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Structural dynamics of innovation networks in German Leading-Edge Clusters

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Abstract We study the effects of a German national cluster policy on the structure of collaboration networks. The empirical analysis is based on original data that was collected in fall 2011 and late summer 2013 with cluster actors (firms and public research organizations) who received government funding. Our results show that over time the program was effective in initiating new cooperation between cluster actors and in intensifying existing linkages. A substantial share of the newly formed linkages is among actors who did not receive direct funding for a joint R&D project, which indicates a mobilization effect. Furthermore, we observe differential developments regarding clusters' spatial embeddedness. Some clusters tend to increase their localization, whereas others increase their connectivity to international partners. Changes in centrality are mainly determined by initial positions in the network, but the determinants of these changes differ substantially between clusters.

Keywords Cluster · Innovation policy · Evaluation · Social network analysis

JEL Classification O38 · L14 · R10 · R32

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1 Introduction

The evaluation of economic policy programs (in general, and of innovation policy in particular) has gained importance over the last two decades. Their principle objective is to identify the causal effects of the policy instrument implemented on the outcome variable of interest. To accomplish this, proper methods with a quasi-experimental design are available. However, whenever the time between initiating the policy and the realization of expected results is unclear and hard to predict, such a design is not easily applicable. Next to such kinds of ex-post evaluations, which are usually implemented several years after policy implementation, more and more so-called accompanying evaluations have been launched. As their special design feature, this type of evaluation looks at early indicators and attempts to use them to derive statements about the expected efficacy of the policy instrument under consideration. To achieve this end, intermediate outcomes rather than final economic benefits—as in ex-post evaluations—need to be addressed by evaluators. On this basis, their focus is primarily on proper mechanisms and structures suitable for the expected final outcomes in the future.

In this paper, we present evaluation results from such an accompanying evaluation, related to R&D networks in the German "Leading-Edge Cluster Competition" (LECC, Spitzencluster-Wettbewerb), a large scale cluster policy. Over the past few decades, a distinctive shift in innovation policy in Germany and many other countries towards an increased funding of cooperative R&D is observable (Fier and Harhoff 2002). More recently, competitive allocation of research funds to network and cluster initiatives pushed this trend even further by adding a regional perspective, increasing the scope of funding, and fostering interaction between a large number of actors. Prominent examples of these policies in Germany are the competitive programs BioRegio and InnoRegio (Dohse 2000; Eickelpasch and Fritsch 2005; Engel et al. 2013). In the context of its high-tech strategy, the German Ministry for Education and Research (BMBF) started the LECC in 2007. The conceptual foundation of this and related policies is mainly to be found in the literature on clusters, but also on regional innovation systems and innovation networks. At the core of the LECC is the funding of R&D activities within collaborative projects that are pooled within larger research themes on topics with high innovation opportunities. From a network perspective, this policy approach aims at cluster formation through the establishment of new linkages (initiated linkages) or the strengthening of existing ones (intensified linkages) to R&D-cooperation networks.

As yet, empirical validations of the benefits of the policy impact on the process of cluster formation, development, and success have been sparse (Martin and Sunley 2003; Duranton 2011). Since evaluations, especially of innovative funding schemes, are crucial for learning of the adaptive policy maker (Metcalfe 1995), there is obviously a need for this type of empirical analysis. Following the suggestions of Giuliani and Pietrobelli (2014) and building on a previous analysis on networks in LECC clusters (Cantner et al. 2013), we employ social network analysis to study the influence of the LECC on interaction structures. Our goal is to identify the extent to which the LECC influences the structure of the network of the most important R&D-cooperation partners within the funded clusters. This influence can be exerted directly through the funding of joint research projects or indirectly through potential mobilization effects that create additional value beyond the research grants. We focus especially on R&D-cooperation and the corresponding networks covering various kinds of actors engaged in R&D and innovation processes, such as firms, research institutes, and universities within and outside of the funded cluster.

The paper is structured as follows: Sect. 2 covers the theoretical background for our analysis as well as a general description of the LECC. In Sect. 3, we introduce the data and research methodology. In Sect. 4, we present our results concerning three levels of analysis with respect to the impact of the LECC on the structure of R&D cooperation networks. First, we study the relationship between funded partnerships and the perceived strengthening and inducement of these partnerships, especially to identify mobilization effects that go beyond direct project funding. Second, we analyze the structural effects of the LECC on the R&D networks; a focus is on changes in network density due to increased interaction and on centralization, which occurs if the distribution of newly formed linkages is skewed. Third, in order to investigate the role of the LECC in altering cluster centralization, we study the determinants of network centrality on the actor level. Section 5 concludes.

2 R&D cooperation and the "Leading-Edge Cluster Competition"

2.1 Rationale for cluster policies

Due to the increasing complexity of new knowledge, division of labor within the knowledge creation process has become more and more important (Chatterji 1996). Therefore, the level of openness and the distribution of tasks within the knowledge and innovation generation process have increased over the last several years (Coombs et al. 2003). The positive effect of cooperation, networking and interconnectedness on the innovative success of innovation oriented actors has been shown by many authors (Freeman 1991; Lundvall 1992; Becker and Dietz 2004; Schilling and Phelps 2007; Breschi and Lissoni 2009; Cantner et al. 2010; Graf and Krüger 2011). Such cooperation can be bilateral—between two partners—or multilateral—between a group of actors trying to solve a general or specific (technological) problem together as a kind of formal or informal research consortium or simply as joint research project. An active participation in innovation related networks can be an important mechanism for firms as well as for research institutes and universities to gain access to external knowledge sources. On the one hand, it fosters the creation of new knowledge via the exchange of knowledge and information and by combining complementary capabilities (Granovetter 1973; Ahuja, 2000) and, on the other hand, it provides a possibility for monitoring and controlling actual developed knowledge (Powell et al. 1996). The diffusion of knowledge is accomplished via different transmission channels, such as joint activities within formal industrial networks or clusters, through joint R&D projects or simply through informal contacts between employees and/or researchers of different firms, universities or research institutes (Cowan and Jonard 2009).

Regarding the relationship between network position and performance, there is ample evidence of a positive effect of holding a central position within a network and innovative success due to better direct and indirect access to different sources of knowledge (e.g. Ahuja 2000; Schilling and Phelps 2007). On a more aggregated level, the structure of a network influences communication and knowledge flows among all involved actors and influences the overall availability of knowledge and thereby innovative success (Cowan and Jonard 2004; Fleming et al. 2007). However, it is very difficult to state which specific structure of a network fosters innovation, since the correlation between network structure and innovation strongly depends on the innovative environment (Rowley et al. 2000; Verspagen and Duysters 2004). Nevertheless, Fleming et al. (2007) and Schilling and Phelps (2007) suggest that network connectedness—characterized by high density or few components—and medium centralization affect the performance of networks positively. While centralization fosters communication and the speed of knowledge diffusion, it can also indicate a high dependence on single actors and lead to an unequal knowledge distribution. Centralized networks have also been found to be relatively more embedded in their surrounding environment than decentralized ones (Owen-Smith et al. 2002; Graf and Kalthaus 2016).

The discussion above highlights the benefits of collaboration in R&D so that a lack of cooperation could be interpreted as a system failure in which possibilities for improving innovative performance of an industry or a cluster remain unexploited. In case of such a system failure, policy interventions in the form of promoting joint R&D activities can help to overcome this problem and increase innovative activities. The success of such policies depends, last but not least, on actor characteristics. In the literature on absorptive capacity, the role of the own knowledge stock to be able to understand and to implement external knowledge has been widely discussed (Boschma and ter Wal 2007). The same holds also for R&D cooperations, which, according to Gomes-Casseres et al. (2006), are the most important source for accessing external knowledge. Miotti and Sachwald (2003) argue that a firm's characteristics are more important for successful cooperation than any specific cooperation that is publicly promoted, and Boschma (2005) emphasizes the importance of (social) proximity between actors to create a "climate of trust" that fosters collaboration. Consequently, it is not sufficient for a policy to try to stimulate cooperation within a cluster or a region by promoting joint R&D activities; rather it also needs mechanisms to help actors find the right and fitting partners (Fornahl et al. 2011). Duranton (2011) points out that cluster policies need to solve coordination problems among the involved actors and thereby decrease uncertainty without being captured by any group of interests. If policies fail in this respect, expected productivity gains will not occur, as in the case of the French cluster policy "Systèmes Productifs Locaux" (Martin et al. 2011).

2.2 Leading-Edge Cluster Competition

As a follow up to competitive policy programs in Germany, such as BioRegio and InnoRegio, the German Ministry for Education and Research (BMBF) initiated the LECC in 2007 as one prominent instrument within its high-tech strategy. The aim of this program was to strengthen innovative capabilities and to support highly productive and efficient regional clusters to achieve or to maintain international leadership. Hence, regional innovative capacities should be exploited, leading in the end to economic growth. To address these targets, different opportunities had been established to create an innovative environment or to increase innovative performance inside a region due to intensified R&D cooperation between different actors, such as firms, research institutes, and universities.

Within this program, 15 clusters were selected in three waves (in 2008, 2010 and 2012) and received a funding of up to 40 million Euro each for a 5-year period. The funding was split into two phases, where the allocation of funds in the second phase depended on a positive evaluation of the achievements of the cluster and its projects in the first 2 years. The competition was open to all technologies and the selection of clusters was consigned to an independent jury of renowned experts from industry and academia. In order to foster the innovative success of the clusters, the BMBF formulated two requirements—amongst others –that seem especially important from our perspective.

The first requirement was that clusters needed to have a cluster management, capable of coordinating activities within the cluster. This management would also serve as intermediary between cluster actors, linking those with complementary competencies. As such, the

LECC implemented the function of local coordination among cluster actors, as suggested by Duranton (2011), and stimulated science-industry linkages, which was an additional goal of the LECC. An important coordinating function in the initial phase was to ensure the quality of the portfolio of project applications. The cluster managements preselected projects together with a committee of cluster members. Furthermore, in most of the clusters, these managements offered additional services to the cluster partners aligned with the needs and requirements of its member organizations (Wolf et al. 2017).

A second requirement was that the R&D project proposals should be linked within a common strategy that pursues a joint vision for the cluster and the surrounding cluster region. A broad commitment to this strategy could be achieved by establishing a formal cluster organization in which the actors who applied for funding would participate. Previous cooperation among cluster actors was certainly helpful during this process and was taken into account by the jury. At the same time, social proximity within the cluster increased through shared membership and during the process of developing a joint vision and strategy. Social proximity increased even more during the project phase of the LECC through different cluster activities, such as regular meetings of the cluster organization, informal gatherings, open seminars, as well as other activities offered by the cluster management.

The technological openness of the LECC as well as the absence of strict rules regarding the specific set-up of the cluster (management) organization or the composition of actors led to a large heterogeneity between the clusters in terms of technological focus, formal structure and existing boards, as well as the set of activities within the clusters and their managements. Due to the open interpretation of the cluster concept, the size of the cluster regions and distances to cluster members differed substantially as well (Hinzmann et al. 2017).

3 Data, methodology and variables

Our analyses are based on primary data collected with members (firms, universities and research organizations) of the five successful clusters of the first wave of the LECC (in 2008), all of which also received funding for the second period. In addition, we use information on project funding. We study the networks of most important cooperation partners and focus on their actor composition as well as their geographic reach. We focus especially on the structural changes of these networks and on the presumed policy influence.

As noted above, the LECC was not restricted to a specific set of technologies, so that the clusters differ quite substantially in that respect.

- "Hamburg Aviation" combines two aspects of the aviation industry. First, there are activities related to aerospace technology and engineering, especially development, construction and production of cabin systems, together with innovative applications for fuel cells. Second, many actors cover a broad spectrum of services related to aeronautical technics and air traffic. Besides a few large anchor companies as well as several research institutes and universities, the cluster includes a notable number of small-or-medium-sized enterprises (SMEs). The technological focus of the cluster members is much broader than the cluster concept and covers a heterogeneous field of knowledge intensive services from natural science to software development.

- The cluster “BioRN” is active in the field of red biotechnology—and therefore many actors can be assigned to the pharmaceutical industry supplemented by knowledge intensive services from life science and software development. Due to this composition, SMEs are the majority of cluster actors in BioRN. However, large pharmaceutical companies play an important role as the main costumers of innovative SMEs. The reason for this is the difficulty of transforming from an SEBCO (Small Emerging Biopharmaceutical Company) to a FIBCO (Fully Integrated Biopharmaceutical Company) due to heavily increasing costs during later stages of R&D projects. Therefore, large firms often take over their projects via licensing or even absorb the whole SME.
- The cluster “Cool Silicon” focuses on increased energy efficiency in microelectronics. Consequently, cluster actors are related to electronic semiconductors and electronic devices and as well medical technology and industrial process and control technology. Additional knowledge intensive services are related to engineering and software development. In contrast to other large IT-clusters, such as Silicon Valley in the USA, R&D activities and productive activities are not decoupled.
- The main focus of “Forum Organic Electronics” (FOE) is the cross-sectional technology organic electronics, which offers a wide range of potential applications for the processing industry. The actors mainly focus on more advanced and high tech applications of this young technology. Due to the novelty of the technology and a strong focus on basic research, the composition of cluster actors is dominated by large companies as well as renowned research institutes and universities. The number of small-or-medium-sized enterprises in comparison to the other four clusters is relative low. Within FOE, the cluster actors concentrate their R&D activities on organic LED, organic photovoltaic, organic sensors and organic memories and circuits.
- The technological core of the cluster “Solarvalley” is silicon based photovoltaic and also thin film technology. Its value chain is closely related to the semiconductor industry, which is why cluster actors focus, as in Cool Silicon, on electronic semiconductors and electronic devices and on fine mechanical optical devices, mechanical testing machinery and the production of optical instruments. The joint aspect of this cluster at its origin was the vision to achieve grid parity in 2015. For that reason, R&D activities within the cluster have a strong application-orientation with a focus on the accuracy of fitting along the value creation chain.

The data for our empirical analysis were collected in fall 2011 and again in late summer 2013 in the form of questionnaires sent to representatives of the cluster actors who received a government grant within the cluster initiative. These representatives have been named as contact partner of the respective organization concerning all LECC related issues (including the formal requirements of the funding). Therefore, we assume these representatives to be sufficiently knowledgeable about internal management and organization processes to answer to our survey. Typically, the representatives gathered the relevant information by circulating the questionnaire within the organization.

For the reconstruction of the networks, we followed a free recall approach (Giuliani and Pietrobelli 2014). The actors were asked to provide the names and addresses of a maximum of ten of their most important R&D-partners.[1] We chose this design for several reasons. First, we wanted to avoid a strict limitation in the size of the networks that would result if

[1] Among all 159 answers, we only had three respondents who filled the whole list. As such, we are confident that this restriction did not bias our results.

we had presented a list of potential partners, i.e. cluster actors. In addition, this list would have been based on information provided by the respective cluster management and the governmental project management. However, both apply different definitions of the respective clusters, which would have led to biases in the geographical and technological demarcation of the clusters and associated problems in comparing the clusters. Second, with a predefined list of actors, we would not have been able to identify linkages with partners that are not members of the cluster. However, since these external linkages—often with more geographically distant partners—are highly relevant for innovative success (Bathelt et al. 2004), the information about partnerships with these external actors is crucial for evaluating the effects of the LECC on the network structures. Finally, a predefined list of actors filled with cluster members would have biased responses towards these actors, even if we would have allowed for the adding of important R&D-partners to this list.

In addition, we asked the respondents to provide supplementary information regarding the properties of these linkages. Most importantly, we asked if the partnership was initiated by the LECC, if it existed before the contest was started in September 2007 and, if so, whether the linkage was intensified through the LECC. Furthermore, we asked for typical characteristics of the organization. Additional information on the funding of partnerships within the LECC is based on data provided directly by the BMBF and partially from the publicly available database "foerderkatalog.de" about R&D project funding of the German government. To complement our quantitative analysis, we conducted several interviews with different actors to obtain qualitative insights on the clusters.

Table 1 provides a summary of the data for the years 2007, 2011, and 2013 with respect to the total number of identified actors within all networks, the composition of networks in terms of actor type (large company, small-or-medium-sized enterprise (SME), university, or research institute) and the geographical dimension of actors and linkages. The data for 2007 are based on retrospective answers provided in the 2011 survey and cover all actors

Table 1 Description of the dataset

	Total sample (all clusters)		
	2007	2011	2013
Sample size (beneficiaries)	136	136	178
Number of responses (related to network question)	65	65	94
Response rate (item related)	47.8%	47.8%	52.8%
No. of actors	188	285	319
Cluster members: no. of actors being member of the cluster association	101	132	135
Actors located in cluster region	49.5%	45.3%	41.7%
… in Germany	39.4%	38.6%	39.5%
… in Europe	6.9%	7.7%	8.5%
… outside Europe	4.3%	8.4%	9.1%
Number of linkages	171	380	463
… into cluster region	49.7%	55.5%	55.5%
… to Germany	38.0%	32.4%	31.5%
… to Europe	7.6%	5.8%	5.8%
… to outside Europe	4.7%	6.3%	6.3%

and linkages that have been reported as existing already before the beginning of the LECC—if the cooperation was established before September 2007. Therefore, the response rate for 2007 and 2011 are identical and 2007 is to be viewed as a subset of the 2011 network. With about 50%, the response rates are satisfactory, although not all subjects responded to the network questions in both surveys. This restricts us with respect to the methods to apply in the analysis, especially when it comes to the dynamics of tie formation (e.g. triadic closure, homophily).

The sample consists of two different types of actors, those that are part of the formal cluster organization and those without a formal membership. The former are defined as having received funding within the LECC. However, not all of them are respondents in our sample. If they chose not to provide answers to our questionnaire, they can still appear within the networks if named as an important partner for at least one of the respondents. While cluster members are typically but not exclusively located within the cluster region, the overall networks are geographically more dispersed. Still, the majority of all actors are located inside the cluster region or inside Germany and only 11.2% (in 2007) to 17.6% (in 2013) are international collaboration partners. R&D cooperation with partners inside the cluster region account for roughly half of all linkages, those with partners inside Germany make up one third, and only a small fraction are related to a region outside Germany. Since we collected the data from actors mostly located inside the cluster region, this pattern of the geographical distribution of linkages is not surprising, and the interviews with funded actors confirm that they prefer geographically close partners. Nevertheless, roughly 50% of the strategically important R&D partners are not located inside the core region of the cluster. The linkages to these actors provide access to external knowledge hubs complementing the available knowledge inside the cluster and, as Bathelt et al. (2004) point out, these external partners are important sources of knowledge, fostering the innovative success of a cluster. Without these external linkages, a cluster might face the danger of a regional lock-in (Bathelt et al. 2004, Boschma 2005). Slight differences between the clusters regarding the geographical distribution of linkages, as shown by Cantner et al. (2013), are due to peculiarities of the technological systems to which the clusters belong but will not be further explored here.

4 Influence of the LECC on R&D networks

In the following, we present our results concerning three levels of analysis with respect to the impact of the LECC on the structure of R&D cooperation networks. First, in Sect. 4.1, we study the relationship between the perceived strengthening and inducement of partnerships due to the LECC and collaborative project funding during the LECC with the goal to identify mobilization effects that go beyond direct project funding. Second, in Sect. 4.2, we analyze changes in the structure of R&D networks during the funding period of the LECC. A focus is on changes in network density due to increased interaction and on centralization, which occurs if the distribution of newly formed linkages is skewed. By taking into account the linkages that were reported to be initiated or intensified due to the LECC, we claim that observed changes can at least partly be attributed to the policy. Third, in order to investigate the role of the LECC in changing cluster centralization, we study the determinants of network centrality on the actor level in Sect. 4.3.

4.1 Cluster network ties

To identify the general impact of the LECC on clusters' R&D networks, we rely on two attributes of the linkages. First, by matching survey data with information on project funding, we can identify reported linkages that are also funded by the LECC.[2] Second, based on the self-assessment of the cluster actors in our survey, we know if these linkages are perceived to be influenced by the LECC. These two dimensions lead to four classes of linkages, namely "not funded and not influenced", "funded but not influenced", "not funded but influenced", and "funded and influenced". Information on LECC influence is based on the survey as described in the previous section. A cooperation is influenced if it was reported to be either intensified or initiated through the LECC.

Figure 1 illustrates for 2011 that the establishment of new linkages and the intensification of existing ones occurs not only via funded joint research projects. A mobilization effect of the LECC can be assumed for those linkages that are either intensified or initiated but did not receive public funds for a collaborative project. The share of these partnerships ranges between 10% and 36%, which suggests that, besides the direct effects of the policy—the funding of concrete joint R&D projects—a non-negligible indirect impact exists. One reason for these indirect effects could be the common membership in a funded cluster and the related commitment to a joint strategy of the whole cluster –one of the requirements of the LECC. Cluster membership increases the visibility of actors and their expertise and potentials for new partnerships among cluster actors are exploited. At the same time, the accessibility of prominent actors improved, allowing small and more peripheral actors to cooperate with these anchor companies. This was the case in Hamburg Aviation, the cluster with the largest mobilization effect, where, during the process of cluster formation, the openness for new cooperation of the established, large companies such as "Airbus" or "Lufthansa Technik" increased. During our interviews, representatives of SMEs confirmed that, thanks to the cluster creation process, it was much easier to meet these large companies at eye level, which fostered the formation of cooperation with them. Simultaneously, with the development of the joint cluster strategy, missing competences among cluster actors could be identified and, as a result of the subsequent partner search, new partnerships could be established to remedy this shortage. Nevertheless, we also observe cases of ineffective funding in terms of network formation—funded but not intensified linkages—but on a lower level (2% to 12%). The largest share of such ineffective funding (12%) was reported by actors in the Solarvalley. One explanation for this is that secrecy is especially important in the photovoltaic industry. According to our interviews, this is the main strategy to protect newly gained knowledge. Consequently, trust among partners was a dominant precondition for cooperation—especially in the field of R&D. Therefore, a reasonable share of LECC funded joint projects was established between actors who had previously cooperated. The prosperous establishment of a new partnership happened mostly through a third, well-known cooperation partner, who already cooperated successfully with the unknown partner. The net effect of mobilization and ineffective funding for the R&D cooperation networks remains positive in all clusters except one (Solarvalley).

[2] We use this information only to qualify existing linkages in the R&D networks but did not add funded partnerships which were not mentioned in the survey.

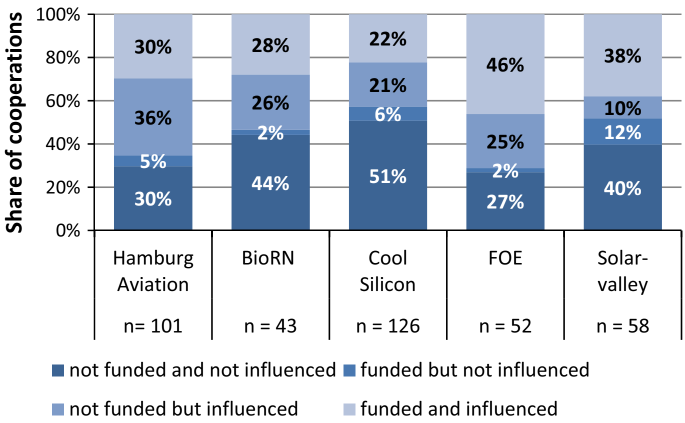

Fig. 1 Impact of the Leading-Edge Cluster Competition on strategic cooperation in 2011. n: number of linkages, tests of equal proportions show significant (< 5%) differences between the clusters for all categories, except 'funded but not influenced

4.2 Network structures

For an additional analysis, we distinguish the influenced linkages as intensified or initiated. The former are defined as linkages that already existed before the LECC and are influenced by it; the latter are linkages that were reported to have been established because of participating in the LECC. The first three rows of Table 2 show for each cluster that a substantial share of the identified linkages had been influenced by the LECC, either as being intensified or being initiated. Especially in Hamburg Aviation and FOE, more than the 50% of all linkages that existed before the introduction of the LECC in 2007 were intensified by the policy. Based on our interviews, we know for FOE that, due to its technological newness, there were only a limited number of competent actors in the field of organic electronics in the cluster region. Most of them knew each other already before the beginning of the LECC but, thanks to the design of the policy with its requirement of a joint strategy, these actors increased the level of cooperation to foster the development of organic electronics. In the other three clusters, one third of the existing links in 2007 were intensified by the LECC. This overall high share of strategic R&D cooperation, which was intensified by the cluster policy, reflects a first, short run impact of the policy. In these cases, already existing structures of the network of strategically important R&D cooperation were strengthened due to the introduction of the policy. Over time, the influence of the LECC on the network changed. While in 2011 the influence was mainly via new partnerships (initiated), the strengthening of existing linkages (intensified) is relatively more frequent in 2013.

Regarding the network structural properties (Table 2, rows 4–6), we report network density among respondents only, indegree centralization based on the whole sample of linkages, and indegree centralization without the initiated linkages. For the period 2007 to 2011, we observe an increase in network density (realized linkages divided by all possible linkages), implying an increasing interconnectedness between funded actors. Considering the change between 2011 and 2013, a high level of network density seems to be sustained for Hamburg Aviation, Cool Silicon, and FOE. For Solarvalley, turbulences within the

Table 2 Influence of the Leading-Edge Cluster Competition on network structures

	Hamburg Aviation			BioRN			Cool Silicon			FOE			Solarvalley		
	2007	2011	2013	2007	2011	2013	2007	2011	2013	2007	2011	2013	2007	2011	2013
No. of edges	36	101	143	17	43	51	75	126	152	17	52	56	26	58	61
Initiated linkages by LECC	–	45.5%	25.9%	–	41.9%	27.5%	–	20.6%	27.6%	–	53.8%	35.7%	–	34.5%	19.7%
Intensified linkages by LECC	55.6%	19.8%	35.0%	29.4%	11.6%	17.6%	37.3%	22.2%	36.8%	52.9%	17.3%	17.9%	30.8%	13.8%	42.6%
Initiated or intensified linkages by LECC	55.6%	65.3%	60.8%	29.4%	53.5%	45.1%	37.3%	42.9%	64.5%	52.9%	71.2%	53.6%	30.8%	48.3%	62.3%
No. of actors	39	61	85	25	44	51	71	97	89	21	35	35	32	48	59
Density (among respondents)	0.040	0.154	0.132	0.023	0.068	0.038	0.070	0.132	0.155	0.000	0.167	0.133	0.015	0.106	0.027
Centralization (indegree)	0.056	0.141	0.173	0.057	0.024	0.082	0.058	0.081	0.153	0.115	0.106	0.163	0.073	0.104	0.052
Centralization without initiated linkages	–	0.053	0.130	–	0.034	0.046	–	0.042	0.124	–	0.070	0.090	–	0.048	0.056

German photovoltaic industry should serve as an explanation why the increase of network density during the first period of the LECC was followed by a decline for 2013. On the one hand, due to the change of the market environment, the relevance of previously important partners may have changed and, on the other hand, there was a non-negligible shake out of actors with a negative influence on the availability of partners.

All five case study clusters are centered around one or more prominent global players and/or an excellent research institute or university. As such, observing a moderate or high degree of network centralization is no surprise. However, ex ante, it is unclear in which way the LECC influences the network structure in terms of centralization. If peripheral actors grab the opportunity to connect with the more prominent central actors, we would observe an increase in centralization, whereas if peripheral actors learn about each other and become aware of their complementary capabilities, centralization should decrease. We decided to calculate network centralization based on actors' indegree, which is independent of own responses, to avoid distortions from the fact that not all actors answered our questionnaire. We observe an increasing centralization in all but one network during the funding period from 2011 to 2013. This result also holds if we calculate centralization without links that were initiated by the LECC. This means that each network, with the exception of Solarvalley, tends to focus increasingly on the network core. These actors mostly played a prominent role inside the technological field of the cluster but also within the associated cluster organization. For Solarvalley, the special situation of the PV-industry in general and especially in Germany might explain this different development. Some of the large actors in this cluster either left the market or had been taken over by Asian investors and therefore lost—according to our interviews—attractiveness for R&D partnerships due to the fear of unintended knowledge spillovers.

4.3 Determinants of network centrality

The aforementioned increase in network centralization indicates that potential knowledge flows become more concentrated and that some actors benefit more than others from the policy. Consequently, we are interested in the characteristics of actors that become more central to study the selective nature of the LECC. Considering that almost all policies—and especially those that are picking winners—create distortions, it is important to understand the structural changes on a micro-level. Therefore, we proceed to analyze the structural specificities and changes of the R&D networks of the clusters during the LECC, based on a balanced panel of actors observed, i.e. either as respondent or named as one of the most important R&D partners, in 2011 and 2013. This restricted dataset leaves us with observations for 142 actors. On this basis, we analyze changes in indegree centrality between 2011 and 2013 ($\Delta indegree$), with a special focus on the policy influence.

In network research, it is common to assume that individual observations are not independent, since connected actors might influence each other in their behavior. To account for this specificity, we apply a network autocorrelation regression model (Ord 1975, Doreian 1980, Leenders 2002). Our basic model specification has the form:

$$\Delta indegree = \beta_1 * indegree_{2011} + \beta_2 * P + \beta_3 * C + \varepsilon, \quad \varepsilon = \rho W * \varepsilon + \upsilon$$

Where P is a matrix of policy related characteristics, such as funding and the number of projects, C is the matrix of control variables, W is the weights matrix, and ε and υ are error terms. The weights matrix is constructed by joining the adjacency matrices of the R&D networks of each of the five clusters in 2011. In addition to the β coefficients, the model also estimates ρ, which accounts for the interdependence of disturbances along the weights matrix W.

In the econometric analysis, we employ the following variables (Table 3): The dependent variable is the difference between an actor's indegree centrality in 2013 and in 2011 ($\Delta indegree$). Our main explanatory variables related to a direct policy impact are based on research funding within the LECC. We use information on the number of funded projects in 2013 (num.proj) and the natural logarithm of the total amount of funding for the second period of the LECC (2013) (log.fin). Formal membership in the cluster organization (cluster.actor) can be viewed as an indirect policy effect, since most of the cluster organizations were established during the application process.

The autoregressive term (indegree.2011) is included based on the preferential attachment argument. Being more embedded can make an increase the indegree more likely due to a more exposed position or more experience with R&D cooperation (Barabasi and Albert, 1999; Wagner and Leydesdorff, 2005; Kim and Jo, 2010). Therefore, the initial position inside the network should positively influence the change in centrality.

To control for additional actor characteristics, the following independent variables are included: First, location is taken into account (region) where we distinguish between "inside the Cluster", "Germany", "Europe" or "World". We expect the geographical distance to the cluster to be negatively related to the change in indegree; this is due to the observation that, in high-tech research, intraregional innovation linkages are typically of high importance (Koschatzky and Sternberg, 2000; Lublinski, 2003; Torre, 2008). Second, we distinguish between private and public organizations (public). High-tech clusters are oriented towards more advanced innovation and, therefore, cooperation with universities and public research institutes should be considered relevant (Tödtling et al. 2009); hence the indegree centrality of public actors should increase relatively more than those of firms. Third, we control for firm size by including a dummy variable for large firms with more than 500 employees (actor.large). Lastly, activities within the clusters, as offered by the cluster management or other cluster members towards networking, could influence tie formation within the clusters. To account for such cluster specific activities, we include cluster dummies. The cluster dummy also controls for specific technology and innovation

Table 3 List of dependent and independent variables

Variable	Explanation	Mean	Min	Max
$\Delta indegree$	Change of the (indegree) centrality of the actor from 2011 to 2013	0.296	− 2	8
indegree.2011	(indegree-) centrality of the actor in 2011	1.641	0	10
cluster.actor	Formal member of the leading edge cluster organisation in 2013	0.662	0	1
num.proj	Number of funded projects in second period	1.204	0	15
log.fin	Total funding in second period (2013) (in log scale)	6.972	0	15.961
region	Location of the actor (ordered: inside the Cluster = 1, Germany = 2, Europe = 3, World = 4)	1.620	1	4
public	Public actor (yes = 1/no = 0)	0.373	0	1
actor.large	Large enterprise (more than 500 employees) (yes/no)	0.331	0	1

related factors inside the clusters. Table 3 shows descriptive statistics for the variables included in the regressions. Table 6 in the “Appendix” reports the correlations between all independent variables.

As to the dependent variable, for 26 observations we recorded a decrease of their indegree, implying a decline of their importance within the R&D network. The maximum loss of indegree is 2, which means that the corresponding actor was named an important R&D partner two times less in 2013 than in 2011. Contrariwise, for 42 actors, indegree centrality and therefore their importance in the network (slightly) increased. It is noteworthy that one actor was mentioned eight times more in 2013 than during the 2011 survey. For the remaining 74 actors, the majority, we observe no change of their indegree.

These changes of relative network positions can either be caused by the LECC or appear as a result of strategic decisions with R&D ties regularly being established and dissolved within the innovation processes. To distinguish between these two different effects—policy induced and regular changes—we test a first set of models (models 1a and 1b in Table 4) including only variables not directly related to the LECC or LECC funding.

For the basic specification, without accounting for prior network position, only cluster specificities have a significant impact. Adding initial indegree centrality to our estimation, we find the expected significant positive impact on the observed changes of the indegree. The positive coefficient indicates that those actors considered important in 2011 increased their importance until 2013—the networks as a whole tended to become more centralized with a few increasingly important actors at their respective core. For neither model 1a nor 1b do we find any indication for—at least within this short period of time—the importance of regional proximity for the loss or creation of linkages.

In a second set of models, we include cluster membership as a rather indirect measure for the policy impact of the LECC (model 2a) and interact this policy measure with our cluster dummies (model 2b) to see whether there is a differential policy effect. Despite the correlation between the variables region and cluster membership, we include both since the low variance inflation factors indicate no problem of multicollinearity. The initial position within the network remains significant, while cluster membership has no influence on the change in importance of an actor for the network. Apparently, cluster membership by itself cannot be seen as a driver of increased centralization.

To identify a potential direct impact of the LECC on the structure of the R&D network, we add the number of granted projects (num.proj) to models 3a and 3b and the log of project funding (log.fin) in model 4a. We find a highly significant effect of the number of funded projects (model 3a) if we do not control for initial network position. When adding the starting position, the significance drops to the 5% level, but the initial position itself is not significant. Interestingly, for the second direct measure, the amount of received funding, we find no effect, but the initial position has a strong impact on the observed indegree change (model 4a). Lastly, we implement two models (5a and 5b) where we include all three measures of a potential LECC impact. Only when we ignore the initial network position do we find a significant impact of the number of funded projects on the change of indegree centrality. In the full specification, however, none of the explanatory variables except some of the cluster dummies and the network autocorrelation term (rho) appear to influence the observed changes.

Since one of the funded clusters reacts significantly different to the others (Solarvalley) in most of the specifications, we include interaction terms between the cluster dummy and

Table 4 Determinants of changes in centrality

	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b	Model 3c	Model 4a	Model 4b	Model 5a	Model 5b
intercept	0.779**	− 0.026	− 0.372	− 0.662	0.014	− 0.099	− 0.033	− 0.389	− 0.447	− 0.336	− 0.187
	(0.298)	(0.333)	(0.495)	(0.548)	(0.325)	(0.333)	(0.367)	(0.396)	(0.468)	(0.502)	(0.494)
region	− 0.113	0.022	0.118	0.095	0.034	0.046	0.006	0.103	0.107	0.104	0.088
	(0.114)	(0.113)	(0.152)	(0.158)	(0.113)	(0.112)	(0.114)	(0.122)	(0.126)	(0.151)	(0.151)
public	− 0.041	− 0.305	− 0.265	− 0.182	− 0.039	− 0.150	− 0.127	− 0.195	− 0.207	− 0.128	− 0.022
	(0.270)	(0.262)	(0.266)	(0.270)	(0.250)	(0.267)	(0.259)	(0.268)	(0.269)	(0.269)	(0.256)
actor.large	0.390	0.090	0.171	0.284	0.297	0.199	0.232	0.147	0.107	0.228	0.338
	(0.277)	(0.273)	(0.286)	(0.289)	(0.262)	(0.274)	(0.272)	(0.274)	(0.279)	(0.286)	(0.273)
indegree.2011		0.258***	0.245***	0.233***		0.112	0.078	0.224***	0.219**	0.123	
		(0.062)	(0.064)	(0.064)		(0.094)	(0.101)	(0.065)	(0.067)	(0.098)	
cluster.actor			0.290	0.687						0.114	0.165
			(0.307)	(0.483)						(0.342)	(0.341)
num.proj					0.244***	0.171*	0.201			0.139	0.234***
					(0.054)	(0.082)	(0.141)			(0.101)	(0.068)
log.fin								0.030	0.039	0.009	0.001
								(0.018)	(0.033)	(0.024)	(0.023)
BioRN × policy				− 0.453			− 0.208		− 0.031		
				(0.699)			(0.298)		(0.056)		
CoolSilicon × policy				− 0.167			0.099		− 0.001		
				(0.560)			(0.131)		(0.039)		
FOE × policy				− 1.097			− 0.001		0.011		
				(0.654)			(0.185)		(0.048)		
Solarvalley × policy				− 0.819			− 0.324		− 0.054		
				(0.779)			(0.168)		(0.051)		
BioRN	− 0.509	− 0.124	− 0.137	0.197	− 0.222	− 0.145	0.022	− 0.078	0.084	− 0.131	− 0.225
	(0.323)	(0.308)	(0.310)	(0.519)	(0.311)	(0.312)	(0.405)	(0.310)	(0.463)	(0.316)	(0.313)

Table 4 continued

	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b	Model 3c	Model 4a	Model 4b	Model 5a	Model 5b
CoolSilicon	0.191	0.465*	0.436*	0.557	0.327	0.399	0.217	0.487*	0.503	0.408	0.316
	(0.220)	(0.217)	(0.221)	(0.453)	(0.219)	(0.224)	(0.328)	(0.219)	(0.400)	(0.231)	(0.224)
FOE	− 0.719**	− 0.387	− 0.440	0.368	− 0.422	− 0.370	− 0.368	− 0.390	− 0.464	− 0.394	− 0.451
	(0.261)	(0.253)	(0.261)	(0.547)	(0.262)	(0.260)	(0.371)	(0.254)	(0.472)	(0.266)	(0.269)
Solarvalley	− 1.045***	− 0.591	− 0.620*	− 0.043	− 0.930**	− 0.769*	− 0.137	− 0.606	− 0.132	− 0.752*	− 0.936**
	(0.316)	(0.311)	(0.314)	(0.660)	(0.305)	(0.328)	(0.452)	(0.311)	(0.551)	(0.333)	(0.306)
rho	− 0.149*	− 0.151**	− 0.145*	− 0.161**	− 0.118*	− 0.126*	− 0.113	− 0.142*	− 0.142*	− 0.125*	− 0.115*
	(0.059)	(0.056)	(0.056)	(0.058)	(0.057)	(0.058)	(0.058)	(0.056)	(0.056)	(0.058)	(0.057)
R^2	0.135	0.199	0.203	0.219	0.214	0.217	0.253	0.210	0.218	0.219	0.216
Adj. R^2	0.076	0.138	0.137	0.126	0.154	0.151	0.164	0.144	0.125	0.141	0.143
AIC	483.585	469.371	470.481	474.903	466.527	467.120	466.701	468.590	474.616	470.671	470.232
BIC	513.143	501.885	505.951	522.196	499.041	502.590	513.994	504.060	521.910	512.052	508.658

Dependent variable: $\Delta indegree$

Linear network autocorrelation model as implemented in the lnam routine of the sna package for R. In the interaction terms, 'policy' stands for 'cluster actor' in model 2b, 'num.proj'in model 3c, and 'log.fin'in model 4b

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

the policy variables (model 2b, 3c and 4b), although none of them turned out to be significant.

With respect to the direct policy impact, only the number of projects shows a significant effect on the observed changes in indegree centrality. This effect is more pronounced in the cases where we do not control for the initial indegree. Furthermore, we do not find any indication that the LECC favors specific types of actors in terms of increasing centrality. The network autocorrelation term (rho) is significant in almost all models, indicating the relevance of network effects and the adequacy of the econometric model.

Overall, we find quite robust differences between the clusters. In particular, we find negative coefficients for actors in the Solarvalley and positive effects in Cool Silicon. This strengthens our suspicion that a general and overall analysis might not be sufficient to identify all potential impacts of the LECC. Therefore, we estimate models 1b, 2a, 3b and 4a for each cluster separately. The results are reported in Table 5.

Compared with the regressions for the whole sample, we observe quite different results for the individual clusters (Table 5). In Hamburg Aviation, public actors tend to show a lower increase in importance in the R&D network as compared to firms. According to our interviews, this might be explained by increased cooperation with suppliers, which was fostered during the LECC. Furthermore, actors who were initially central can improve their positions. Direct policy effects on centrality cannot be observed. For BioRN, none of the variables except rho are significant. In contrast to that, we find for Cool Silicon a high impact of the initial position in 2011, large firms find themselves in more central network positions as well as actors with many funded projects. The attractiveness of large firms in this cluster is a result of their larger research capacities (laboratories) as well as their capacities for test production, both being simply too costly for SMEs to provide by themselves. For the cluster FOE, we find both direct policy measures highly positive and significant, while the initial position in 2011 loses its explanatory power in models 3b and 4a. This can be explained by the history of this cluster, which is characterized by its young technology and a small number of actors active within this field. During our interviews, these cluster members reported to more or less know all other firms within the field of organic electronics and they decided to build up this cluster with its institutions and research facilities with the help of the LECC to foster technological change. Actors receiving funds by the LECC could make comparably more progress in the field of organic electronics and become attractive partners for actors lagging behind in terms of technological know-how, having less equipment for R&D or entering the technology at a later stage. Finally, we find for the Solarvalley compared to all other clusters contrary results. Public actors as well as large ones become less important for the R&D network. This holds also for actors with a central position at the beginning of the LECC. These findings reflect the development within the German photovoltaic industry. As discussed above, in this cluster, central positions inside the network were especially held by large firms that either exited the industry or were bought by Asian investors. Both alternatives resulted in less attractiveness as a partner for R&D activities. The shakeout of firms during the LECC funding period also explains the decrease of indegree centrality of public actors. Because of the increased competition in the field of photovoltaics, the number of firms declined and R&D activities were reduced and shifted towards applied research in cooperation with other firms rather than with public research institutes.

Overall, the clusterwise regressions show that the within cluster network dynamics for the period 2011 to 2013 differ substantially and are driven by the respective technological

Table 5 Determinants of changes in centrality, clusterwise regressions

	Hamburg Aviation (N = 31)				BioRN (N = 20)				Cool Silicon (N = 49)			
	1b	2a	3b	4a	1b	2a	3b	4a	1b	2a	3b	4a
intercept	0.694	0.905	1.052	1.031	0.146	0.546	0.074	0.224	− 0.031	− 0.347	− 0.013	− 0.065
	(0.847)	(1.752)	(0.931)	(1.179)	(0.441)	(0.616)	(0.522)	(0.591)	(0.396)	(0.669)	(0.407)	(0.483)
region	− 0.053	− 0.091	− 0.139	− 0.108	− 0.143	− 0.275	− 0.122	− 0.158	− 0.255	− 0.172	− 0.242	− 0.243
	(0.457)	(0.534)	(0.462)	(0.475)	(0.097)	(0.173)	(0.126)	(0.123)	(0.182)	(0.230)	(0.187)	(0.206)
public	− 1.619*	− 1.718	− 1.945*	− 1.790	0.290	0.317	0.273	0.309	0.235	0.264	0.587	0.247
	(0.822)	(1.092)	(0.891)	(0.916)	(0.307)	(0.299)	(0.313)	(0.322)	(0.402)	(0.403)	(0.384)	(0.413)
actor.large	− 0.457	− 0.609	− 0.689	− 0.642	0.255	0.137	0.265	0.231	0.755*	0.832*	0.997**	0.756*
	(1.039)	(1.513)	(1.039)	(1.127)	(0.329)	(0.341)	(0.331)	(0.351)	(0.360)	(0.381)	(0.367)	(0.360)
indegree.2011	0.323*	0.340	0.496*	0.358*	0.163	0.216	0.189	0.124	0.489***	0.472***	0.101	0.484***
	(0.153)	(0.195)	(0.248)	(0.174)	(0.237)	(0.235)	(0.257)	(0.308)	(0.102)	(0.106)	(0.196)	(0.112)
cluster.actor		− 0.158				− 0.420				0.260		
		(1.148)				(0.463)				(0.445)		
num.proj			− 0.240				0.045				0.301*	
			(0.275)				(0.174)				(0.123)	
log.fin				− 0.024				− 0.005				0.003
				(0.058)				(0.026)				(0.025)
rho	− 0.169	− 0.179	− 0.198	− 0.189	0.624***	0.686***	0.617***	0.625***	− 0.165	− 0.178	0.031	− 0.163
	(0.108)	(0.128)	(0.114)	(0.118)	(0.180)	(0.186)	(0.181)	(0.180)	(0.119)	(0.118)	(0.168)	(0.121)
R^2	0.240	0.237	0.259	0.239	0.144	0.151	0.144	0.145	0.389	0.387	0.479	0.388
Adj. R^2	0.058	0.015	0.043	0.017	− 0.223	− 0.306	− 0.318	− 0.315	0.303	0.285	0.392	0.287
AIC	128.229	130.211	129.491	130.065	45.932	47.150	47.864	47.894	151.577	153.238	149.543	153.562
BIC	138.267	141.683	140.963	141.537	52.902	55.116	55.830	55.860	164.820	168.373	164.678	168.696

Table 5 continued

	FOE (N = 24)				Solarvalley (N = 18)			
	1b	2a	3b	4a	1b	2a	3b	4a
intercept	− 0.683	− 0.724	− 0.730	− 1.857**	0.471	0.671	0.062	0.115
	(0.776)	(0.932)	(0.709)	(0.681)	(0.280)	(0.690)	(0.306)	(0.366)
region	0.061	0.078	0.409*	0.624**	0.099	0.017	0.337	0.193
	(0.246)	(0.321)	(0.198)	(0.204)	(0.159)	(0.305)	(0.174)	(0.162)
public	0.508	0.484	0.101	− 0.126	− 0.768**	− 0.760**	− 0.866***	− 0.722**
	(0.686)	(0.745)	(0.605)	(0.534)	(0.268)	(0.268)	(0.250)	(0.260)
actor.large	− 0.450	− 0.458	− 0.546	− 0.696	− 0.771**	− 0.769**	− 0.765**	− 0.637*
	(0.647)	(0.654)	(0.592)	(0.547)	(0.294)	(0.294)	(0.264)	(0.294)
indegree.2011	0.455**	0.451**	− 0.123	0.198	− 0.179***	− 0.183***	− 0.280***	− 0.210***
	(0.145)	(0.151)	(0.200)	(0.168)	(0.053)	(0.053)	(0.064)	(0.052)
cluster.actor		0.047				− 0.115		
		(0.589)				(0.363)		
num.proj			0.525**				0.140*	
			(0.173)				(0.065)	
log.fin				0.117***				0.024
				(0.032)				(0.018)
rho	0.206	0.204	− 0.347	− 0.140	− 0.428**	− 0.426**	− 0.611***	− 0.522**
	(0.106)	(0.107)	(0.296)	(0.223)	(0.144)	(0.143)	(0.181)	(0.183)
R^2	0.284	0.283	0.347	0.477	0.453	0.450	0.503	0.512
Adj. R^2	0.045	− 0.012	0.079	0.262	0.179	0.099	0.187	0.201
AIC	79.757	81.750	77.285	72.609	27.795	29.694	25.790	27.880
BIC	88.003	91.175	86.709	82.033	34.027	36.817	32.913	35.003

Dependent variable: Δ*indegree*

Linear network autocorrelation model as implemented in the lnam routine of the sna package for R

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

and industrial environments rather than by policy. Regarding actor types, we observe that, in Hamburg Aviation, firms gain central positions relative to public research organizations, while in Cool Silicon, large firms benefit and in Solarvalley particularly SMEs. The nature of the LECC lead to the strongest structural effects in the early stages where the cluster organization was established and research strategies were developed. Actors most strongly involved in this process show a high indegree centrality in 2011 and we observe that they benefit from further improved positions in Hamburg Aviation, Cool Silicon, and FOE but lose positions in Solarvalley. As to the direct policy effects, involvement in many funded projects leads to increased centrality in the three clusters Cool Silicon, FOE, and Solarvalley. The amount of funding seems relevant only in FOE. With respect to our initial question regarding the drivers of increased network centralization, there is some path dependency introduced by the competition format where initially strong actors and/or those with many projects improve positions.

5 Conclusion

This paper addresses evaluation results from an accompanying evaluation, namely the one related to the German LECC, a large scale cluster policy in Germany. This policy instrument aimed at fostering innovation activities for the sake of proper international competiveness of Germany in a broad set of high-tech technologies. To reach this goal, mainly measures to mobilize innovation collaboration and to build up respective actors cluster and networks were implemented. From these, beneficial effects on competitiveness, welfare, and employment on the local, regional, as well as the national level are expected to arise. Due to the character of an accompanying evaluation, we look at the intermediate outcomes “mobilizing innovation cooperation” and “structure of innovator networks”. For that, we applied social network analysis methods to inspect the impacts of the LECC. We base our study on original data on the strategically most important R&D partners collected in five successful clusters at two points in time. Additional information on these linkages was provided by collecting data on collaborative funding within the cluster program. This makes our study unique in that we are able to observe changes in the network structures due to the policy.

With respect to “mobilizing innovation cooperation”, our results show that the LECC program was effective in initiating R&D cooperation between cluster actors and in intensifying existing partnerships. A substantial share of the newly formed linkages is among actors who did not receive direct funding for a joint R&D project, which indicates a mobilization effect of the policy that goes beyond government sponsored collaboration. With respect to “structure of innovator networks” this mobilization leads to an increased network density in the first period accompanied by an increased centralization, i.e. concentration of collaboration activities. While the effect on density fades out during the second period, centralization still increases slightly. Since increased interaction is one of the core goals of any innovation driven cluster policy, the program was certainly effective in that respect. Increased centralization is a side effect of the policy and its implementation with theoretically ambiguous and empirically not well understood effects on innovation performance aspects. To understand better these concentration patterns, we further attempt (by network regression techniques) to characterize actors benefiting most from the policy measure, directly or indirectly, in terms of increased network centrality. We find that the policy program in general does not favor any specific type of actor (large or small firm, firm or research institute/university) but has some structural impact since actors already central in the previous period benefit most. If direct policy measures, such as the number of funded projects and the total amount of funding are included, this structural is partly replaced by the positive effect of direct funding on actor centrality. In this sense, the policy induces cluster development only via direct funding but does not favor any specific type of actor. Analyses for each cluster separately lead to heterogeneous results with respect to actor type, initial centrality, and direct policy measure. This suggests that quite different, cluster specific mechanisms are at work, which may have the specific impact on final outcomes.

Apparently, evaluations of cluster policies that are open to the type of technology, cluster demarcation and actor composition face the problem of broad heterogeneity that impairs with a direct cluster comparison and with the usage of aggregated statistics. Cluster or technology specific impacts are not to be ignored as they may exert a specific influence on the policy outcomes. We suspect that such differential impacts are especially prevalent if clusters are as diverse and heterogeneous as within the LECC.

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Appendix

See Table 6.

Table 6 Correlation between independent variables

	region	public	cluster.actor	Indegree.2011	actor.large	num.proj	log.fin	Cluster
region	****	0.051	− 0.662	− 0.229	− 0.002	− 0.358	− 0.504	0.104
public	0.551	****	− 0.052	0.134	− 0.512	0.016	− 0.134	0.009
cluster.actor	< 0.001	0.536	****	0.212	− 0.119	0.423	0.667	0.119
Indegree.2011	0.006	0.112	0.011	****	0.136	0.708	0.331	− 0.117
actor.large	0.98	< 0.001	0.158	0.106	****	0.042	0.038	0.142
num.proj	< 0.001	0.846	< 0.001	< 0.001	0.62	****	0.659	0.027
log.fin	< 0.001	0.112	< 0.001	< 0.001	0.657	< 0.001	****	0.043
cluster	0.217	0.916	0.157	0.167	0.091	0.751	0.609	****

Upper diagonal part contains correlation coefficient estimates/lower diagonal part contains corresponding *p* values

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