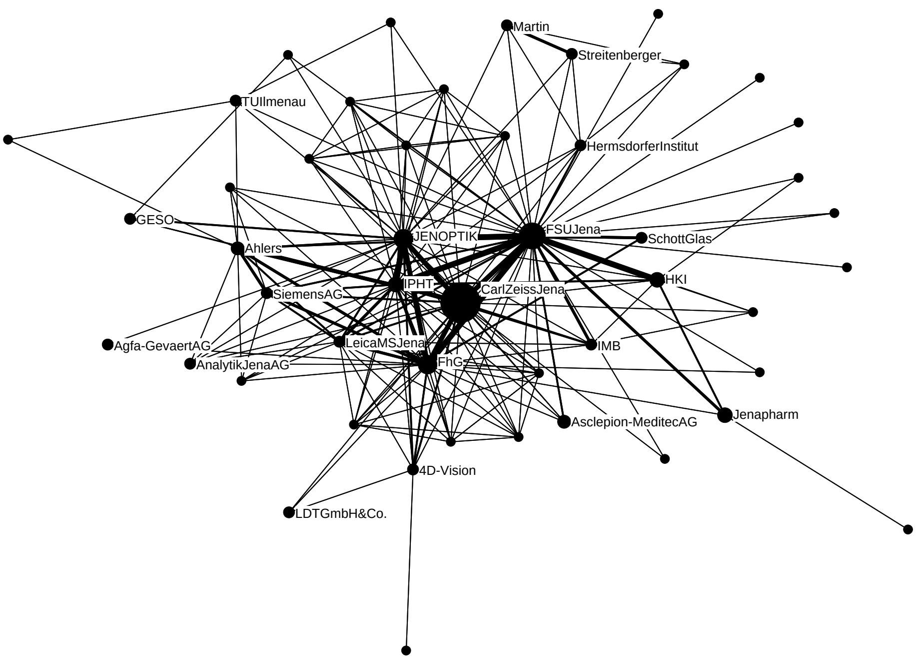


Figure 2: Potential for cooperation in Jena. Nodes are patent assignees irrespective of organizational form, edges between A and B result from holding patents in at least two common technologies. The size of a node is determined by the number of patents granted, the width of an edge is related to the number of overlapping technologies. Isolated innovators are not displayed for reasons of lucidity.

Jena and Jenoptik are the successors of the former VEB Carl Zeiss which dominated the economic structure of Jena during the socialist era in the GDR. This VEB was a highly differentiated "Kombinat", i.e. integrated firm and already by visual inspection we see that they move towards the periphery of the network as they follow a strategy of higher specialization. The University (FSU) on the other hand moves towards the center of the network and covers the broadest range of research fields in the second period[5].

We do not observe any clear cut cluster formation within Jena for either period, it rather seems that the core has become denser while small innovators position themselves in the same types of technologies as the core. Even though we applied equal time spans for the division of the data, the size of the network almost doubles from 25 innovators[6], that have at least two technologies in common, to 48 innovators in the second period.

Table 2: Descriptive statistics of the networks of technological overlap

	$tech^{95-97}$	$tech^{99-01}$
No. of actors	153	209
Density	0.151	0.165
Network Centralization[a]	0.598	0.700
Overall graph clustering coefficient	1.238	1.178
No. of Components	5	2
Components with 2 or more members	2	1
Size of largest component	148	208

[a] Networks have been dichotomized.

Table 2 summarizes the descriptives of these two networks. If g is the size of the network and $d(n_i)$ is the degree, the number of connections, of actor i, then the density D of the network is defined as the number of all linkages divided by the number of possible linkages within the network $D = \sum_{i=1}^{g} d(n_i)/(g^2 - g)$. The observation from the visual inspection that the network has become more tightly connected is confirmed

[5] See also table 7.

[6] Innovators that have patented in at least two technologies, that are also covered by other network members.

by the measures (0.15 to 0.17).

The degree centrality of an actor i is the number of its ties divided by the number of possible ties $C_D(n_i) = d(n_i)/(g-1)$. The *network centralization* is then given by $C_D = \sum_{i=1}^{g} \left(\max(C_D(n_i)) - C_D(n_i)\right)/(g-2)$. We find an increase in centralization of the network from 0.6 to 0.7, which means that the periphery of the network has more connections to the core but less connections within itself. Since there are only 30 technological classes, the *number of components* (disconnected parts of the network) is very small. But the fact that the number of components decreased from 5 to 2, so that in the second period all innovators - except one - are connected hints towards a stronger concentration on core competencies of the network.

Another structural measure for a network is the *overall clustering coefficient.* It is calculated by averaging the clustering coefficients of all actors within the network. The node level clustering coefficients are calculated as the density of the neighborhood (i.e. the network of actors directly linked to the respective actor) of this actor. The decrease of the overall graph clustering coefficient from 1.238 in the first period to 1.178 in the second period provides another result in favor of the above argument.

As was already noted before, we can characterize the innovators according to their innovator status (entry, exit, permanent). If network positions really matter for the performance of single actors, one would suspect that innovators that exit the system have to do this because of a weak position therein. For the entering firms we should observe a close relation to the core of the existing network. Why would this be so? The literature on entrepreneurship tells us that people often found their firms where they are already located (e.g. Fornahl and Graf 2003, Cooper and Folta 2000). Being educated within a particular system or having worked there would lead to a higher probability to be engaged in the same activities as before. Even if there are firms that are relocating, we could expect them to be quite aware of the characteristics of this site, and technological competencies of the region would - at least for innovative firms it should - be a relevant criterion.

Analyzing these differences we calculate block densities for the network of both periods, where the blocks are the different groups mentioned. The resulting values and standard deviations within and between the groups are given in table 3. First, we notice an increase in the density of the network of permanent innovators between the two periods from 0.43 to 0.54 (second and third row, second column). The technological overlap of the core members of the innovation system has increased. Secondly, regarding the different roles of exiting innovators and entrants we observe a stronger connectivity within the entering group itself (0.12 compared to 0.09 for the exiting group), but also with respect to the linkages with the permanent group (0.23 compared to 0.21 for exit). This can be interpreted as a result of a self-organizing process where actors in technologies with a number of co-located innovators below the critical mass either leave the system and search for a better location or just stop innovating at all, new entrants on the other hand are attracted by the strengths or core capabilities within the network.

Table 3: Technological overlap: Block-densities / average value within and between blocks

		exiting innovators	permanent innovators	entering innovators
P1	exit	0.0903 (0.2877)	0.2056 (0.4466)	
	permanent	0.2056 (0.4466)	0.4317 (0.8550)	
P2	permanent		0.5413 (1.0067)	0.2336 (0.4692)
	entry		0.2336 (0.4692)	0.1206 (0.3310)
	N	117	36	173

Standard Deviations in parentheses

3.2 The innovator network weaved by interpersonal relations

In the previous section we focused on the technological competencies of the innovators in Jena. Performing within the same technological field, however, does not imply to be actually related to one another though. What really matters when we talk about local innovation systems, innovator networks, clusters or whatever it is called are the interpersonal relationships in such systems.

Arrow (1962) already recognized worker mobility as a distinct source of knowledge spillovers. Saxenian (1994) and Almeida and Kogut (1999) show that the mobility of individuals is one possible mechanism of knowledge diffusion to existing firms, whereas Klepper (2001) as well as Gompers, Lerner, and Scharfstein (2003) focus on start-ups as a means of commercializing knowledge. Cooper (2001) shows theoretically that a higher rate of job mobility corresponds to greater overall technological progress because parts of the knowledge generated by the worker can be utilized by both firms involved.

Due to the data that we use, we have the possibility to analyze a network of innovators that can be viewed as the lower barrier of actual relationships. On each patent we find information about all the scientists and engineers that were involved in the creation of the knowledge that led to this innovation (inventors). By creating an incidence matrix where the assignees (innovators) are the nodes (rows) of the network and the inventors on the patent are the characteristics (columns) of these innovators we can identify those inventors that have worked on research projects for more than on assignee, thereby creating linkages between these assignees. We assume that the more scientists have worked for two distinct assignees, the closer the latter are related.

We can distinguish two different possibilities how this relationship is established. The first way is by direct cooperation. Whenever we find a patent with more than one assignee we assume it to be a cooperation. Of course, all the inventors on such a patent are then a "common event" of all the assignees. We call the resulting network *cooperation*. The other possibility is less direct. If an inventor is mentioned on patents (which are not cooperative in the sense above) assigned by different innovators within one of the two periods of observation (1995-1997 and 1999-2001) we end up with a link between those innovators that we call *scientist mobility*.

Besides the obvious increase in size of the visualized networks (figure 3) both types of networks are characterized by a different evolution of the network structure. In table 4 we report the same statistics as in the last section for the networks of cooperation (co^t), scientist mobility (sm^t), and the network of personal relationships (pr^t) which does not distinguish between the two former types of relations.

The density of the cooperation network decreases (0.026 to 0.022) while it increases slightly for the scientist mobility network (0.004 to 0.005). The overall effect is dominated by the effects of cooperation, which leads to a network of personal relationships which is less connected in the second period (0.036 to 0.031). The overall network becomes more centralized (0.113 to 0.171), which is also due to the development in formal cooperation (0.046 to 0.124) whereas centralization decreases in the scientist mobility network (0.048 to 0.040). This network also shows a tendency towards stronger clustering (0.638 to 0.885), which is opposite to the development for cooperation (3.835 to

Table 4: Descriptive statistics of the interpersonal networks

	pm^{95-97}	pm^{99-01}	co^{95-97}	co^{99-01}	sm^{95-97}	sm^{99-01}
N	153	209	153	209	153	209
Density	0.036	0.031	0.026	0.022	0.004	0.005
Network Centralization[a]	0.113	0.171	0.046	0.124	0.048	0.040
Overall graph clustering coefficient	2.758	2.044	3.835	2.808	0.638	0.885
No. of Components	67	80	100	135	126	150
Components with 2 or more members	17	19	20	14	7	14
Size of largest component	63	101	14	61	20	39

[a] Networks have been dichotomized.

2.808). Again the combination of both networks is dominated by cooperation (2.758 to 2.044). Only the analysis of components shows a similar trend towards less fragmentation. The share of innovators that are part of the largest component of the cooperation network increased from 0.09 to 0.29 and the share of innovators connected by scientist mobility in the largest component increases from 0.13 to 0.19. If we abstract from the type of interaction connecting the innovators, almost 50 % of all innovators are part of the largest component of the network.

It seems that the large core actors within the network focus more on formal cooperation while the smaller surrounding or peripheral actors rather have contacts through informal personal relations.

As in the analysis of the network of technological overlap we are interested in the relative positions of different groups of the network. Tables 5 and 6 report the results for block-densities, calculated for exiters, permanent innovators, and entrants in the two periods.

The first observation regards the change in structure of the networks of permanent innovators. Its density almost doubled for cooperative linkages (0.057 to 0.102) and more than tripled for scientist mobility (0.016 to 0.051). We also notice a higher density within the exiting group (0.0237) compared to the entrants (0.0119) in the cooperation network. On the other hand, the entrants are better connected with the permanent innovators (0.0390) than are the exiters (0.0254).

Regarding the scientist mobility network, we observe higher density for the entrants within the group (0.0012) compared to the exiters (0.0010) and also more connections between entrants and permanent innovators (0.0103) than between the exiters and the core network (0.0078).

Table 5: Cooperation: Block-densities / average value within and between blocks

		exiting innovators	permanent innovators	entering innovators
P1	exit	0.0237 (0.3173)	0.0254 (0.3405)	
	permanent	0.0254 (0.3405)	0.0571 (0.5827)	
P2	permanent		0.1016 (0.8428)	0.0390 (0.4292)
	entry		0.0390 (0.4292)	0.0119 (0.2189)
	N	117	36	173

Standard Deviations in parentheses

Table 6: Scientist mobility: Block-densities / average value within and between blocks

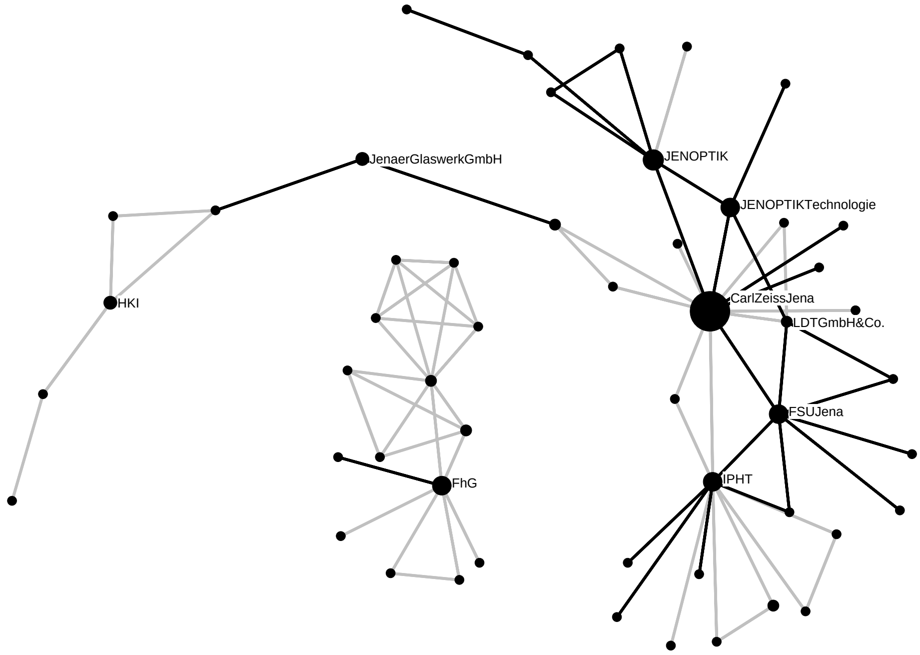
		exiting innovators	permanent innovators	entering innovators
P1	exit	0.0010 (0.0364)	0.0078 (0.2279)	
	permanent	0.0078 (0.2279)	0.0159 (0.1586)	
P2	permanent		0.0508 (0.3952)	0.0103 (0.1407)
	entry		0.0103 (0.1407)	0.0012 (0.0418)
	N	117	36	173

Standard Deviations in parentheses

Overall, entrants in Jena seem to be better integrated into the network as actors that, for which ever reasons, stopped innovating. This finding is consistent with the results of Powell, Koput, Smith-Doerr, and Owen-Smith (1999) that the network position has an important influence on firm performance.

Since we only analyze two periods, its difficult to view this finding as a general result. Surely, it needs to be qualified through further research. Let us nevertheless assume this conjecture holds: Would this not lead to ever increasing density of the network? We think not. Since the ties that constitute the networks cannot assumed

Cooperation and scientist mobility 1995-1997



Cooperation and scientist mobility 1999-2001

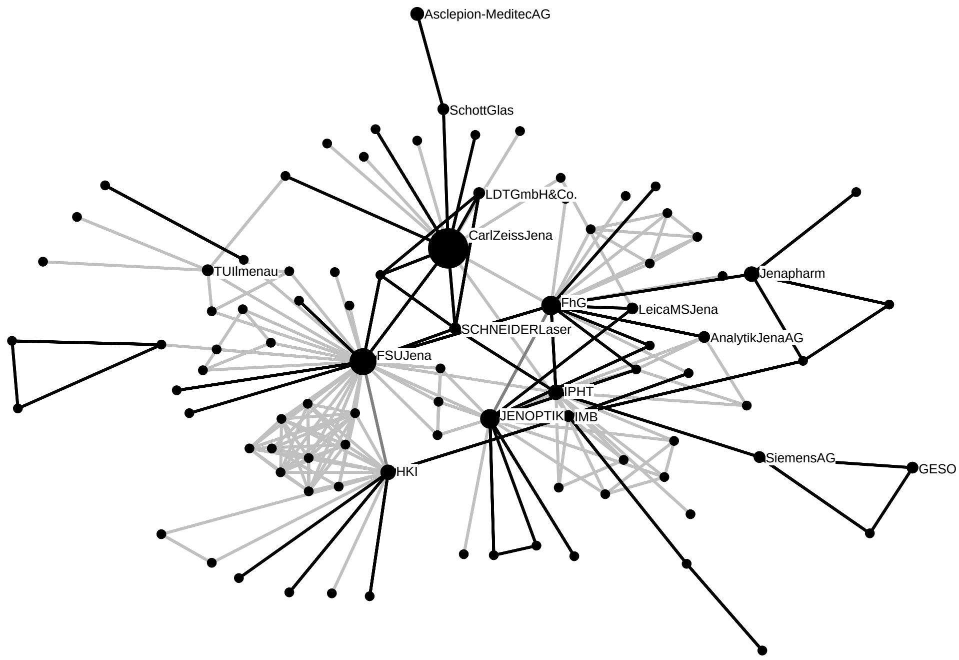


Figure 3: The network through interpersonal relations in Jena. Nodes are patent assignees irrespective of organizational form, edges between A and B result from an inventor who shows up on patents held by both A and B. In the network visualization of the first period the two largest components are displayed, in the second period only the largest one. Linkages through cooperation are light grey, linkages through scientist mobility are black, if both types of linkages apply, we use a dark grey. Note that for large firms like Siemens, which are not located in Jena, we only include patents with at least one inventor living in Jena.

to be persistent over very long periods of time, it might well be that formerly well connected actors become more isolated over time, therefore becoming a candidate for subsequent exit.

3.3 The core network members

The last two sections provided a description of the network as a whole. Now we will focus on the role of the core network members. To measure the importance of single actors, social network theory employs several measures for centrality. We use degree centrality, explained above, and the betweenness of an actor, i. It is defined as $C_B(n_i) = \sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}}, \forall i \neq j, k$, where g_{jk} is the number of geodesics linking j and k and $g_{jk}(n_i)$ is the number of geodesics from j to k that pass through i. Conceptually, high-betweenness vertices lie on a large number of non-redundant shortest paths between other vertices; they can thus be thought of as "bridges" or "boundary spanners."

In table 7 we report the ranking of the innovators according to these centrality measures for the 15 innovators that were most active in both periods. For reasons of clarity we only present the rank scores on degree and betweenness centrality within the three different types of networks (cooperation, scientist mobility, and technological overlap), separate for each period.

The first observation is that the local innovation system is clearly dominated by public research institutions (marked with an asterisk) and the large successors of the VEB Carl Zeiss (Jenoptik and Carl Zeiss Jena). Secondly we notice the centrality of the three actors within the top 15 that are not located in Jena (Hermsdorfer Institut, Siemens AG and LDT GmbH & Co.) to be decreasing over time. Finally, the university of Jena (FSU) can strengthen its position and is top ranked in all types of networks of the second period. Especially the betweenness measures indicate that the university plays the central role in mediating between the local actors. The FSU is central within the technology based network, meaning that it covers the knowledge fields most important for the region. It is the central partner for research cooperations and for the transfer of knowledge to the private sector via scientists.

Table 7: Centrality ranks of the core network members

	Degree						Betweenness					
	1995-1997			1998-2001			1995-1997			1998-2001		
	co	sm	tech	co	sm	tech	co	sm	tech	co	sm	tech
FSUJena*	10	2	2	1	1	1	6	1	1	1	1	1
CarlZeissJena	2	3	3	5	3	2	1	2	4	5	4	3
FhG*	3	7	5	3	2	4	3	6	3	3	2	5
JENOPTIK	7	1	1	6	5	3	6	3	2	2	8	2
IPHT*	1	3	4	4	11	5	2	4	5	4	6	6
HKI*	5	8	7	2	3	9	4	6	6	6	3	8
Jenapharm	10	8	10	10	6	11	6	6	8	8	7	7
Ahlers	10	8	6	10	15	6	6	6	9	8	12	4
IMB*	10	8	14	7	9	10	6	6	13	7	5	11
SchottGlas	4	6	9	10	13	14	6	6	10	8	10	13
HermsdorferInstitut*	6	8	12	9	9	13	5	6	12	8	11	10
LDTGmbH&Co.	8	3	8	10	8	15	6	5	11	8	12	15
SiemensAG	10	8	13	10	11	8	6	6	13	8	9	9
LeicaMSJena	10	8	15	8	6	7	6	6	13	8	12	12
GESO	9	8	11	10	13	12	6	6	7	8	12	14

Innovators are sorted according to the average rank across all columns.
* Public research institutes.

4 Explaining the cooperation network

4.1 Research cooperation

In this section we want to investigate whether certain linkages between the actors in one period will lead to stronger interaction in the following period. More specifically: how can we explain the linkages between innovators in Jena that arise through co-assigned patents during one period by various linkages between these actors in a preceding period. Before we attempt to give an answer, we first have to briefly discuss the incentives for firms to cooperate and, second to identify possible explanatory variables.

An innovative firm planning to either improve its products or to place a completely new product on the market, always faces a number of strategic questions before starting the new project. Usually a large amount of research and development is necessary to succeed, but when creating something new it is also the already existing knowledge of scientists and engineers working on those projects that is relevant. Forming an alliance with either competitors, upstream and downstream firms or public research institutes might be advantageous for the project.

Harabi (2002, p. 94) summarizes the arguments as follows: (i) overcoming the R&D financial constraints in individual firms (i.e. expensive research projects can be realized as a result of cost-sharing); (ii) exploitation of economies of scale and scope in R&D; (iii) reduction of wasteful duplication in R&D; (iv) internalization of technological spillovers and other forms of externality; (v) better use of synergies because each firm can contribute distinct capabilities to a common research project; and, finally, (vi) reduction of investment risks due to demand uncertainties.

A lot of work has been published on the subject of the research cooperation; a deep discussion of this literature is beyond the scope of this paper. Arguments related to cooperation in R&D are discussed in various ways in the existing literature.[7]

Since we examine cooperations that exist or have existed and since we have no information about firms having thought about it and decided against it, we turn our focus to the question how the cooperating actors find each other.

In the last decades a strong policy towards technology transfer from universities to industry has emerged. Universities all over the world institutionalize this mode of knowledge transfer. Also when searching the internet there are numerous networking platforms where firms and non-profit research organizations present themselves to be found as a networking or cooperation partner. We view this development is a strong indication that the matching of cooperation partners is not a marginal problem. Besides these transaction cost reducing institutions there are definitely other ways by which appropriate partners come together. Powell, Koput, and Smith-Doerr (1996, p. 117) mentions *"[...]each partner's size and position in the "value chain," the level of sophistication, resource constraints, and prior experiences with alliances"* as factors influencing the partnering decision. In the following sections we will examine the role of existing relations between actors as an explanation of future cooperations.

4.2 The data sample

We suspect to identify these relations by building networks of innovators according to the three types of commonalities that we discussed above: The first commonality, which can be viewed as a necessary condition for a research cooperation, has to be

[7]Katz and Ordover (1990) provide an overview of the literature related to the social effects of cooperative R&D, Oerlemans and Meeus (2001) discuss the topic from the transaction cost perspective, whereas Combs and Ketchen (1999) reconcile the theoretical differences arising from the resource-based view of the firm vs. organizational economics.

a common knowledge base. Even though research partners want to create something new, they need to have an overlapping knowledge base to facilitate know-how exchange and development, i.e. for cooperation to be mutually beneficial, the partners both need the absorptive capacity to learn from each other (Cohen and Levinthal 1990). In their empirical study on interfirm cooperation Mowery, Oxley, and Silverman (1998) find strong evidence in favor of their hypothesis that joint venture partners display a higher degree of technological overlap compared with non collaborators. We define technological overlap as the number of technological classes in which two actors both hold patents.[8]

When this condition is fulfilled the firm might approach someone with whom they have successfully cooperated before. This is an idea of know-who on the institutional level since researchers of the earlier cooperation have not to be involved directly. The third commonality involves scientists that have worked for both companies or organizations. Usually the contacts between colleagues are not terminated (at once) when they change the job. Actually sometimes firms hire skilled people especially for their contacts hoping to benefit from their networks.

We use the networks of permanent innovators for the regressions, i.e. the assignees that patented in both periods of observation. This constraint decreases our sample dramatically from 326 innovators, patenting in either of the two periods, to 36 permanent innovators in Jena. The correlations between the networks, as shown in table 8, suggest that cooperation partners have overlapping technologies in the period before. This result is not very surprising but table 8 also suggests that it is not the cooperations between firms in the former period that determines who will cooperate in the second period, but rather the linkages between the firms that result from the job mobility of the scientists. Further we notice an increase of the correlation between technological overlap and cooperation comparing the two periods. This is probably due to the fact that overall cooperation activity has increased. Another result is that firms do not seem to have both types of personal linkages in the same period. We observe almost no correlation between sm^{95-97} and co^{95-97}.

[8]This is a very simple measure of technological closeness, which has to be improved in subsequent versions of this study.

Table 8: Network correlations

	co^{99-01}	co^{95-97}	sm^{95-97}	$tech^{95-97}$	sm^{99-01}
co^{99-01}	–	-0.012	0.095	0.294	0.456
co^{95-97}	-0.012	–	-0.010	0.145	0.056
sm^{95-97}	0.095	-0.010	–	0.277	0.038
$tech^{95-97}$	0.294	0.145	0.277	–	0.245
sm^{99-01}	0.456	0.056	0.038	0.245	–

4.3 Network regression

To investigate these differences with more sophisticated methods, we employ multiple regression analysis with dyadic data (e.g. Krackhardt 1988, Butts and Carley 2001). This literature provides us with tools to investigate the structural equivalence of different networks. Think of the network as a $n \times n$ adjacency matrix, $\mathbf{Y}$, where $y_{i,j}$ equals zero if the actors i and j have no relation and $y_{i,j}$ is equal to any positive integer representing the strength of the relation between both. The structural representation of our network variable is then given by:

$$\mathbf{Y} = \begin{pmatrix} 0 & y_{1,2} & \cdots & y_{1,n} \\ y_{2,1} & 0 & \cdots & y_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{n,1} & y_{n,2} & \cdots & 0 \end{pmatrix}$$

For using regression techniques the original adjacency matrix, without the diagonal elements, is transformed into vector form as follows:

$$\mathbf{y} = \begin{pmatrix} y_{1,2} \\ y_{1,3} \\ \vdots \\ y_{n,n-1} \end{pmatrix}$$

Performing this transformation with all network variables leads us to the generalized formulation of the regression equation.

$$y_{ij} = \alpha + \boldsymbol{\beta}'\mathbf{x}_{ij} + \varepsilon_{ij} \quad \text{for all } i \neq j \text{, where}$$

y_{ij} is the value of the interpersonal link between i and j that is to be explained. The matrix $\mathbf{x}_{ij}$ contains the explanatory variables relating i and j. This model is estimated using a standard OLS procedure with the usual interpretation of the coefficients. As opposed to regular regression data, a problem of structural autocorrelation might appear either in rows or in columns of the network matrix (Krackhardt 1987). Therefore the significance levels of the regression coefficients as provided by the t-statistic or the p-value have to be handled with care.

Krackhardt (1987) suggests a different method to evaluate the significance of the coefficients.[9] QAP-tests (Quadratic assignment procedure) (Hubert 1987) are applied to make more correct inferences about the significance of the coefficients. In these tests the null-hypothesis is that the test-statistic of association equals the expected value of the test-statistic under a permutation distribution. A major advantage of that technique is that the test makes no assumptions about the distribution of the parameters. QAP constructs a reference distribution of random parameters that could have been derived from a dataset with the same structure but different node assignments as the dataset under evaluation. A permutation distribution is constructed that is similar to the underlying distribution for which inference is drawn by randomly permuting the rows and columns of the dependent variable. When related to the independent variables these permutations of the dependent network provide random estimates of the relation between the variables. Since there are too many (n!) possible permutations, random samples of these permutations are used to generate a reference distribution (Hubert 1987). If the observed coefficient is greater than 95% of the coefficients based on random permutations, for instance, then, according to this randomization test, it is said to be significant at the .05 level, because an index that large or larger was found just five times out of 100 total permutations.[10]

Performing the above transformation with all network variables leads us to the econometric model:

$$y_{ij}^{99-01} = \alpha + \boldsymbol{\beta}' \mathbf{x}_{ij}^{95-97} + \varepsilon_{ij} \quad \text{for all } i < j \text{ }^{11}\text{, where}$$

y_{ij}^{99-01} is the number of interpersonal linkages between patent assignees i and j which

[9] For a more detailed explanation than the following see the illustrative example in Krackhardt (1987) on pages 175-78.

[10] Referring to table 9 this means that in 17 out of 1000 permutations of the co$^{99-01}$-network the observed coefficient of the scientist mobility network was larger than 0.061.

[11] Since our data is undirected, only the upper triangle of the relevant matrices are used.

result from a formal cooperation of both in the second period. The matrix $\mathbf{x}_{ij}^{95-97}$ contains the explanatory variables from the first period, like cooperational linkages, linkages through scientists mobility, and technological overlap between i and j. We also include dummy variables for linkages between public funded research institutes (uni) and private organizations (priv).

The difference between the two models reported in table 9 is the inclusion of "scientist mobility$^{99-01}$" in the second regression. In the first model we only include the explanatory variables from the first period thereby assuming long term relations being relevant for cooperative linkages. In the second regression we also control for scientists changing their jobs in the same period where the cooperations that are to be explained take place. Our results can at least give some hints on the mechanisms relying the matching process of cooperation partners. Regarding the R^2's we observe a tremendous increase in explanatory power when controlling for short term relationships. The variance in the data, explained by our model increases from about 0.1 to 0.25. This is still rather small but not surprising given the data that we use. One factor that we have left aside is the role of the above mentioned technology transfer institutions. Like it was already said, their purpose is to bring actors together that did not know each other before. Also, we admit that there are definitely more linkages between innovators than are documented in patents.

After these drawbacks let us focus on the relationships between the different types of linkages. Without the information documented in table 8 we would have expected a positive influence of the earlier cooperation network on the later one. Seemingly though, the theoretical argument of the persistence of linkages does not apply to this case. This result is confirmed by both network regressions of table 9. The estimated coefficient for "cooperations$^{95-97}$" is negative and significantly different from what we should expect under the random assignment hypothesis.[12]

The importance of personal linkages in weaving a network of organizations cannot be overseen. Even though the coefficients of "scientist mobility$^{95-97}$" are not significant

[12]Significance is the minimum of $Pr(\geq b)$ (which is documented) and $Pr(< b)$. If the observed coefficient is larger than all coefficients resulting from the permutation of $\mathbf{Y}$ the influence is significantly higher than we would expect from random assignment, if, on the other hand, our observed coefficient is exceptionally low, this is also a significant, since not random result.

Table 9: Network regression

Dependent Variable: Cooperations$^{99-01}$						
	β	$Pr(>\|t\|)$	$Pr(\geq \beta)^a$	β	$Pr(>\|t\|)$	$Pr(\geq \beta)^a$
(intercept)	-0.007^{**}	0.893	0.984	0.014^{**}	0.782	0.956
Cooperations$^{95-97}$	-0.100^{***}	0.073	1.000	-0.104^{***}	0.041	1.000
Scientist mobility$^{95-97}$	0.068	0.745	0.120	0.127	0.508	0.110
Tech. overlap$^{95-97}$	0.273^{***}	0.000	0.001	0.177^{***}	0.000	0.007
Scientist mobility$^{99-01}$				0.858^{***}	0.000	0.000
Public linkages	0.406^{**}	0.002	0.024	0.238^{*}	0.048	0.081
Private linkages	-0.065	0.337	0.741	-0.088	0.155	0.815
Res.st.err.:	0.800			0.730		
Mult. R^2 (Adj.):	0.108	(0.101)		0.258	(0.251)	
F-statistic (p-value):	15.160	(0.000)		36.040	(0.000)	
Obs. (Nodes):	630	(36)		630	(36)	

[a] Nullhypothesis is QAP; i.e. the probability to observe a coefficient of this magnitude or larger under the assumption of random assignment of actors to nodes.
Significance-levels according to QAP: *** $\leq$ 0.01, ** $\leq$ 0.05, * $\leq$ 0.1; Significance is the minimum of $Pr(\geq b)$ (which is documented) and $Pr(< b)$; No. of Permutations: 10000

by standard measures in both regressions they are close enough to be analyzed. Here we can also see the largest difference between the standard p-value, which would suggest absolutely no influence of scientist mobility on cooperations, and the significance provided by testing the QAP hypothesis. We observe a positive influence of this type of network which is even getting stronger when we control for "scientist mobility$^{99-01}$". This is actually the variable that adds most information to our model. The coefficient is by far the largest, highly significant, and, as already said, more than doubles the R^2. This result speaks strongly in favor of the prominent role of interpersonal linkages in building networks of innovators or local innovation systems.

The results concerning the technological overlap of the first period come as no surprise and affirm our predictions that actors have to share a common knowledge base. There are only two (out of 12) linkages by cooperation where there is no technological overlap in the first period. Finally, chances of a collaborative agreement between two public organizations are higher than between two private ones.

5 Concluding remarks

We performed a case study on the local innovation system of Jena. The analysis of the network of technological overlap leads us to conclude that the dynamics of the system is directed towards an increasing focus on core competencies of the local innovation system; i.e. innovators on the periphery of the network exit and new entrants position themselves closer to the core of the network. Thus, new innovators and exiting innovators in Jena have shown to be different regarding their network positions. From this we presume that a critical mass of innovators is necessary for a specific technology to "survive" within a LIS. A success-breeds-success mechanism on the level of the technology will then lead to an increasing specialization of the LIS in these technologies. The same dynamics regarding the network positions of entering and exiting innovators are observed when analyzing the cooperation and scientist mobility networks. Other studies of this type will have to find evidence in favor of the hypothesis that network positions are a crucial factor in explaining the innovative performance of the actors.

It has been suggested that the partnering in R&D cooperation is a problem for firms and has even led to political intervention. We showed that personal relationships that arise through the job mobility of scientists are an important variable in explaining the formation of cooperation networks. Our result, that a dominating firm is losing its position to the local university is regarded as a specificity that might be typical to the transformation process in east Germany.

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