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Abstract

Cluster policies are often intended and designed to promote interaction in R&D among co-located organisations, as local knowledge interactions are perceived to be underdeveloped. In contrast to the popularity of the policy measure little is known about its impact on knowledge networks, because most scientific evaluations focus on impacts at the firm level. Using the example of the BioRegio contest, we explore cluster policy effects on local patent co-application and co-invention networks observed from 1985 to 2013, in 17 German regions. We find that the initiative increases network size and innovation activities during the funding period but not afterwards. The impact of the BioRegio contest on network cohesion is moderate. In contrast, general project-based R&D subsidisation is found to support cohesion more robustly.

Keywords: Cluster Policy; Knowledge Networks; Network Analysis; Patent Data; Regional Innovation; Policy Evaluation

JEL Classification: O31; Z13

1 Introduction

Despite the popularity of cluster policies, no consensus exists around their justification, means of application, benefits or timing of their implementation (Martin & Sunley, 2003; Brenner & Schlump, 2011). This attracts the attention of researchers seeking to analyse these policies from different perspectives. However, most studies evaluate cluster policies solely by identifying their effects on individual firms (Falck et al., 2010; Engel et al., 2013; Martin et al., 2011; Nishimura & Okamuro, 2011a; Broekel et al., 2015). While such evaluations are very useful, they may still miss important effects of cluster policies at the aggregated network or system level. These effects are important since they are frequently advanced to justify the implementation of such policies in the first place. More precisely, it is often argued that cluster-internal potentials for positive externalities are not fully exploited (Moodysson & Zukauskaite, 2014). Being a system of interconnected organisations, cluster performance 'does not depend only on how individual actors (firms, universities, organizations, research institutes, governmental institutions, etc.) perform, but rather on how they interact as parts of a system' (Andersson & Karlsson, 2006, p. 61). An important aspect of such interactions includes knowledge sharing and co-creation activities. These appear to be below an 'optimal' level, implying underdevelopment of cluster-internal knowledge diffusion. Consequently, positive externalities related to interorganisational knowledge sharing remain unexploited. Therefore, policy interventions intended to solve this system failure are needed (see Buisseret et al., 1995; Broekel et al., 2015). Accordingly, cluster policies are also intended and designed to spur embeddedness of organisations into local and non-local knowledge networks (Vincente, 2014). They thereby aim to alter the configuration and organisation of the cluster 'system'. Firm-level evaluations are inadequate for investigating such contributions of cluster policies, and system-level analyses are required. However, the literature offers few empirical insights into how policies affect and shape clusters at the system level (Edler et al., 2016; Uyarra & Ramlogan, 2016). Complexity and high dimensionality of the programs and impact patterns, as well as varying time dimensions of policy effects, are proposed as reasons for the difficulty of evaluating policies at aggregate levels (Rothgang et al., 2017b).

Complementing the works of Vicente (2017) and Lucena-Piquero & Vicente (2019), we seek to fill parts of this gap by identifying the impact of policy on clusters' interorganisational knowledge networks. Policy that provides monetary incentives for collaborations is likely to alter such network structures. Policy thereby influences organisations' access to knowledge, cluster internal knowledge diffusion, and dependency relations. In other words, policy may alter the interaction structures within the 'system' cluster and thus significantly influence its underlying organisational principles, as well as its mechanisms of self-organisation.

Our empirical investigation looks at the German BioRegio contest to identify short- and long-term effects on its clusters' internal network structures. The networks are based on patent applications at the applicant and inventor levels (Cantner & Graf, 2006; Graf & Henning, 2009; Graf, 2017). We reconstruct networks of 4 successful clusters and 13 clusters that applied to the BioRegio contest. The analysis covers 23 periods from 1985 to 2013, including the times before, during and after the contest funding period.

Our results indicate a positive effect of the cluster policy on inventive activity in the subsidised clusters during the funding period, but not afterwards. Concerning cluster network structures, we find that networks in the winner clusters are more centralised during the funding period and only a weak indication of strengthened cohesion in the winner clusters. However, for general biotech R&D subsidies outside the BioRegio contest, we find a consistent positive association with cohesion in applicant and co-inventor networks. In sum, our findings cast doubt on the existence of a significant effect of cluster policies on increased local interaction and network cohesion. Rather, standard project-based R&D subsidisation appears to generate effects originally intended for cluster policies to accomplish.

In section 2, we provide a review of the relevant literature on knowledge networks and cluster policy. Section 3 introduces the BioRegio contest. Section 4 presents our data sources and variable descriptions. Results appear in section 5 and section 6 concludes the paper.

2 Clusters, networks and policy

2.1 Clusters and cluster policy

The literature widely discusses the (potential) benefits of regional clusters, i.e. of the agglomeration of related and complementary economic activities. Already Marshall (1890) pointed out that externalities related to specialised labour markets, input suppliers and knowledge spillovers accrue from the agglomeration of industries. Firms might also benefit from location in a cluster characterised by the presence of demanding customers, competitive rivalry and complementarities in products or technologies (Porter, 1998). A large number of success stories of regional clusters strengthened the view of clustering's benefits (see examples provided by Hospers & Beugelsdijk, 2002). However, the empirical evidence regarding the benefits of clustering or specialisation is mixed or inconclusive (see reviews by Martin & Sunley, 2003 and de Groot et al., 2015). Baptista & Swann (1998) find that firms located in clusters (regions with high employment in their own industry) are more likely to innovate than non-clustered firms. Beaudry & Breschi (2003) further delineate this result by showing that the benefits of clustering only arise when the co-located firms are innovative themselves. Audretsch & Feldman (1996) find that innovative activities cluster particularly during early stages of the industry life cycle, while congestion effects dominate at later stages, so that innovation is more dispersed. Delgado et al. (2014) show that 'industries located in a strong cluster register higher employment and patenting growth', and that 'new regional industries emerge where there is a strong cluster' (p. 1785). Nevertheless, in his case against cluster policies, Duranton (2011) concludes that 'the findings are generally not supportive of strong clustering effects on innovation', and that 'clustering offers small "static" productivity benefits and there is no strong evidence of positive dynamic (or innovation) benefits' (p. 33).

Irrespective of the ambiguous empirical findings, many countries and different levels of governance (supra-national, national, regional) have adopted cluster policies (Sternberg et al., 2010; Kiese, 2017; Uyarra & Ramlogan, 2016). One of the frequently raised criticisms of the cluster concept is its fuzziness (Martin & Sunley, 2003), which translates into persistent variety in interpreting and applying it, as well as in the rationales for cluster policies and their targets (Sternberg et al., 2010, p. 1065). Due to its roots in different types of policies, such as science and technology policy, industrial policy and regional policy (Sternberg et al., 2010), cluster policies show various forms and types of governmental effort (Hospers & Beugelsdijk, 2002, p. 382).

For instance, Nauwelaers & Wintjes (2008) identify three types of clusters that policy might target: the mega cluster, the local-network cluster and the knowledge-based cluster. Closest to Porter's ideas is the mega cluster, defined at the national or regional level and focusing on industry competitiveness. The local-network cluster resembles the archetypal industrial district in more traditional industries, with a strong territorial basis and a pronounced involvement of SMEs. Finally, the knowledge-based cluster focuses on innovation and knowledge diffusion in a network often centred around a large technology company or public research organisation.

Cluster policies may also differ with respect to their objectives. Some cluster policies are intended to strengthen developments within specific localities or regions. Others target a specific industry and seek to support its competitiveness. For example, in Germany, two subsequent cluster policies (or regionalised innovation policies) had very different goals. The BioRegio contest aimed at the biotechnology industry to induce an international catch-up process. In contrast, the Innoregio policy focused explicitly on regions in the former GDR and aimed at decreasing regional disparities by supporting innovation activities (Dohse, 2007). Other important elements in which cluster policies may differ are cluster identification (top-down versus bottom-up), cluster selection (competitive or non-competitive), or the specific mix of policy instruments (R&D funding, setting up intermediaries, venture capital funds, competence centres, support of training activities, networking and identity building) (Uyarra & Ramlogan, 2016).

2.2 Clusters and knowledge networks

Knowledge networks are among the essential components of technology and industrial clusters (Giuliani & Bell, 2008; Morrison & Rabellotti, 2009; Sydow et al., 2010). They are particularly important for cluster development by shaping the intensity, kind and direction of knowledge diffusion (He & Hosein Fallah, 2009). This applies to cluster internal networks, whose structures shape the extent to which organizations benefit from location in a cluster (Boschma & ter Wal, 2007), and to cluster embeddedness in external knowledge networks. In many instances, the linking of internal and external knowledge networks decides cluster long-term success (Bathelt et al., 2004). Thereby, the inflow of external knowledge is as important as its cluster internal diffusion since both prevent long-term lock-in situations and general stagnating innovation processes (Hassink, 2007; Broekel, 2012).

From a cluster policy perspective, three aspects make knowledge networks a good point of departure. First, they are known to drive the economic and innovation performance of organisations and regions (Powell et al., 1996, 1999; Fornahl et al., 2011; Broekel, 2012; Breschi & Lenzi, 2016). Accordingly, by influencing knowledge networks, policy may indirectly support cluster development.

Second, the existence of market failures that prevent cluster knowledge-exchange activities from reaching their full 'innovation-enhancing' potential justifies policy intervention. More precisely, market failures exist with respect to inter-organisational knowledge access and exchange (Lundvall, 1992; Nelson, 1993; Malerba, 2004). Identifying, absorbing and using knowledge involve significant costs. In the context of innovation and learning activities, the extent to which later returns will compensate these costs is usually unclear (Bleek & Ernst, 1993). This particularly applies to collective learning and collaboration activities. While benefits of mutual learning exist, actors must overcome significant obstacles to collaboration to realise them (Kesteloot & Veugelers, 1995; Hagedoorn, 2002). Investments in collaboration are always at risk of free-riding and unintended knowledge spillovers that may compromise organisations' core competencies (Cassiman & Veugelers, 2002). Hence, organisations may underinvest in knowledge sharing, collective learning and collaborative activities, implying that inter-organisational knowledge-diffusion levels are likely to remain below a 'social optimum' (Buisseret et al., 1995). While this argument is one of the core justifications for network-oriented cluster policy, to the best of our knowledge, there is no empirical evidence of the existence of such a market failure.

Third, from a policy perspective, impacting knowledge networks appears to be relatively easy. In general, innovation processes are nonlinear and complex. It is hard to define where they start and where they end, and which actors they involve (Storper & Scott, 1995). In contrast, knowledge networks emerging from collaborative activities are relatively more straightforward and clearly defined, and hence they can be targeted with greater precision. For instance, policy may provide monetary incentives for two or more parties to jointly engage in narrowly defined R&D projects. Moreover, policy may make grants conditional on a collaborative research design that requires partners to provide access to each other's knowledge, resources and expertise. In this case, policy will indirectly facilitate collective learning and knowledge spillover (Broekel & Graf, 2012). This effect of subsidies for joint R&D is frequently labelled as *behavioural additionality* (Wanzenböck et al., 2013). This additionality is distinct from *input* and *output* additionalities, which are of greater relevance in the case of individual R&D subsidies. The first refers to encouraging organisations to invest in R&D, the second to increasing the number of successful R&D projects or the quality of their outcomes (Czarnitzki & Hussinger, 2018).

Besides encouraging knowledge exchange and learning, stimulating collaborative R&D will also yield positive effects in terms of pooling resources for projects too large for individual organisations. It may also push toward enlarging R&D projects to realise economies of scale (Wanzenböck et al., 2013). A prime example of such a policy approach is the EU-Framework programmes that make subsidisation conditional on collaborative research designs (Breschi & Cusmano, 2004).

In the context of support for cluster internal relations, stimulating collaboration appears to be particularly fruitful, as targeted organisations are located within geographic proximity, belong to the same industry and frequently can rely on existing social relations. In other words, multiple forms of proximity, all of which ease collaboration and make knowledge exchange more efficient, characterise such relations (Nooteboom et al., 2007; Boschma, 2005). Accordingly, when it comes to technology or industrial clusters, supporting collaboration should be particularly efficient in creating larger and denser knowledge networks.

2.3 Integrating a network perspective into cluster-policy evaluation

However, as stated above, there is no evidence supporting the argument of market failure in terms of too little collaboration and knowledge sharing as well as too sparse knowledge networks in general or within clusters in particular. The lack of knowledge on the effectiveness of these types of policies is similarly severe. Yet, evidence exists of organisations sharing a history of successful collaboration in acquiring R&D grants (Breschi & Cusmano, 2004). In this case, organisations might only team up to obtain funds for joint R&D without transforming those collaborations into significant and lasting relations. That is, despite funding, their collaboration remains restricted to already existing partners or to the specific project and will not persistently (re-)shape knowledge networks. These two situations arising frequently implies that significant portions of network-building policies reinforce existing knowledge networks, rather than promoting their growth or structural evolution.

So far, cluster policy evaluations have treated these aspects rather indirectly. For instance, Falck et al. (2010) evaluate cluster policies introduced in Bavaria in 1999, and confirm positive effects on firms' innovation output and access to external knowledge sources. Using a Japanese cluster policy as an example, Nishimura & Okamuro (2011a) do not observe any effect on R&D productivity in participating firms. They rather suggest that firms would benefit from collaborative networks within and beyond clusters. In a related investigation, Nishimura & Okamuro (2011b) report cluster participants expanding industry-university-government networks after participating in the support scheme. Besides such rather direct effects on firm performance, Broekel et al. (2015) identify another benefit associated with participating in EU-Framework Programmes and national biotech cluster schemes in the early 2000s. Participants in these programmes appeared to gain better access to future EU funding, as well as better embeddedness in inter-regional R&D networks.

Hence, while some studies analyse the effect of R&D subsidisation at the organisational level (see also Wanzenböck et al., 2013), so far, few studies have attempted to investigate the effect of R&D policy on knowledge network development (see Giuliani & Pietrobelli, 2014 for a review). Those that do rather focus on general collaboration and knowledge-sourcing activities, without assessing policy-induced changes to the structures of local knowledge networks. One exception is the study by Töpfer et al. (2017), who observe structural changes in R&D collaboration networks related to the German leading-edge cluster competition. More precisely, they find that during the funding period, networks became more localised, more cohesive and more centralised. However, any long-term assessment of policy effects on cluster knowledge networks remains missing.

3 The BioRegio contest

To discuss and then test if and how policy may alter the structures of cluster internal knowledge networks, we focus on the German BioRegio Contest initiative. At the turn of the millennium, Germany was said to lag behind leading countries, such as the USA or the UK, in the development of a biotechnology industry (Cooke, 2001). As a response to its backwardness in this promising technology, Germany's federal government, as well as regional and local governments, intensified activities to support the biotech industry there (Kaiser & Prange, 2004). One of the early support measures was the BioRegio Contest, initiated in 1995 by the German Federal Ministry of Education and Research (BMBF) (Dohse, 2000).

The support measure was designed as a competitive scheme that aimed to 'develop life science clusters, increase start-up creations, support the growth of existing firms, foster venture capital, and improve acceptance of biotechnology among the broader population' (Champenois, 2012, pp. 799-800). The competition invited proposals from consortia of regional organisations, highlighting their core competencies and how their networks could contribute to the achievement of these objectives (Müller, 2002; Dohse & Staehler, 2008). An international independent jury of scientists, as well as representatives of labour unions and industry, evaluated the concepts by considering the following aspects (based on Staehler et al., 2007):

- Existence and characteristics of participating biotechnology firms and research organisations (public and private)
- Embeddedness of local biotechnology research in interdisciplinary networks
- Supportive services (e.g. patent offices, consultancy)
- Strategies to commercialise biotechnology knowledge
- Measures to facilitate expansion or foundation of biotechnology firms in the region
- Readiness of banks and private financiers to invest in biotechnology

- Cooperation with research and health organisations
- Legal approval procedures for biotechnology facilities and in-field applications (p. 6)

Notably, the program followed a bottom-up, self-organisation approach, implying that neither the size nor the composition of the consortia was predefined, nor what constituted a 'region' (Champenois, 2012; Staehler et al., 2007). However, neighbourhood and geographic proximity clearly played a role in the formation processes of the consortia, as the vast majority of their core actors were located within the same meso-regions (Engel et al., 2013). In the end, 17 consortia (hereafter 'regions') submitted their proposals (Müller, 2002). Of these, three were directly awarded: Munich, Rhineland (Cologne) and BioRegio Rhine-Neckar (Heidelberg). In a special vote, Jena was additionally considered, as best proposal from an East German region. The three winner regions were supported with 25 million EUR each, and Jena received about 15 million EUR in public funds (Staehler et al., 2007).

A direct consequence of the BioRegio support was the establishment of a coordination office in each region. These offices, most of which still exist, have a broad set of tasks, including gathering and disseminating information, location marketing, technology transfer, networking, entrepreneurial consultancy and sometimes even supporting the financing of projects (Staehler et al., 2007). In addition to the establishment of coordination offices, some of the funding was spent on the development of biotechnology-oriented incubators and technology parks, which especially helped entrepreneurial activities. Other uses of the funds included direct monetary support for R&D projects, either exclusively or as co-financing of other support programs by the federal states or the regions (Champenois, 2012). Moreover, developing the BioRegio concept as such arguably increased the knowledge of participating actors about commercialisation possibilities and potential collaboration partners (Staehler et al., 2007). It also stimulated the development of trust among regional participants, a key prerequisite for future bids and grant applications. Lastly, winner regions benefited from a (positive) signalling effect to potential investors and entrepreneurs.

At the time, this innovative cluster approach of the BioRegio contest was incorporated in several subsequent programs in Germany,[1] such as BioProfile, InnoRegio, Leading Edge Cluster Competition and InnoProfile. It also received wide attention from policymakers and in academia (Dohse, 2000, 2007; Eickelpasch & Fritsch, 2005; Fornahl et al., 2011).

Several studies evaluate this policy and come to generally favourable conclusions with respect to its short-term policy effects. Dohse & Staehler (2008) compare the German Biotech clusters funded within both the BioRegio and BioProfile contests and identify the superior performance of the former 'with respect to nearly all of the usual (and available) performance measures' (p. 18). In their evaluation of the BioRegio contest and the subsequent BioProfile competition, Engel et al. (2013) show that winners generally outperformed non-winning participants during the treatment period. From a policy perspective, funding tournaments have the advantage of initiating regional networking activities, even within the regions that do not receive funding. The proposed reason for this mobilisation effect is that the application process requires collaboration and joint efforts in the development of a common strategy, which obviously brings many actors

[1] For an overview, see Commission of Experts for Research and Innovation (2017, p. 59).

together. However, in the case of the regions that did not win in the BioRegio contest, Engel et al. (2013) could not detect any mobilisation effect during the application phase.

So, even though the BioRegio contest arguably was successful in fostering inventive activity, employment and new firm formation, the existing studies do not inform us how this policy may have altered cluster internal network structures. Also unclear is the extent to which the particular design of the BioRegio initiative induced effects different from the 'usual' widely applied subsidisation of joint R&D projects. Consequently, in light of the previously outlined importance of regional knowledge networks, we still lack important insights into the effects of such policies on these relational structures in general and with respect to effects of the BioRegio contest in particular.

4 Data

4.1 BioRegio clusters and their boundaries

The BioRegio contest was designed with a two-stage application procedure, in which applicants received funding to develop a strategy and elaborate their final proposals. Research grants at this application stage are documented in the German funding catalogue (subsidies database) (foerderkatalog.de) (for an introduction to the database, see Broekel & Graf, 2012).

We use this information to identify all program participants and define the spatial boundaries of the clusters. Overall, 17 regions participated in the BioRegio contest at the application stage (see Figure 1). Four of these regions were successful in the contest and received research grants at the program stage (winner regions), while 13 regions did not go on to the funding stage (applicant regions). The cluster regions do not necessarily coincide with administrative regions, so we aggregate smaller NUTS-3 regions to larger spatial areas. For the subsequent collection of patent data, we define the cluster regions as aggregates of all NUTS-3 regions in which at least one BioRegio funding recipient is located.

4.2 Reconstructing knowledge networks from patent applications

For the cluster-region networks, we collect Biotech patent applications[2] for all regions in our sample from the OECD REGPAT database version of spring 2018. A patent is allocated to a region if at least one of the inventors is located in that region. In reconstructing the applicant networks, we follow the work of Cantner & Graf (2006) and Graf (2017), linking patent applicants by common inventors—i.e. we assume that knowledge can flow more easily between two applicants if they are linked by inventors who know each other from collaborating on a patent. Thereby, we acknowledge different channels of knowledge transfer: applicant collaboration via co-patents, as well as cases of mobile inventors and so-called hidden collaborations between applicants who develop inventions jointly but file individual patents (Cantner et al., 2010). Inventor name cleaning is performed by following a series of steps in which we remove accents and corrupted and foreign characters, as well as name modifiers and extra blanks; and make all entries upper case (Graf, 2017). For the applicant names, we rely on the cleaning and matching procedures employed in the preparation of the Harmonized Applicant Names (HAN)

[2] At least one IPC class among the ones listed in appendix A.

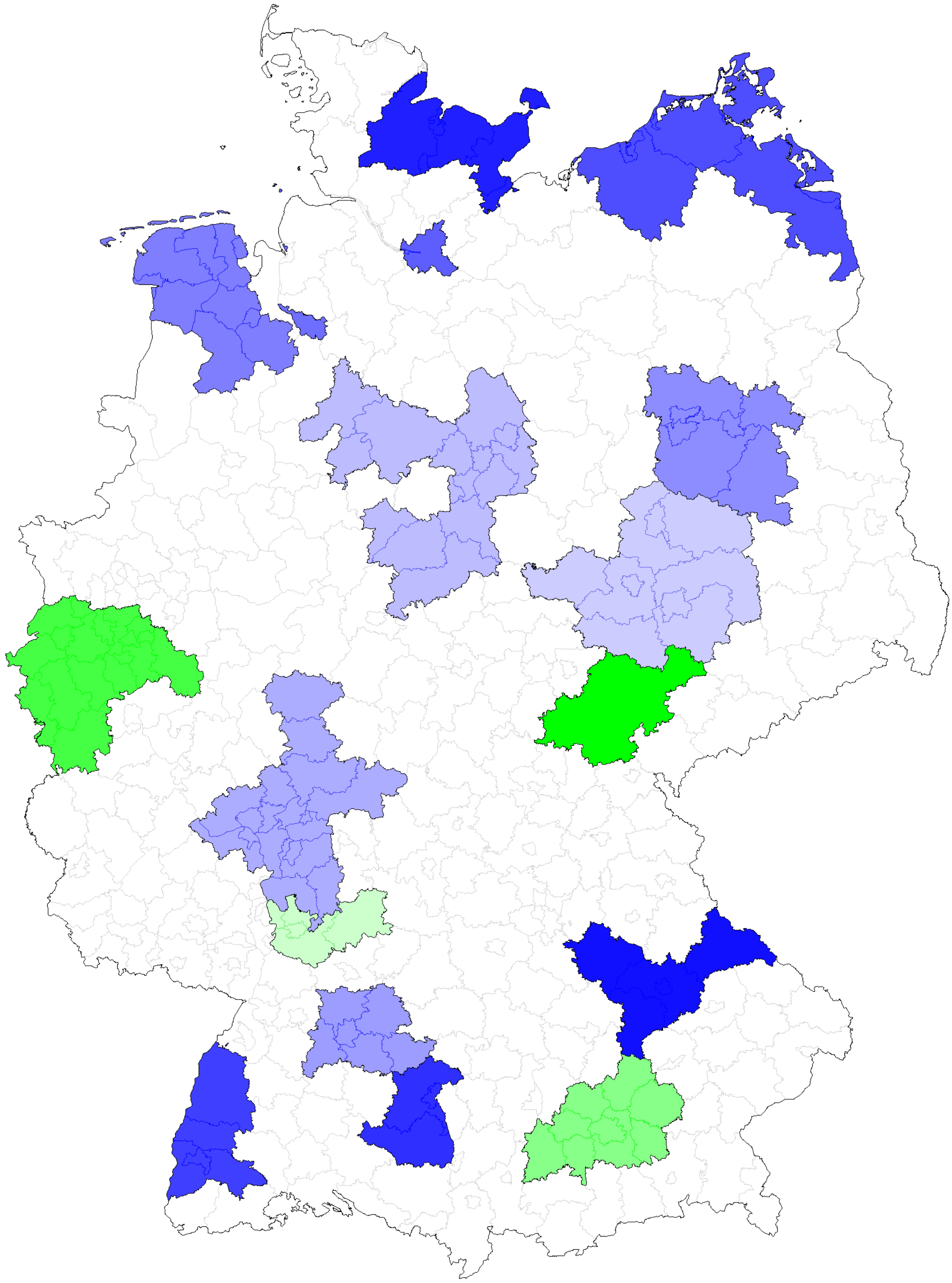

Figure 1: BioRegio applicant regions (blue) and winner regions (green)

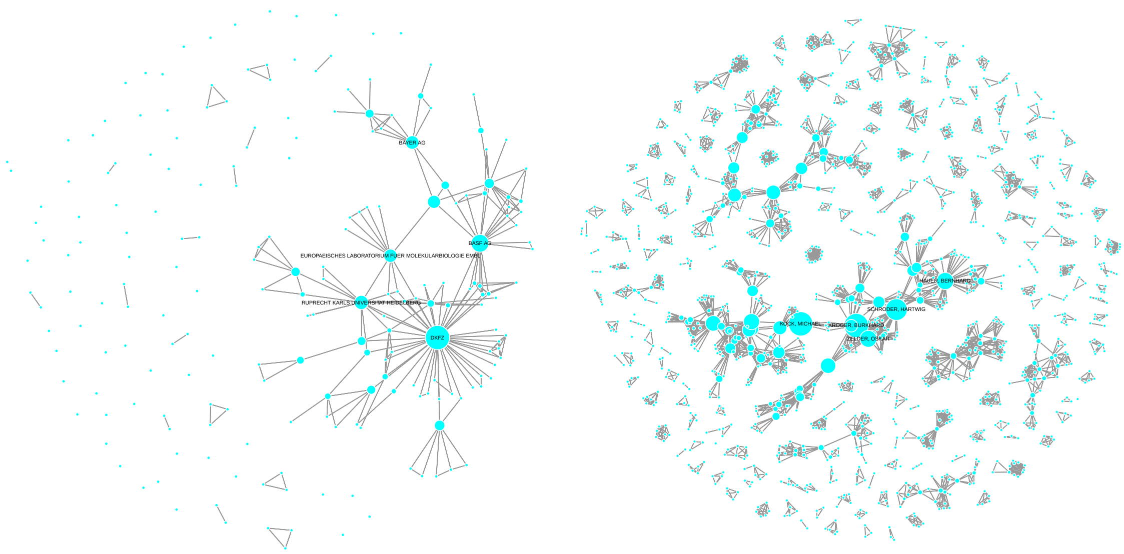

Figure 2: The applicant (left) and inventor (right) networks in the cluster Rhine-Neckar in the period 1998 to 2004. Nodes are patent applicants (inventors), links are common inventors (patents). Node size is proportional to betweenness centrality.

database of the OECD, spring 2018. In addition, we reconstruct co-inventor networks where the nodes are inventors linked by jointly patented inventions. The networks are reconstructed for 23 overlapping seven-year periods starting with the period 1991 (which includes information on patent applications with a priority date from 1985 until 1991) and ending with the period 2013 (2007 until 2013). As such, regarding link decay, we assume that links that are not renewed dissolve after seven years.[3] Figure 2 illustrates the applicant and inventor networks of the winning cluster Rhine-Neckar during the period 1998 to 2004.

For the networks, we calculate several statistics related to network size, cohesion and topology, discussed in the 'Variables' section below. Since some measures of network structure are quite sensitive to single patents with many applicants and/or inventors, we remove outlier patents before reconstructing the networks. Outliers are defined as the top 1% in the applicant-per-patent and inventor-per-patent distribution of patents in each region for the whole period 1985 to 2013.[4] By removing outliers, the overall number of patents is reduced by 208, from 18,422 to 18,214. The removed patents average 13.6 inventors per patent (maximum is 40), while the average within the retained patents is 3.9 (maximum of 16).

4.3 R&D subsidies

The second main source of data is information on R&D subsidies. In Germany, R&D project funding usually takes place within the frameworks of general innovation policy or specific initiatives. The respective ministries publish a funding guideline or program tender. Organisations can then apply for temporary project-specific funding within the scope of these programs. This

[3]To test whether our results are sensitive to this assumption, we performed all analyses with 25 overlapping five-year periods. Since the changes are only marginal, we abstract from presenting them here and provide them upon request.

[4]While the exclusion of the outliers improves the reliability of our empirical analysis, it does not significantly impact the direction of our results.

principle also applies to R&D project funding by the Federal Government of Germany, upon which we rely for data—more precisely, we use the publicly accessible part of the BMBF's PROFI database (project funding information system), which contains the majority of project-based national research funding in Germany. The database lists more than 204,000 subsidisation grants for R&D projects since 1965. The data includes information on the supported organisation, its sectoral affiliation, location, eligibility period with start and completion dates, grant size, a thematic categorisation, a distinction between beneficiary and executing agency and whether the support project is an individual project or a joint project. A detailed description of the data can be found in Broekel & Graf (2012).

The analysis focuses on the period 1985 to 2013, and all projects classified into the main category 'B' (biotechnology) of the internal thematic classification scheme (*Leistungsplansystematik*). The category covers 3,224 individual grants that belong to 1,992 projects; 976 organisations benefited from these grants, which, in turn, can be subdivided into 1,801 'executing units'. Following Broekel & Graf (2012), the beneficiaries are not considered to be relevant actors since particularly large organisations are often active in different regions and their distinct establishments generally operate largely independently in terms of R&D projects. Therefore, individual actors are identified as unique combinations of the name of the beneficiary, e.g. 'Siemens AG', and the name of the location of the executing unit e.g. 'Aachen'. Accordingly, 1,132 individual actors are identified, located in 240 NUTS-3 regions.

4.4 Variables

Based on patent and funding information, we generate several variables at the level of the cluster region for the periods 1985–1991 until 2007–2013. Table 1 presents summary statistics, and correlations appear in table 5 in the appendix.

Dependent variables

We have two sets of dependent variables that we expect the BioRegio cluster policy to influence. The first set captures innovation activities within the clusters. We consider the number of patent applications (*Patcount*), distinct applicants (*Vcount.app*) and distinct inventors (*Vcount.inv*). The latter two variables are measures of the size of both versions of the local networks (applicant and inventor).

The second set of variables provides insights into the local knowledge network structure and topology. Five different measures capture network cohesion. Network density (*Density*) is calculated as the share of active links over all possible links in the unweighted network. Since an additional actor increases the number of potential linkages for every other actor, density typically decreases with network size. Since we expect that cluster policy has a positive influence on the number of realised collaborations (the numerator) as well as on the number of actors participating in the network (the denominator), we expect a negative policy influence. We also include cohesion measures that are more robust against size effects and expected to be positively affected by the cluster policy. *Mean degree* is the average number of connections in the unweighted network and *Mean strength* is the weighted version of mean degree, so that a higher number of common inventors (patents) implies a stronger connection in the applicant

Table 1: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
Dependent variables: innovation activity					
Patcount	391	280.913	331.738	0	1,245
Vcount.app	391	96.706	93.193	0	370
Vcount.inv	391	587.588	630.800	0	2,312
Dependent variables: applicant network structure					
Density	386	0.027	0.030	0.000	0.333
Mean degree	387	1.337	0.757	0.000	3.289
Mean strength	387	4.234	2.551	0.000	11.581
Connectedness	386	0.083	0.073	0.000	0.350
Share MC	387	0.246	0.139	0.047	1.000
Centralization	386	0.095	0.051	0.000	0.276
Transitivity	320	0.600	0.237	0.000	1.000
Dependent variables: inventor network structure					
Density	387	0.037	0.061	0.002	0.714
Mean degree	387	4.712	0.781	2.286	6.877
Mean strength	387	6.923	2.271	2.375	15.258
Connectedness	387	0.076	0.086	0.011	1.000
Share MC	387	0.175	0.123	0.036	1.000
Centralization	387	0.057	0.042	0.000	0.336
Transitivity	387	0.796	0.125	0.458	1.000
Independent variables: policy					
BioRegion	391	0.235	0.425	0	1
RD.funds.Bio	391	41.136	52.719	0.011	277.130
BioRegio.funds	391	2.687	8.129	0.000	46.185
AfterBioReg	391	0.391	0.489	0	1
Independent variables: controls					
Teamsize.inv	387	4.035	0.507	2.583	5.505
Teamsize.all.inv	391	3.076	0.534	2.045	4.452
East	391	0.235	0.425	0	1

and/or inventor network. *Connectedness* is the share of actors that can reach each other via any path in the same component. Closely related is the share of actors in the main component (*Share MC*).

Degree centralisation (*Centralisation*) is a distributional measure of link concentration and is bound between 0 (all actors have the same number of links) and 1 (a star network). There are some indications that cluster policies requiring a common strategy for a large number of otherwise independent actors lead to an increase in centralisation (Töpfer et al., 2017). The proposed reason is that coordination requires a small group of highly active actors, who will be involved in more projects than other participants. Finally, it could be expected that cluster policies have an effect on clustering or transitivity (*Transitivity*)—i.e. the likelihood that neighbours of a node are connected themselves. A positive effect could be interpreted as the policy strengthening social relations (Uzzi, 1997) and being able to bridge structural holes. A negative effect would signal that policy helps to form less cliquish networks with fewer redundant ties. The literature is inconclusive as to which type of network is more beneficial for innovation. However, it seems that especially young industries, where innovation is explorative (i.e. driven by the search for new combinations and applications), need diverse ties rather than dense structures (Rowley et al., 2000).

Of course, there are many alternative ways to approximate the structure of networks. However, we are particularly interested in those that are most likely to impact local knowledge diffusion, which primarily depends on network size and cohesion (e.g. Cowan & Jonard, 2004).

Independent variables

Our main variables of interest are policy variables related to the BioRegio contest. *BioRegion* is a dummy variable, set to 1 for all four winning regions. *BioRegio.funds* is the amount of public funding by the BioRegio program within a seven-year period in millions of EUROs. *AfterBioReg* is a dummy set to 1 for all periods after the BioRegio contest, i.e. 2005 and all subsequent years.[5]

Among the control variables, we consider the amount of biotechnology-specific R&D subsidy funding granted to actors located in the region (*RD.funds.Bio*) as most important. This measure serves as an indication of general R&D policy impact. Note that we subtracted all subsidies related to the BioRegio contest from this variable.[6] Figure 3 displays funding for general R&D in biotech (*RD.funds.Bio*) and BioRegio funding (*BioRegio.funds*) for each seven-year period, aggregated for all 17 regions. The figure illustrates the overall growing trend of biotechnology subsidisation until about 2007, and a clear drop after 2010. Clearly, the BioRegio program fits perfectly into this development.[7]

In addition, we control for average inventor-team size on all regional biotechnology patents (*Teamsize.inv*) and all regional patents (*Teamsize.all.inv*) to account for the general trend toward increased division of labour in research activities (Wuchty et al., 2007). Since structural

[5] Engel et al. (2013) define the treatment period from 1997 to 2002. Since we still observe BioRegio funding in 2004, we set this year as the end of the programme.

[6] We used the number of subsidised projects and the number of partners in subsidised projects as alternative measures, but both proved to be empirically less relevant than the amount of subsidies.

[7] We refrain from considering additional public support programs due to a lack of coherent and complete information thereof. In particular, support measures at the level of the federal states are generally unavailable or non-transparent.

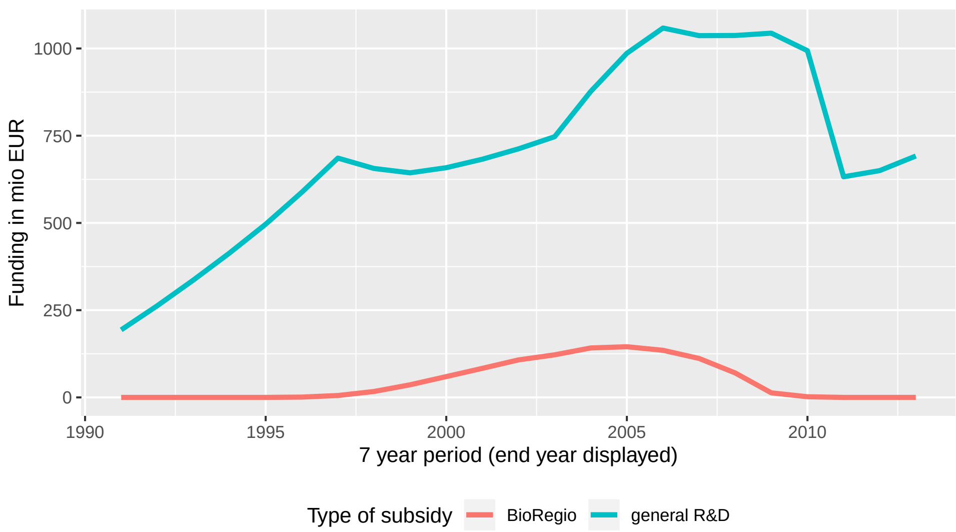

Figure 3: General R&D in Biotech and BioRegio funding in all cluster regions

differences between West and East German regions might exist, we also control for location in East Germany (*East*).

5 Results

5.1 Inventive Activity

Before investigating the impact of BioRegio on regional networks, we focus on its effect on inventive activity. Empirically, we regress the first difference in patent and (actor) node counts respectively on the policy and control variables. In addition to the control variables, we include the one-period lagged level of the respective innovation activity indicator to account for potential size effects.

Table 2 presents the results of two econometric specifications with the three different dependent variables. The first three columns show fixed-effects OLS models; columns 4 to 6 present the results for a pooled model in which we include the two regional dummies, *BioRegio* and *East*. The results highlight that the amount of funding in the BioRegio contest (*BioRegio.funds*) is significantly positive related to patent growth and to changes in the numbers of network actors (FE models 1 to 3). However, its positive relation with patent growth becomes only visible in the pooled models. Our findings corroborate previous results on the BioRegio contest that underline its generally positive effects on innovation activities in winning regions (e.g. Engel et al., 2013). These findings are confirmed by the pooled models, with the dummy *BioRegion* obtaining a significantly positive coefficient, indicating that BioRegio winner regions positively deviate in terms of innovation activity, compared to the non-winning regions. However, there is no control for any selection effect in our models, implying that these findings might be subject to endogeneity.

Interestingly, general R&D subsidies (*RD.funds.Bio*) are weakly negatively related to changes in the size of the applicant networks in the FE model (Δ *Vcount.app*). Accordingly, general subsidies for R&D projects do not seem to promote the growth of regional networks, but

Table 2: Inventive activity, first differences, FE-panel and pooling

	Dependent variable:					
	Δ Patcount.app	Δ Vcount.app	Δ Vcount.inv	Δ Patcount.app	Δ Vcount.app	Δ Vcount.inv
	(1)	(2)	(3)	(4)	(5)	(6)
RD.funds.Bio	−0.018	−0.043**	−0.126	0.056	−0.007	−0.010
	(0.064)	(0.021)	(0.115)	(0.044)	(0.016)	(0.083)
BioRegio.funds	2.678***	0.443**	3.633***	1.931***	0.162	1.655
	(0.608)	(0.207)	(1.135)	(0.568)	(0.197)	(1.079)
BioRegion				16.120***	7.779***	44.674***
				(5.418)	(1.874)	(10.275)
AfterBioReg	−49.014***	−15.906***	−95.634***	−47.788***	−14.380***	−87.168***
	(5.832)	(2.010)	(11.003)	(5.926)	(2.057)	(11.270)
BioRegion:AfterBioReg	−27.992***	−8.158***	−38.444***	−41.077***	−11.511***	−64.299***
	(7.549)	(2.484)	(13.845)	(7.159)	(2.469)	(13.551)
RD.funds.Bio:BioRegio.funds	−0.009**	−0.002	−0.020**	−0.007*	−0.002	−0.015*
	(0.005)	(0.002)	(0.009)	(0.004)	(0.001)	(0.008)
Teamsize.inv	1.473	0.782	7.321	−3.011	−0.875	−2.971
	(3.786)	(1.289)	(7.061)	(3.424)	(1.182)	(6.488)
Teamsize.all.inv	−2.847	−1.381	−12.320	−3.804	−0.803	−8.530
	(9.139)	(3.095)	(17.014)	(4.258)	(1.447)	(8.110)
east				4.319	0.851	4.757
				(4.520)	(1.533)	(8.666)
lag(Patcount.app, 1)	−0.053***			−0.001		
	(0.015)			(0.007)		
lag(Vcount.app, 1)		−0.053***			0.019*	
		(0.016)			(0.010)	
lag(Vcount.inv, 1)			−0.059***			0.015**
			(0.016)			(0.007)
Year	2.443***	0.841***	5.320***	1.862***	0.405**	3.074***
	(0.527)	(0.190)	(1.015)	(0.466)	(0.165)	(0.888)
Constant				−3,683.132***	−797.015**	−6,075.032***
				(926.965)	(328.008)	(1,767.688)
Observations	371	371	371	371	371	371
R^2	0.458	0.414	0.430	0.438	0.370	0.391
Adjusted R^2	0.419	0.371	0.388	0.420	0.351	0.373
F Statistic	32.450***	27.056***	28.885***	25.402***	19.187***	20.968***
Note:	*p<0.1; **p<0.05; ***p<0.01					

rather focus on supporting incumbent actors. The interaction term of both types of funding (*RD.funds.Bio:BioRegio.funds*) obtains a negatively significant coefficient in the models with changes in the number of patents and those with the size of the inventor networks being the dependent variable. This suggests a substitutive relationship, rather than a complementary one, between both policies. In addition, the finding indicates that the BioRegio contest is relatively stronger in embedding new actors into regional networks and in increasing regional patenting activities.

With respect to the long-term policy influence on innovation activities, we identify two negative effects of substantial magnitude. In the years following the BioRegio contest, we observe a decline in innovation activities in all regions, which translates into a significantly negative coefficient of *AfterBioReg*. This decline is even more severe in the case of the winner regions. Here, the interaction term of the years after the last final round of BioRegio funding and having been a winning region, *BioRegio:AfterBioReg* is significantly negative. The former result coincides temporarily with the burst of the 'dotcom bubble', calling for some caution in the interpretation. The burst of the bubble clearly had adverse effects on early-stage technologies, including biotechnology. However, this development is unlikely to explain our finding for the interaction effect, as it would suggest that former BioRegio winner regions have been hit comparatively harder by the burst of the bubble than non-winner regions. Yet, we find no evidence for this in our data nor in the contemporary literature. Therefore, a more plausible explanation, also in line with the findings of Engel et al. (2013), is that during the period of the contest, patent, inventor and applicant numbers had been overshooting in winner regions. This was 'corrected' when the support ended.

5.2 Effects on Applicant Network Structure

We are primarily interested in the potential (long-term) effects of cluster policies on the structures of regional networks, which we explore for the applicant network first. In this case, structural network variables describing the cohesion and topology of regional networks are regressed on the policy and control variables. Table 3 presents the estimation results of linear fixed-effects regressions. The empirical observations include all time periods. That is, for winning and non-winning regions, all periods before, during and after the BioRegio contest are considered. This allows for identifying changes in network features induced by the contest, using the pre- and post-contest years of winning regions, as well as all years for the non-winning regions as counterfactuals.

Starting with the short-term effects of the BioRegio contest, we observe some structural effects being statistically related to BioRegio funding (*BioRegio.funds*). While there are no effects of this policy on network cohesion in terms of density, mean degree, mean strength or the share in the main component, we identify positive effects on networks' connectedness and centralisation as well as negative effects on transitivity. The positive effect on connectedness is in line with our expectations: In combination with the negative effect on transitivity, it indicates that BioRegio funding helped to connect actors within the biotech field, and this counteracted the emergence of cliques in the network. Moreover, the significantly negative coefficient of *BioRegio.funds* on transitivity suggests that these subsidies facilitated the emergence of local structural holes. That is, these subsidies seem to have been used to explore new knowledge and to connect to actors to whom an organisation is not (already) directly linked. This is can be seen as an indication that these subsidies support rather explorative R&D processes Menzel et al. (2017).

We also observe an indirect effect of this policy on cohesion, in terms of mean degree and the share of actors in the main component, expressed by the number of actors (*Vcount.app*) (previously shown to be positively influenced by BioRegio funding). The finding on centralisation supports the views of Töpfer et al. (2017), who argue that a small group of actors drives the coordination process within the cluster, which, consequently puts them in a more central position in the knowledge network.[8]

In the long-run, potential effects shaping cluster networks are captured by the interaction term *BioRegio:AfterBioReg*. Here, we identify a significantly positive effect for the share of actors in the main component (*Share MC*), but not for any other measure of cohesion. Consequently, the BioRegio contest seems to have had only a modest impact on the long-term cohesion of the networks in the funded clusters. In contrast, we observe another long-term effect with respect to network transitivity. According to our findings, after funding, the BioRegio networks remained less cliquish than those in non-winner regions. Since transitivity has been identified previously as a strong driver of network evolution (Ter Wal, 2013), we interpret this as a rather positive policy effect, because less cliquish networks tend to offer greater knowledge diversity for explorative knowledge creation (Rowley et al., 2000; Gilsing & Duysters, 2008).

We also find several significant changes in the networks that are not specific to the winner clusters (*AfterBioReg*). For instance, while *Density* increases, other measures of cohesion decline (*Mean degree*, *Connectedness*), and *Centralisation* also decreases after the end of the funding period.

A particularly interesting result in the context of this study concerns the general subsidies for project-based R&D in biotech, beyond the BioRegio contest, captured by the variable *RD.funds.Bio*. These appear to have had a more notable effect on the networks than the BioRegio contest. For instance, for all cohesion measures except *Density*, we observe a significantly positive relation with these subsidies (*RD.funds.Bio*). Like the BioRegio support initiative, they also lead to more centralised (model 6) and less clustered (model 7) networks.

Regarding the interaction effects of these two types of funding (i.e. BioRegio and general biotechnology R&D subsidies), we find them to be substitutive rather than complementary. In both models with a significant interaction effect (models 4 and 6), the coefficient has the opposite sign of the individual effects.

In summary, our findings show that project-based R&D subsidies have the potential to support regional networks and thereby, stimulate local, inter-organisational knowledge diffusion. The comparison between the BioRegio funding and general R&D subsidies reveals that both worked in similar directions, and consequently substitute rather than reinforce each other.

[8] An alternative interpretation would be that there is a process of concentration along the industry life cycle, which may also facilitate a strengthening of the network core. However, additional analyses revealed a decreasing concentration of patents across applicants (measured by the Herfindahl-index) before and during the funding period. Consequently, industry R&D activities seem to have been expanding rather than consolidating.

Table 3: Network structure (Applicants), levels, FE-panel, outliers removed

	Dependent variable:						
	Density	Mean degree	Mean strength	Connectedness	Share MC	Centralization	Transitivity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RD.funds.Bio	0.00001	0.002*	0.010***	0.0003***	0.001***	0.0002**	−0.001***
	(0.00005)	(0.001)	(0.003)	(0.0001)	(0.0002)	(0.0001)	(0.0003)
BioRegio.funds	−0.0003	0.013	0.025	0.002**	0.002	0.002*	−0.012***
	(0.0005)	(0.009)	(0.029)	(0.001)	(0.002)	(0.001)	(0.004)
AfterBioReg	0.008*	−0.304***	−0.165	−0.017*	−0.023	−0.020**	−0.021
	(0.005)	(0.086)	(0.286)	(0.010)	(0.021)	(0.010)	(0.040)
BioRegion:AfterBioReg	0.009	−0.066	0.513	0.020	0.053**	−0.0002	−0.084*
	(0.006)	(0.104)	(0.344)	(0.012)	(0.025)	(0.012)	(0.044)
RD.funds.Bio:BioRegio.funds	0.00000	−0.0001	−0.0001	−0.00002**	−0.00003	−0.00000	0.0001***
	(0.00000)	(0.0001)	(0.0002)	(0.00001)	(0.00002)	(0.00001)	(0.00003)
Vcount.app	0.00001	0.002***	0.002	0.0001	0.0004**	−0.0004***	−0.0002
	(0.00004)	(0.001)	(0.002)	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Teamsize.all.inv	0.019***	−0.087	−0.730*	0.009	−0.041	0.008	0.222***
	(0.007)	(0.121)	(0.401)	(0.014)	(0.030)	(0.014)	(0.064)
Year	−0.003***	0.026***	0.107***	−0.002**	−0.005***	0.001	−0.001
	(0.0004)	(0.008)	(0.026)	(0.001)	(0.002)	(0.001)	(0.004)
Observations	386	387	387	386	387	386	320
R^2	0.211	0.180	0.303	0.150	0.172	0.125	0.109
Adjusted R^2	0.159	0.126	0.257	0.093	0.117	0.066	0.040
F Statistic	12.097***	9.942***	19.709***	7.949***	9.374***	6.417***	4.516***
Note:	*p<0.1; **p<0.05; ***p<0.01						

5.3 Effects on Inventor Network Structure

Since the recipients of R&D subsidies and cluster actors are typically organisations (mainly firms, research centres and universities), investigating the inter-organisational network is the natural choice (see previous subsection). However, one can also argue that knowledge diffusion and collaboration ultimately take place at the individual level. Therefore, we conduct the same analyses as above, using co-inventor networks. Table 4 presents the corresponding regression results.

With respect to effects related to BioRegio (*BioRegio.funds*), we observe similar results as in the case of the applicant networks: Cohesion is exclusively influenced in terms of the share of actors in the main component (model 5). As before, we also observe a positive effect on centralisation (6) and a negative one on transitivity (7). The interpretation and implications apply as described.

Regarding long-term effects of the initiative in the winner clusters (*BioRegion: AfterBioReg*), we hardly observe any substantial changes in network structures. There was a slight decline in the interaction intensity, as measured by the mean degree (model 2), and some increase in centralisation (6). However, both effects are weakly significant. One interpretation of the effect on centralisation is that when inventive activities declined in the winner clusters after the funding period, those inventors with many linkages remained active in R&D in the cluster. This process seems to have been part of a general trend, as we observe a general increase in network centralisation (*AfterBioReg*). We also observe growth in network density (1) in all clusters during the post-funding period; however, that is due to the decrease in inventive activity in later periods. This translates into smaller networks, and network density is known to react sensitive to such changes.

Our results reveal that general biotech R&D subsidies (*RD.funds.Bio*) show more or less the same positive effects on inventor networks as we observe in the case of applicant networks. Again, the effects on cohesion (models 2 to 5) are consistently positive. These analyses also further substantiate their relevance for (decreasing) transitivity (7). More precisely, the negative coefficient indicates that they support knowledge-sourcing activities beyond already established and socially close connections, which is usually associated with explorative R&D (Menzel et al., 2017). With respect to the effects of the instrument mix (*RD.funds.Bio:BioRegio.funds*), we find confirmation for a substitutive relationship between the two types of funding.

Overall, the impacts of the BioRegio contest and general R&D subsidies differ only slightly between applicant and inventor networks. While we expected a relatively stronger impact of the BioRegio contest on network cohesion, our results indicate that generalsubsidies for collaborative R&D perform at least as well, and even have similar effects on centralisation and transitivity, as those within the BioRegio initiative. Undoubtedly, BioRegio was highly successful in terms of activating innovation potentials during the funding period, because of its emphasis on entrepreneurship and research infrastructure. At the same time, the effects on collaborative R&D and regional networks appear to be similar, if not inferior, to those of general project-based R&D subsidisation.

Table 4: Network structure (Inventors), levels, FE-panel, outliers removed

	Dependent variable:						
	Density	Mean degree	Mean strength	Connectedness	Share MC	Centralization	Transitivity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RD.funds.Bio	−0.00000	0.005***	0.014***	0.0003**	0.001***	0.0001	−0.001***
	(0.0001)	(0.001)	(0.003)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
BioRegio.funds	−0.001	−0.008	0.036	0.001	0.004**	0.001**	−0.007***
	(0.001)	(0.010)	(0.035)	(0.001)	(0.002)	(0.001)	(0.001)
AfterBioReg	0.018**	0.067	0.812**	0.021	0.018	0.014**	−0.0004
	(0.009)	(0.100)	(0.341)	(0.014)	(0.017)	(0.007)	(0.013)
BioRegion:AfterBioReg	0.008	−0.237*	0.249	−0.006	−0.017	0.019**	−0.0003
	(0.011)	(0.122)	(0.415)	(0.017)	(0.021)	(0.008)	(0.016)
RD.funds.Bio:BioRegio.funds	0.00000	0.0001	−0.0002	−0.00001	−0.00002*	−0.00001**	0.00005***
	(0.00001)	(0.0001)	(0.0003)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Vcount.inv	0.00004***	−0.0002	0.001	−0.00001	−0.00004	−0.00001	0.00004**
	(0.00001)	(0.0001)	(0.0005)	(0.00002)	(0.00003)	(0.00001)	(0.00002)
Teamsize.all.inv	−0.040***	0.515***	0.916*	−0.087***	−0.095***	−0.017*	0.104***
	(0.013)	(0.141)	(0.481)	(0.019)	(0.024)	(0.009)	(0.018)
Year	−0.004***	0.016*	0.017	−0.004***	−0.005***	−0.002***	−0.003***
	(0.001)	(0.009)	(0.030)	(0.001)	(0.002)	(0.001)	(0.001)
Observations	387	387	387	387	387	387	387
R^2	0.208	0.308	0.360	0.288	0.328	0.205	0.177
Adjusted R^2	0.156	0.262	0.317	0.241	0.283	0.152	0.122
F Statistic	11.904***	20.137***	25.411***	18.343***	22.089***	11.651***	9.730***
Note:	*p<0.1; **p<0.05; ***p<0.01						

6 Conclusion

Cluster policies are designed to support clusters by increasing and strengthening innovation activities and interaction between co-located actors. Most evaluations of such policies focus on firm-level effects and test for increased R&D efforts, higher innovation output, or grown productivity, commonly known as input and output additionalities. However, such policies may also alter collective learning and collaboration behaviour. Such effects are summarised as behavioural additionality (Wanzenböck et al., 2013; Gök, 2010). So far, little is known about cluster policies' effects on these.

The present study seeks to fill this gap by assessing the short- and long-term effects of a specific cluster policy. More precisely, we focus on the policy impact on the structure of regional networks, as these are known to be key determinants of cluster innovation performance and long-term development. Yet, the lack of knowledge about policy effects on these crucial relational structures turns collaboration- and network-oriented support schemes into a 'shot in the dark'. First, it is usually unclear how cluster networks actually look and what their potential 'deficits' might be (Vicente, 2017). Second, so far, researchers and policymakers have only speculated about policy impacts on their structures and functioning.

By looking at the German BioRegio contest, we explore whether this prominent example of an industry-specific and region-focused cluster policy significantly altered regional innovation activities and the structure of local knowledge networks. We employ a common approach by approximating innovation activities with patent applications and using that data to construct (knowledge) networks of co-invention and co-application. Moreover, we evaluate the development of regions supported by the BioRegio initiative over time and compare them with regions that were not subject to this policy.

In line with much of the existing literature, our findings reveal a positive effect of the BioRegio initiative on the size of regional networks. However, this effect has not been sustainable; the level of innovation activities dropped substantially in the years after the program's end. A noteworthy structural effect during the BioRegio funding period was on network centralisation. This seems reasonable since, during the application phase, cluster initiatives must rely on some key actors who will then also be better embedded in research and knowledge networks. In the case of BioRegio, we also suspect that the creation of coordination offices contributed to this development. In general, the impact of the BioRegio contest is rather moderate and restricted to individual measures in cases of network cohesion. Notably, for the periods after the program, we observe a larger share of actors in the main component in the winner regions, but a lower mean degree in the respective inventor networks.

When comparing the effects of the BioRegio program with those of general project-based R&D subsidies in the field of biotechnology, we find it quite striking that the latter appear to be more effective and robust in their positive effects on network cohesion. Moreover, our empirical assessment reveals a substitutive relationship of the BioRegio initiative with general project-based R&D subsidies. Put differently, the effects of BioRegio on regional networks are relatively similar to those of general project-based subsidisation schemes, albeit somewhat less impactful.

However, our study might understate potential indirect effects on network cohesion of the

BioRegio initiative. As noted above, BioRegio had positive effects on the size of the networks. At the same time, we observe that larger applicant networks are also more cohesive in terms of mean degree, connectedness and share of actors in the main component. Accordingly, the success of the policy in terms of activating research and innovation potentials might have had some benefits on network cohesion through the back door. Nevertheless, this impact did not alter regional networks in a lasting manner since network growth decreased and even turned negative after the end of the funding period.

Of course, our study has several limitations that must be addressed. Foremost, these concern the use of patent data. The limitations of patent data have been discussed at great length (e.g. Griliches, 1990). Usually, this criticism states that patents do not fully reflect all innovation activities (Ejermo, 2009). In the context of the present paper, the primary criticism is rather about their limited ability to reflect all regional knowledge-related interactions since we exclusively observe those relations that resulted in patented innovations. As such, our study should be viewed as complementary to others, especially qualitative studies on system level effects of cluster policies. Notwithstanding the need for alternative data in future studies, we point out that to influence our results, patent-based knowledge networks in the BioRegions would have to be structurally different from those in the other regions. To be more precise, the relationship between our information on policy support and the structural network characteristics would need to be subject to systematically different patenting behaviour in these regions. We do not see any good reason for the existence of such a systematic difference. The second issue concerns the funding information. Since we exclusively rely on data from national programs, we cannot rule out (collaborative) research grants having been provided by the EU or by the subnational level of the German federal states. For example, we know from comparable programs that there were cases in which state-level funding jumped in to substitute for unsuccessful applications at the national level, or that clusters received funding from both the federal and the state levels (Rothgang et al., 2017a). However, most EU programs focus on supporting interregional collaboration, which only indirectly impacts regional networks, if at all. Consequently, considering them would be unlikely to alter our findings. This cannot be said about state-level funding, but unfortunately, there is no coherent and encompassing information currently available on such support schemes in Germany.

Third, one can argue against our assumption of using seven-year windows in the construction of regional knowledge networks. We employed other specifications, such as five-year moving windows without observing significant changes in the results. Of course, any assumption about link dissolution is debatable, but given the nature of the links, i.e. inventors and applicants who collaborated on a patented invention, we strongly believe that such relations last for several years.

Finally, our analysis concentrates on a very specific cluster policy, the BioRegio contest. It is well known that variations in policy designs do greatly shape their effects (Cunningham et al., 2016). Future studies are needed to validate our findings for other cluster-policy initiatives. These studies may then be able to identify the specific features of these programmes (e.g. selection process, information provision in calls, programme requirements) that determine their influence on cluster networks.

Nevertheless, despite these limitations, our findings cast some doubts on the distinctiveness of the impact of the BioRegio initiative on regional networks. The currently commonplace project-based R&D subsidisation programmes at the federal level seem to be of similar, if not stronger, relevance. For the future, we believe that it is crucial to start investigating what type of network failures are actually present in innovative regions (if any) before designing policies that seek to fix them. Otherwise, cluster policies that address network 'failures' remain well-intended, but also qualify as 'shots in the dark'.

A IPC classes

For the biotech patents, we rely on the OECD definition according to the following IPC classes: A01H1/00, A01H4/00, A61K38/00, A61K39/00, A61K48/00, C02F3/34, C07G11/00, C07G13/00, C07G15/00, C07K4/00, C07K14/00, C07K16/00, C07K17/00, C07K19/00, C12M, C12N, C12P, C12Q, C12S, G01N27/327, G01N33/53*, G01N33/54*, G01N33/55*, G01N33/57*, G01N33/68, G01N33/74, G01N33/76, G01N33/78, G01N33/88 and G01N33/92 (Van Beuzekom & Arundel, 2009).

B Tables

Table 5: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Vcount.app	—	0.98***	0.10*	0.22***	0.38***	0.76***	0.51***	-0.10*	0.19***	0.33***
(2) Vcount.inv	0.00	—	0.09*	0.23***	0.42***	0.73***	0.51***	-0.14**	0.15***	0.27***
(3) Teamsize.inv	0.06	0.08	—	0.49***	0.23***	0.08	0.18***	0.26***	0.25***	0.28***
(4) Teamsize.all.inv	0.00	0.00	0.00	—	0.31***	0.14**	0.20***	0.51***	0.33***	0.41***
(5) BioRegion	0.00	0.00	0.00	0.00	—	0.37***	0.56***	0.02	0.00	0.00
(6) RD.funds.Bio	0.00	0.00	0.13	0.01	0.00	—	0.43***	0.03	0.16***	0.21***
(7) BioRegio.funds	0.00	0.00	0.00	0.00	0.00	0.00	—	-0.06	-0.02	0.10*
(8) East	0.05	0.01	0.00	0.00	0.70	0.55	0.22	—	0.00	0.00
(9) AfterBioReg	0.00	0.00	0.00	0.00	1.00	0.00	0.66	1.00	—	0.83***
(10) year	0.00	0.00	0.00	0.00	1.00	0.00	0.05	1.00	0.00	—

Note: correlation coefficients in the upper triangle, p-values in the lower.

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