Policy Influence in the Knowledge Space: a Regional Application

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Abstract

Cluster policies aim at improving collaboration between co-located actors to address systemic failures. As yet, cluster policy evaluations are mainly concerned with effects on firm performance. Some recent studies move to the system level by assessing how the structure of actor-based knowledge networks is affected by such policies. We continue in that direction and analyze how technology-based regional knowledge spaces are shaped by the introduction of a cluster policy. Taking the example of the German BioRegio contest, we examine how such knowledge spaces in winning and non-winning regions evolved before, during and after the policy. Using a difference-in-differences approach, we identify treatment effects of increased knowledge space embeddedness of biotechnology only in the post-treatment period. Our findings imply that cluster policies can have long-term structural effects typically not accounted for in policy evaluations.

Keywords: BioRegio contest; network analysis; knowledge space; difference in differences; patents

JEL Classification: O31; O38; R11

1 Introduction

Cluster policies are a popular instrument of regional innovation policy, often implemented to deal with so-called systemic failures by establishing and fostering interaction between innovative agents. Despite their systemic nature, most evaluation studies focus on policy effects on individual firms, thereby treating them similar to other types of R&D subsidies. These studies typically identify positive effects on R&D inputs while results on innovation-related outputs are more mixed (Mar & Massard, 2021).

Since clusters are composed of a variety of actors and organizational types, including not only firms but also universities, research centers and research services, a focus solely on the effects on firms poses unjustifiable limitations to their analysis. In addition, policy effects on the composition and structure of relations within a cluster are often overlooked and pose a substantial challenge for cluster policy evaluation (Uyarra & Ramlogan, 2012). Because of the variety of policy targets and complex interactions of different instruments within cluster policies, several scholars call for wider and more systemic evaluations (Mar & Massard, 2021; Rothgang et al., 2021). A few recent studies tackle these shortcomings of the field and apply social network analysis (SNA) to understand how policy affects the overall structure of relationships between different actors (Giuliani et al., 2016; Töpfer et al., 2019; Graf & Broekel, 2020; N'Ghauran & Autant-Bernard, 2020). While cohesive networks have been identified as drivers of innovation-based economic development of regions (e.g. Breschi & Lenzi, 2016), these studies provide only limited evidence for positive effects of cluster policies on network cohesion.

Another important structural feature of regions which has been associated with economic development is the knowledge space (Kogler et al., 2013). The knowledge space is a network of interrelated technologies that can help us understand the structures and characteristics of regional knowledge capacities, i.e., it is a representation of the regional knowledge base. Its structure is considered important for the regional creation and accumulation of knowledge and has been used for comparing the technological structure and evolution of regional innovation systems (RIS) (Kogler et al., 2013; Boschma et al., 2014; Balland et al., 2015). The knowledge space and the related product space shape the direction of change in innovative activities. These spaces set constraints by indicating if required competencies for the development of specific technologies are present in a region, and they create technological opportunities by revealing potential for new knowledge recombinations (Malmberg & Maskell, 1997; Sonn & Storper, 2008). As such, they are considered important determinants of economic development and growth (Hidalgo et al., 2007; Hausmann & Klinger, 2007). Given that many innovation-oriented cluster policies have a technological focus, we expect that such policies are able to shape and redirect the knowledge space of regions to open new technological pathways. However, to our knowledge, this concept has not been used to understand the effects of a cluster policy.

Within the variety of cluster policies, we relate to the innovation-oriented cluster policy which focuses its support on collaborative R&D activities within selected regions. The main goal of such policies is to increase innovativeness and competitiveness of the supported clusters, the regions where they are located or even of the national economy. The main instrument to achieve this goal is to stimulate collaborative, innovation-related activities in more or less precisely defined industries or technology fields. As such, the effects of such policies should show in the structure of the knowledge space. Supported fields of activity should increase their visibility and importance within the knowledge space by either creating or intensifying links within the field itself (along existing trajectories) or by creating links with previously unrelated fields (cross-fertilization). A greater impact on the whole economy or innovation system is to be expected when technological relations with other fields are established and enforced, indicating a broad diffusion of the technology and its applications.

In order to analyze how cluster policies shape the knowledge space, we focus on the German BioRegio contest. This program was implemented when Germany was lagging behind the United Kingdom and the United States in the development and commercialization of biotechnology (Cooke, 2001). The German federal government and local authorities started to develop initiatives to try to close this gap; one of them was the BioRegio contest (Dohse, 2000). There were 17 regions that applied for this program, and four of them won the contest. The program, whose main aim was identifying and strengthening clusters that were already performing well in biotechnology, started in 1997, and funding ended in 2005 (Dohse, 2000).

Other goals of the BioRegio contest were to increase collaboration among existing actors, to support entrepreneurial activities in the field of biotechnology and to combine biotech with other, previously unrelated technologies (Dohse, 2000; Dohse & Staehler, 2008). The latter goal is an important aspect for our analysis, since new combinations between different technological fields enable cross-fertilization effects and change the shape of the knowledge space. We look at these changes in order to evaluate the impact of the BioRegio contest on the regional knowledge space.

We track the evolution of biotech in all 17 regions during and after the policy and expect these technologies to become more central and more connected to other fields. Our results show that the BioRegio contest contributed to an increase in the importance of biotechnology in the four winning regions in terms of connectedness with other fields and importance in the knowledge space. The effect is visible after the policy ceased its funding period. Also, we find that in the post-treatment period, biotechnology in winning regions experienced higher growth than biotechnology in the non-winning regions.

We proceed as follows. In Section 2, we review the literature on clusters, cluster policies and knowledge spaces. We introduce the BioRegio contest in Section 3 and provide a descriptive analysis of changes in regional knowledge space in Section 4. Section 5 presents the econometric approach along with a description of the variables, in particular, betweenness centrality as our measure of knowledge space embeddedness of a technology. Section 6 presents the main results of the difference-in-differences approach and Section 7 concludes.

2 Literature Review

2.1 Clusters and knowledge diffusion

To understand why policy makers are so interested in clusters and why they decide to intervene and support them, we should first define the benefits associated with agglomeration externalities and the clustering concept. Marshall (1890) proposed three different types of agglomeration externalities that arise in environments with specialized industries in the same location: the accessibility to a market with high skilled workers, the availability of auxiliary and supporting activities (technological and knowledge spillovers) and the presence of companies specialized in different phases of the production chain (Martin & Sunley, 2003, 1996).

A revived interest in clusters followed Porter (1990), who proposed a neo-Marshallian cluster concept in his work on international competitiveness. He argues that although the phenomenon of globalization should reduce the importance of local agglomerations, this is not the case. On the contrary, the competitive advantages of international markets are realized locally (Porter, 1998). This is where the proper milieu is formed, characterized by a concentration of elements necessary for creating a competitive advantage (highly specialized knowledge, institutions, competition, cooperation and customers with specific needs). Despite the popularity of Porter's view, there is no consensus on the definition of a cluster (Martin & Sunley, 2003; Duranton, 2011). As noted by Martin & Sunley (2003), the past decades saw economic geographers develop many similar concepts, such as "industrial districts" (Markusen, 1996), "network regions" and "learning regions," which results in ambiguity around the concept of clusters.

There is a broad discussion in the literature about the advantages of being located within a cluster. Several studies point out how firms benefit from the unique mix of collaboration and competition, as well as from complementary goods or technologies present in the region (Porter, 1998, 2000; Belleflamme et al., 2000). In their study on innovative activities in the UK, Baptista & Swann (1998), show that firms located in clusters (high regional employment in own sector) are more innovative. Beaudry & Breschi (2003) show that firms have tangible benefits only if other companies in the same location are innovative themselves. Audretsch & Feldman (1996), studying selected industries and states in the US, find that innovative activities tend to cluster, especially in the early stages of the industry life cycle. They provide evidence of a dispersion of innovative activities during later stages and argue that this is because of a lock-in situation where new space is necessary to develop new ideas. Delgado et al. (2014) show how industries thrive in strong clusters experiencing high employment and increasing in patenting activities. Furthermore, they highlight how the initial endowment (in terms of occupation and patenting activity) positively influences industry development within a region.

Research on clusters then moved beyond the Marshallian conceptualization of knowledge spillovers. One of the strongest criticisms of this view is that it is not sufficient to be located in the same geographical space to benefit from knowledge externalities for innovation. Firms inside a cluster do not equally benefit from knowledge embedded in the region; knowledge is not simply "in the air" (Giuliani & Bell, 2005). To acquire external knowledge, firms need specific characteristics (e.g., the right cognitive distance) as well as the right connections (Boschma, 2005). Therefore, researchers shifted their attention to studying the relationships among the actors within clusters to understand their innovative capacities and performance (Boschma & ter Wal, 2007). Research on clusters and regional innovation has thus been complemented by aspects of the structure and evolution of innovation networks (Koo, 2005; Cantner & Graf, 2006; Giuliani & Bell, 2005, 2008). These ideas also entered the policy realm by an increased support of collaborative activities in innovation policy (Broekel & Graf, 2012; Cantner & Vannuccini, 2018).

2.2 Cluster policies

Policy makers support clusters on national, regional and local levels (Kiese, 2019; Sternberg et al., 2010). Frequently building on Porter's cluster concept, these policies have an increase in competitiveness of the region or nation as their ultimate goal. An intermediate goal to achieve competitiveness is an increase in innovation by means of supporting R&D, collaboration and network formation to facilitate knowledge spillovers. Such innovation-oriented cluster or network policies are justified from different perspectives (see, e.g., Cantner & Vannuccini, 2018; Graf & Broekel, 2020, for more detailed discussions). First, networks are known to drive the economic and innovation performance of organizations and regions (Breschi & Lenzi, 2016; Broekel, 2012; Fornahl et al., 2011). Second, funding of collaborative R&D to support network formation is quite simple to implement in existing funding schemes (Broekel & Graf, 2012) and has been shown to lead to behavioral additionality (Wanzenböck et al., 2013; Lucena-Piquero & Vicente, 2019). Third, system or network failures reduce interorganizational knowledge access and exchange because of intermediation, complementarity and reciprocity problems (Cantner et al., 2011; Cantner & Vannuccini, 2018; Lucena-Piquero & Vicente, 2019).

Cluster policies are rooted in a variety of policy fields, such as science and technology policy, industrial policy and regional policy (Sternberg et al., 2010). Therefore, they come in various forms and can show a wide set of design features (Hospers & Beugelsdijk, 2002, p. 382). Cluster policies focus on actors when their goal is to provide support to specific groups of actors, such as SMEs, start-ups or science industry relations. If the aim is to support specific industries (industrial policy) or technologies with high potentials and expected impact (GPTs, climate change mitigation), theme-related characteristics are of relatively greater importance. As with innovation policy, we can distinguish between technology-specific and unspecific measures in cluster policy. Take, for example, two prominent cluster policies in Germany. The BioRegio contest was focused on promoting biotechnology (and was therefore technology-specific), whereas the subsequent Leading-Edge Cluster Competition was open to all types of technologies and industries (Rothgang et al., 2017; EFI, 2017). In both cases, clusters were selected by an independent jury who took into account the capabilities and experience of actors, their past and future interactions and the type of knowledge or technology to be created. Moreover, the program directors and the jury valued or even expected interdisciplinary approaches and visions regarding the cross-fertilization between related fields to open new technological pathways. For example, Bioinstruments Jena was selected for its innovative coupling of organic chemistry and microbiology with optics and instruments. Therefore, a combination of actors with diverse capabilities and technological backgrounds with a "optimal" level of cognitive proximity could be considered an asset.

The popularity of cluster policies attracts much research on their effects and consequences. According to Mar & Massard (2021), there is ample evidence for positive effects on R&D inputs while results on innovation-related outputs are mixed or inconclusive. Typically, such evaluation studies focus on the economic and innovative effects on single firms (Nishimura & Okamuro, 2011; Broekel et al., 2015; Mar & Massard, 2021) or on regional aggregates (Engel et al., 2013). However, a cluster consists not only of firms but of a variety of actors with different characteristics, as well as the relations between them. In fact, the performance of a cluster is based on how the different actors interact and not on how the single elements perform (Andersson & Karlsson, 2006). Recently, a number of studies tried to fill this gap by applying social network methods within cluster policy evaluation (Giuliani et al., 2016; Töpfer et al., 2019; Graf & Broekel, 2020; N'Ghauran & Autant-Bernard, 2020). Some of these studies indicate that there are short-term intended effects of cluster policies on cohesion in actor networks, but they also point out limited long-term effects and partly unintended structural effects, such as an increase in network centralization (Töpfer et al., 2019; Graf & Broekel, 2020). In contrast to the actor level, we know very little about the cluster policy effects on the direction of technological development. Given that technological innovations are one of the core goals of cluster policy and that politicians strive to become more proactive in terms of the direction of innovation (Cantner & Vannuccini, 2018; Kattel & Mazzucato, 2018), we should also be more interested in effects on the technology dimension.

2.3 Adding the knowledge space to cluster policy evaluation

One of the possible methods to measure knowledge generation over space and time (to map the knowledge space) is to use the concept of relatedness. This method allows calculation of "proximities" between different technologies to give a sense of how knowledge in a particular area (that could be a nation, a region or a city) is connected (Kogler et al., 2013). The concept of relatedness is not new; in fact, it was already present in the innovation literature in the 1980s and 1990s, where it was used to demonstrate the relevance of knowledge spillovers (Rosenberg & Frischtak, 1983; Carlsson & Stankiewicz, 1991). In particular, Pavitt (1984) and Jaffe (1989) argue that innovation is favored by connections between different fields of knowledge. Teece et al. (1994) show how the knowledge base of a firm is linked to the portfolio of technologies it owns. Breschi et al. (2003) use patent data to understand how firms diversification into related technologies affects their performance.

Hidalgo et al. (2007) and Hausmann & Klinger (2007) were pioneers in studying the concept of relatedness using international trade data to understand the "proximity" between exported products among different countries. Their methods allow them to predict countries' future export specialization into related products based on its existing capabilities. Subsequent studies followed this approach and adapted it to the regional level (Boschma et al., 2012; Neffke et al., 2011; Quatraro, 2010; Kogler et al., 2013; Boschma et al., 2014; Balland et al., 2019). Kogler et al. (2013) analyzed the knowledge space of the US and identified systematic differences between cities in terms of knowledge space structure and evolution. For example, relatedness in small cities is higher than in large cities, and higher levels of relatedness indicate higher growth in knowledge production. Boschma et al. (2014) look into the drivers of technological evolution in US cities and find that entry of a new technology in a city is more likely if it is related to existing technologies, while the exit probability declines with increasing relatedness. However, cities with a diverse knowledge space that is proximate to technologies outside their fields of comparative advantage seems to have benefits in terms of higher resilience in phases of technological downturn or crisis (Balland et al., 2015). From these studies, it follows that an expansion of the knowledge space is easier to accomplish if it includes technological fields that are related to the region's existing competencies, thus strengthening its performance.

Despite this evidence on the relevance of the knowledge space for regional development, we know little about policy effects on the knowledge space. In particular, cluster policies, with their focus on actors with specific technological competencies, should affect the structure of the knowledge space. We expect that supported fields of activity increase their visibility and become more important within the knowledge space by either creating and/or intensifying links within the field itself (along existing trajectories) or by creating links with previously unrelated fields (cross-fertilization). In the case of BioRegio, one of the aims was to create bridges between biotech and other technologies (Dohse, 2000; Staehler et al., 2007). Thereby, regions should increase their capabilities to create new applications and a wider diffusion of the technology. Against this background, we assess whether the policy met these expectations, and more importantly, we provide a framework that might be used for other cluster policies.

3 The BioRegio Contest

To analyze if cluster policies have the ability to reshape the knowledge space and change its technological trajectory, we focus on the German BioRegio contest. In the 1990s, Germany was said to be lagging behind other leading countries (such as the US or the UK) in the development of a biotechnology industry (Cooke, 2001). There were some institutional barriers that prevented the formation of a biotechnology industry in Germany. In particular, there was a low number of companies that were performing biotechnology research, a weakly developed venture capital market and governmental barriers connected to the regional support of biotechnology (Krauss & Stahlecker, 2001). Therefore, the German federal government started to develop initiatives to try to reduce the gap, with the BioRegio contest being one of them (Dohse, 2000; Kaiser & Prange, 2004; Dohse & Staehler, 2008). The main aims of this and subsequent policies was to stimulate the development of life science clusters, increase the number of biotech start-ups, enhance the performance of existing biotech firms, support the supply of venture capital and improve the acceptance of biotechnology in the population (Eickelpasch & Fritsch, 2005; Champenois, 2012). Another focal objective was to combine biotechnology with other technologies in novel ways (Dohse, 2000; Dohse & Staehler, 2008). In fact, this last aspect is an important motivation for our analysis, since the creation of new combinations between different technological fields is a driver of knowledge space evolution.

BioRegio was a competitive program, encouraging proposals from different local authorities that could meet these objectives. Submissions should highlight the core characteristics of the respective region and how the network structure could support the achievement of the set objectives (Müller, 2002; Dohse, 2000; Dohse & Staehler, 2008). The evaluation of the projects was performed by an international jury of scientists, representatives of labor unions and industry. The selection criteria for project assessment were the following (Dohse, 2000; Staehler et al., 2007):

- number and size of firms oriented to biotechnology already present in the region;
- number, characteristics and productivity of research facilities and universities in the region;
- ways in which different biotech research branches interact in the region (networking characteristics);
- supporting services (patent offices, information networks and consultancy);
- explanation of the possible strategies to convert biotechnology know-how present in the region into new products, processes and services;
- offer of help on a regional level to support biotechnology start-up activities;
- provision of financial resources through banks and public equity to economically support biotechnology firms;
- cooperation among clinical hospitals and biotech research institutes regionally;
- approval of new experiments and new facilities by the regional authorities through a smooth process.

The regional boundaries were not predefined by the application call (there was no exact indication about the composition of the consortium). Instead, local authorities could decide autonomously which regions to include in their applications (Champenois, 2012). Nevertheless, geographic proximity played a substantial role, and the core actors were all located in close vicinity (Engel et al., 2013). The regions that participated are very different in terms of population. For example, the most populated region (Berlin-Brandeburg) has a population of 6 million inhabitants, while the smallest one (Jena) has only slightly more than one hundred thousand. Some applicants are single cities, while others are larger areas which include several cities (Dohse, 2000).

Overall, 17 regions submitted proposals and three of them won the contest: Munich, Rhineland (Cologne, Aachen, Düsseldorf and Wuppertal) and the Rhine-Neckar triangle (Heidelberg, Mannheim and Ludwigshafen). A special vote was given to Jena because of its specialization in Bioinstruments and as the best proposal from an East German region (Dohse, 2000; Graf & Broekel, 2020). Funding was provided from 1997 to 2005 (Staehler et al., 2007). The three winning regions received support from the BMBF with 25 million EUR each and Jena was supported with 15 million EUR in public funds (Engel et al., 2013). Due to its success, this innovative approach towards clusters inspired other BMBF policy initiatives, such as: InnoRegio, BioProfile, Leading Edge Cluster Competition and InnoProfile (Dohse & Staehler, 2008; Eickelpasch & Fritsch, 2005; EFI, 2017).

Several studies evaluate the BioRegio contest and identify, in general, positive developments according to various indicators, such as short-term R&D activity, venture capital funding, firm births, employment growth and reputation effects (Staehler et al., 2007; Dohse & Staehler, 2008; Engel et al., 2013; Graf & Broekel, 2020). In contrast, Engel & Heneric (2008) find that BioRegio participant regions which were not successful in the contest outperform winning regions in terms of changes in the number of newly founded biotech firms during the funding phase. The few studies that test for long-term effects of BioRegio on innovation activity or innovation networks find mixed or inconclusive evidence (Engel et al., 2013; Graf & Broekel, 2020). One of the reasons for the difficulty of identifying long-term effects is that subsequent biotech-related programs, such as BioProfile on the national level, or funding by the EU and regional governments, had effects on a broader set of regions, which might be included in the control groups of the respective studies. Given that we do not have access to funding data for all levels of government, the present study suffers from the same limitation. However, if untreated regions benefit from such unobserved policies, that should lead to an underestimation of the observed policy effects.

4 Biotechnology in Regional Knowledge Spaces

4.1 Patents and regions

We use PATSTAT (Autumn 2017) as our primary source to detect innovative activities. The International Patent Classification (IPC) on the 4 digit level (IPC4) is used to distinguish between the different technologies. We adopt the OECD standard classification of biotechnology (Van Beuzekom & Arundel, 2009) to identify IPC4 classes as biotechnology[1].

Since patents are associated with different technological domains, they have proven to be a valuable source of information in capability-based research (Breschi et al., 2003; Kogler et al., 2013; Boschma et al., 2014; Balland et al., 2019; Whittle & Kogler, 2019). Their documentation

[1] At the IPC 4 digit level, these are A01H, A61K, C02F, C07G, C07K, C12M, C12N, C12P, C12Q, C12S and G01N.

is highly standardized so that they allow for dynamic analyses over long periods on various levels of aggregation. However, patents also have several well-known limitations (see Griliches, 1990, for an overview). Patent analyses are limited to inventions that can be patented so that they miss many non-patentable inventions, in particular in industries with a lower propensity to patent, such as software or services. Besides, our analysis relies on the patent classification system, and we assume that patents in the same IPC class are similar to each other but different from those in other classes. Since this classification is done by the patent offices for other reasons than this type of analysis, this might not hold true.

For the geographical boundaries of knowledge spaces, we assign each patent to a region if at least one inventor resides in that area (Cantner & Graf, 2006; Toth et al., 2020). The inventor-based approach is used because large companies or research institutes with many locations tend to file patents at their headquarters, which is not necessarily where the invention originates (Graf, 2017).

We consider Labor Market Regions (LMRs) for the regional boundaries. LMRs are aggregates of NUTS3 regions which are designed to account for commuting patterns. By choosing LMRs rather than NUTS3 regions, we better capture patents by inventors who reside in suburbs or rural areas and commute to their workplace in larger cities. There are 141 LMRs in Germany which comprise of cities with their surrounding areas. Our unit of observation are those LMRs where at least one city that won the BioRegio contest is located.

Figure 1 shows a map of Germany with the 17 regions that participated in the BioRegio contest. We distinguish between the four "winner" regions that were successful and received grants and 13 "non-winners" that did not proceed to the funding stage (Dohse, 2000). Since some applications were from networks of cities, LMRs do not always correspond to the areas affected by BioRegio. In those cases, we aggregated smaller LMRs into larger areas.

4.2 Mapping the knowledge space

To map the knowledge space, we consider patent applications from 1986 to 2014 in the winning and non-winning regions. This permits us to have enough time before and after the policy was running to assess its impact. To account for fluctuations of patent applications, we follow Boschma et al. (2014) and use five-year moving windows. For example, 1990 refers to the five-year period 1986 until 1990 and includes all patent applications filed during those years. This choice is motivated by the turbulence observed when using shorter periods, e.g., one year, especially in smaller regions. The nodes of the network are the IPC4 classes, while the edges based on the co-occurrence of IPC4 classes on patent applications, weighted according to their relatedness.

For measuring relatedness (the "proximities" among the different technologies present in the same space at the same time), we follow Basilico & Graf (2020) who use a two-step approach. In the first step, we calculate a co-occurrence matrix and assume that the more patents are assigned to two classes, the higher is their relatedness. To take into account that co-occurrences between highly frequented patent classes are more likely, we standardize co-occurrences and calculate relatedness between all pairs of IPC classes by using the Otsuka-Ochiai coefficient C_{ij} (Ochiai, 1957):

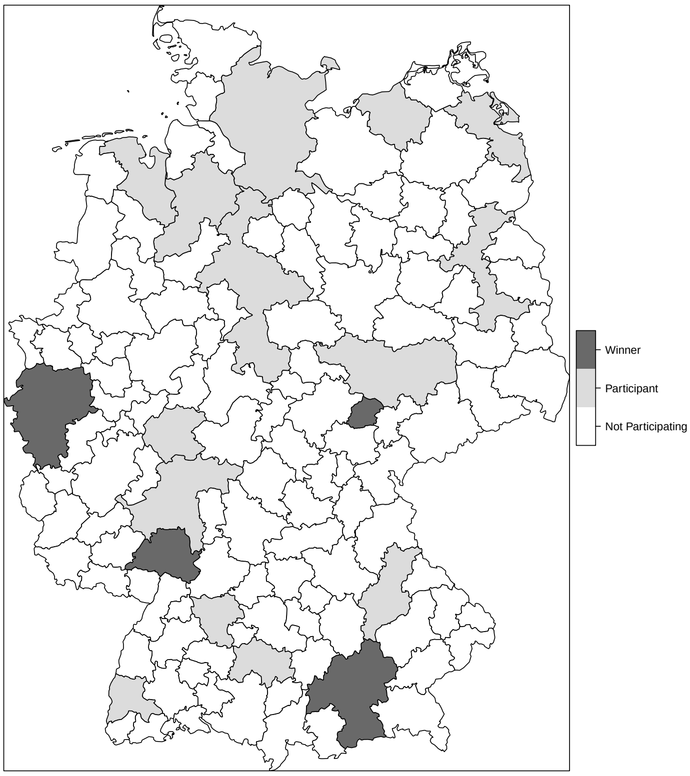


Figure 1: BioRegio Participants and Winners

$$C_{ij} = \frac{c_{ij}}{\sqrt{c_i \cdot c_j}} \tag{1}$$

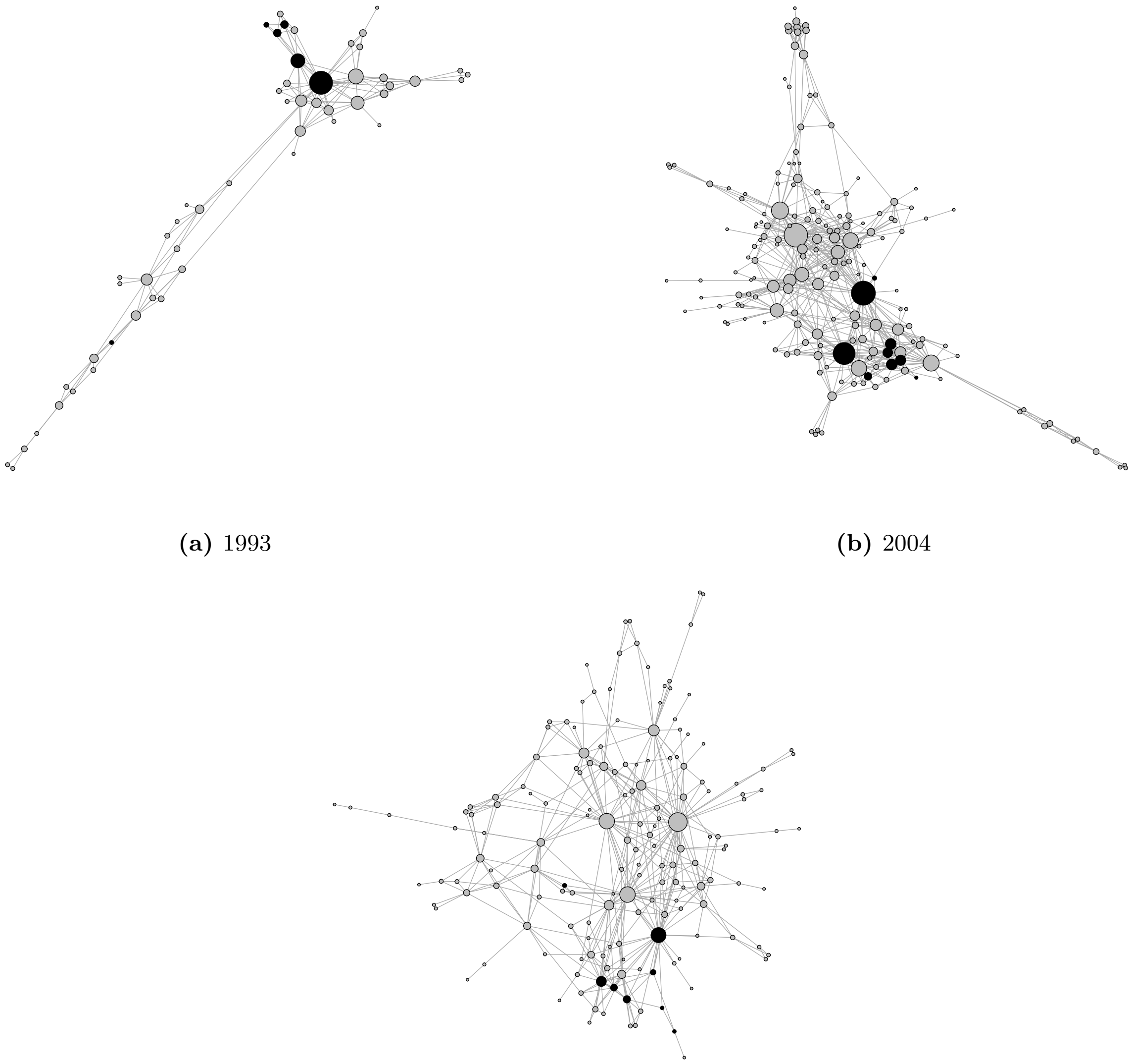
Where c_{ij} is the simple number of co-occurrences between two technologies (i and j), the square root of c_i and c_j represents the geometric mean of the size of the two technologies (occurrence of i multiplied by the occurrence of j). The index can vary between 0 (no overlap) and 1 (i and j always appear together).

In the second step, we compare these relatedness measures for each region (C^r_{ij} during one period) with the world (C^w_{ij} world for the same period).The world relatedness helps us to understand the degree to which the regional relatedness follows global trends. Thereby, we implicitly assume that if two IPC classes are combined frequently in the world, the likelihood that they are associated within any region increases.

The differences between the region (C^r_{ij}) and the world (C^w_{ij}) are used to map the knowledge spaces, i.e., they are the edges in the regional knowledge spaces for each period. In the case of a positive difference ($C^r_{ij} - C^w_{ij} > 0$), the region combines the classes i and j more frequently than expected from observing the world relatedness.

4.3 Relational embeddedness of biotechnology

To illustrate the evolution of the knowledge space in a BioRegio winner region, figure 2 shows the main components of Jena before, during and after the funding period. The black nodes are IPC4 classes identified as biotechnologies by the OECD. In general, the knowledge space of Jena increased in size over time, incorporating new technological sources. Biotechnology classes



(a) 1993

(b) 2004

(c) 2010

Figure 2: Main components of the Jena knowledge space before, during and after the BioRegio program. Node size is proportional to degree centrality with biotechnology IPC4 classes in black.

became central and well-embedded during the funding period. Afterwards, they maintained some connections with other classes of the knowledge space.

In the following, we provide descriptive statistics on the development of the number of connections in the regions that won the BioRegio contest. The most simple and straightforward way to measure embeddedness of biotech classes in the knowledge space is to take a purely relational view by calculating degree centrality[2]. Degree centrality of technology i is calculated by taking the sum of its relations with other technologies in the knowledge space of a specific region r in one period j (Freeman, 1978; Graf, 2017). We expect the biotech classes to interact more intensely and with other technologies in the knowledge space during and after the funding period.

To give a first impression, figure 3 shows the aggregate degree centrality for biotech classes

[2]Structural embeddedness, as measured by betweenness centrality, is addressed in section 5.

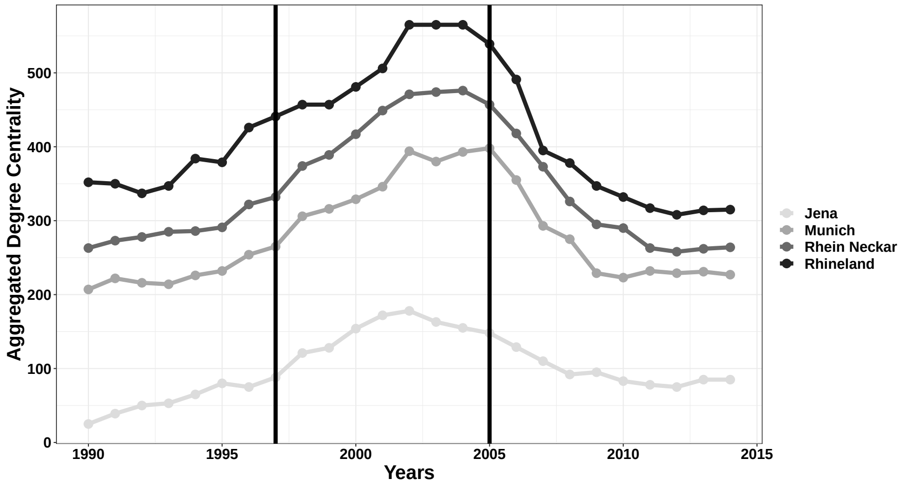


Figure 3: Aggregated degree centrality for biotech IPC4 classes in winning regions

in the four winning regions over time. To aggregate, we take the sum of the degree centralities calculated for each IPC4 class in biotech. The number of interactions with other classes increases during the funding period (1997-2005) and reaches its peak by the end of it in all winning regions. After funding ceases, there is a sharp decline of interactions, reaching levels below the end of the pre-funding period. While this supports our expectation of biotechnological classes becoming more embedded in the knowledge space of winning regions during the funding period, it contradicts our expectations for the post-funding phase.

For a more fine-grained analysis, we take a closer look at the newly formed linkages in the knowledge space. In order to aggregate not only the IPC4 classes belonging to the field of biotechnology but also all other fields, we use the classification by Schmoch (2008). In this classification, the IPC classes are grouped into 35 more broadly defined technology fields. In this way, we can count the number of IPC4 links established (or dissolved) between biotechnology and other fields. Figure 4 shows the number of new connections between biotech and the respective fields for each region during and post-funding (the technologies are ordered according to decreasing new connections during the funding period). New combinations are co-occurences between IPC4 classes that have not been combined previously in the respective region. The combinations with biotechnology classes in the pre-funding period are taken as reference to calculate the new edges created during the funding period. Regarding the post-funding period, both previous periods are taken together as a reference.

In line with our previous observation (figure 3), in all winning regions, most new combinations are established during the funding period. The variety of the technological classes combined with biotechnology in the four winning regions is wide. In Jena during the funding period, biotechnology establishes new connections mostly with *Organic fine chemistry* (14), *Medical technology* (13) and *Chemical engineering* (23). To observe *Medical technology* to be increasingly related with biotechnology is consistent with the focus of the projects in Jena on “Bioinstruments”. After funding, the classes with most new combinations with biotechnology in Jena are *Medical technology* (13), *Chemical engineering* (23), *Basic Materials, chemistry* (19) and *Audio-visual technology* (2).

In Munich, during the funding period, biotechnology is mostly combined with *Basic Ma-*

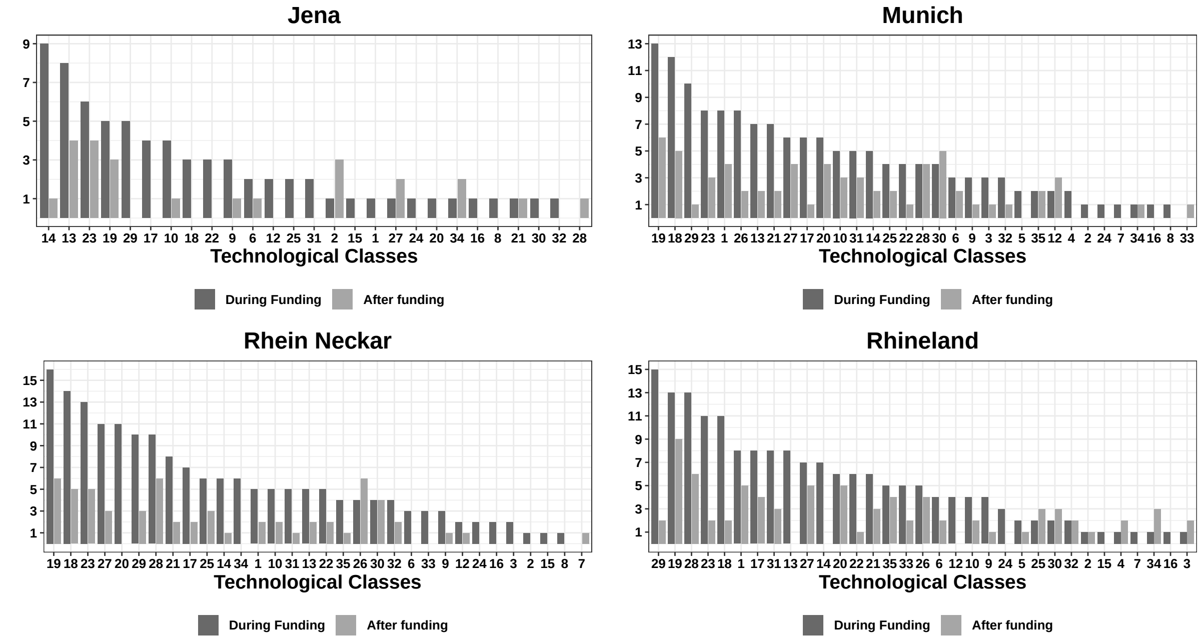


Figure 4: Number and type of new combinations with biotechnological classes created during and after BioRegio

terials, chemistry (19), *Food chemistry* (18) and *Other special machines* (29). While in the post-funding period the classes mostly combined with biotechnology are *Basic Materials, chemistry* (19), *Food chemistry* (18) and *Thermal processes and apparatus* (30).

The region Rhein Neckar during the funding period creates the highest number of edges with biotechnology in *Basic Materials, chemistry* (19), *Food chemistry* (18) and *Chemical engineering* (23). Whereas in the post-funding period, biotechnology is combined mostly with *Textile and paper machines* (28), *Machine tools* (26) and *Basic Materials, chemistry* (19).

Rhineland combines biotechnology in the period during the funding mostly with *Other special machines* (29), *Basic Materials, chemistry* (19) and *Textile and paper machines* (28). In the post-funding period the classes are *Basic Materials, chemistry* (19), *Textile and paper machines* (28), *Electrical machinery, apparatus, energy* (1), *Engines, pumps, turbines* (27) and *Materials, metallurgy* (20).

Figure 5 shows the technological classes that lost connections with biotechnology in the winning regions. Since there are 11 IPC4 classes in biotechnology according to the OECD classification, it might happen that some biotech classes show new combinations while others are less connected compared to the previous period.

In general, as already confirmed by figures 3 and 4, the number of interactions decreases in the post-funding period. Therefore, we observe an increase in combinations that do not exist anymore in the knowledge space of all winning regions. Another interesting result is that the technological classes that scored high in figure 4 during funding also score high in the period after funding, meaning that most of the new combinations created during BioRegio were not maintained after funding. This suggests that the effect on the structure of the regional knowledge space is limited to a short time span (at least in terms of the number of interactions with other technologies).

Figure 6 shows the number of classes in each technological field which were connected with

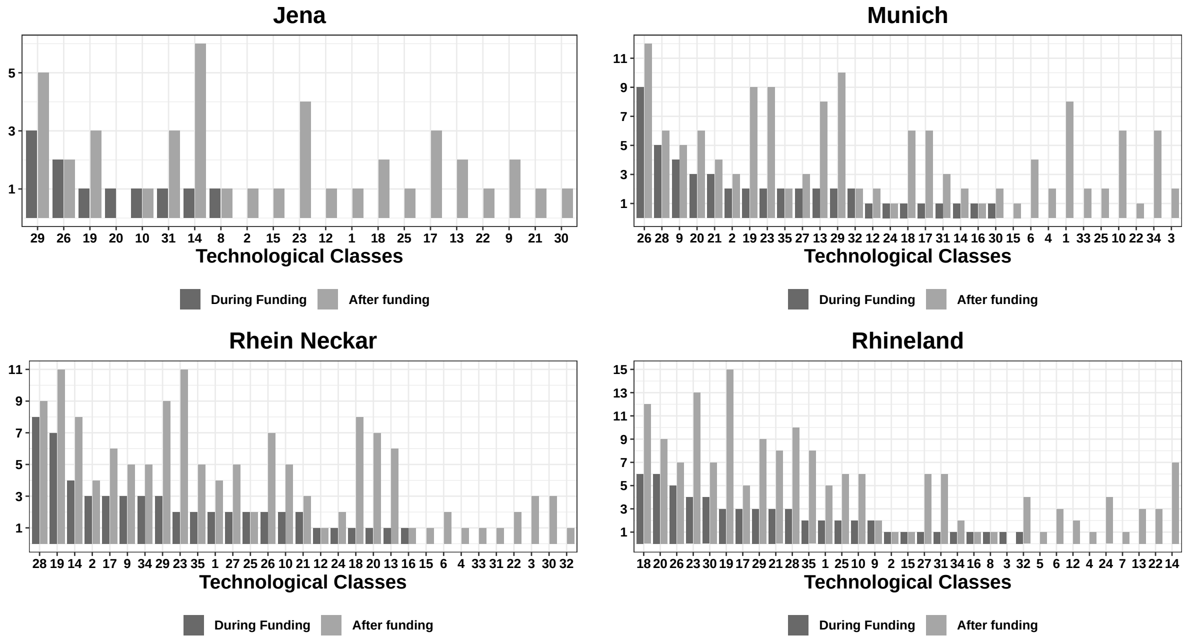


Figure 5: Number and type of combinations with biotechnological classes dissolved during and after BioRegio

a biotech class during the funding period but not anymore afterwards. It is interesting to observe that the classes with the highest numbers here are also the ones that established the highest number of connections in the considered regions (figure 4). As such, most of the edges established during the funding period disappeared afterwards. Apparently, these connections were not maintained over time and in terms of creating new interactions in the knowledge space so that BioRegio had only a short term effect.

For example, in Jena the classes *Organic Fine Chemistry* (14), *Chemical Engineering* (23) and *Macromolecular chemistry, polymers* (17) were among the classes with the highest number of new interactions with biotech classes during the funding period but lost many of these in the post funding period. Similar patterns can be observed in the other regions as well. For Munich it involves the classes *Basic materials chemistry* (19), *Electrical machinery, apparatus, energy* (1), *Medical Technology* (13), *Food chemistry* (18) and *Other special machines* (29). For Rhein Neckar it involves the classes 18, 19, *Materials, metallurgy* (20), 23, *Textile and paper machines* (28) and 29. Finally, for Rhineland it involves classes 18, 19, 23, 28 and 29. However, there are also exceptions, such as *Medical technology* (13) in Jena, which lost almost none of its new combinations. Since this is a fundamental class to be combined with biotech classes in Jena's proposal on "Bioinstruments", this suggests that the program had lasting effects in selected areas of the knowledge space.

5 Econometric Approach

5.1 Structural embeddedness: betweenness centrality

Complementing the descriptive analysis of the previous section, we assess the impact of BioRegio on the embeddedness of biotechnology in the knowledge spaces of regions with an econometric

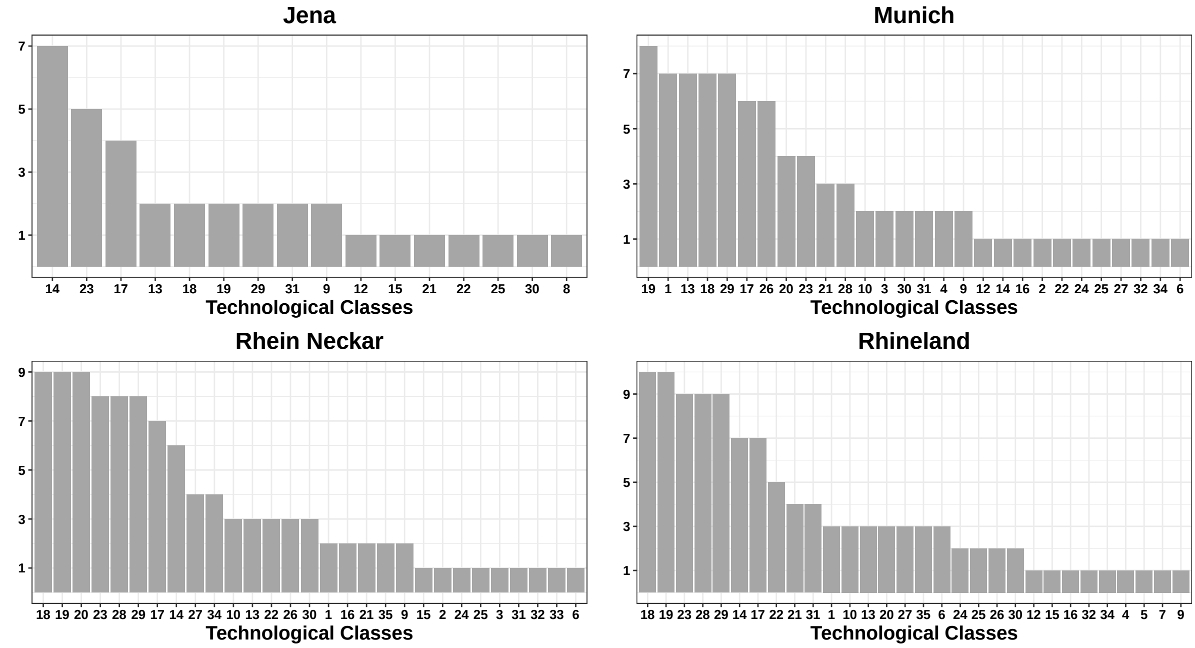


Figure 6: Number and type of combinations with biotechnological classes that are abandoned after the time when BioRegio was running

approach. We measure embeddedness with the betweenness centrality (BC) of each IPC4 class in the regional knowledge space. In contrast to degree centrality, which only considers the direct linkages, this network based statistic captures the bridging function of a technology by considering node positions in relation to all other nodes (Basilico & Graf, 2020). Because of its ability to capture the structural embeddedness, we use it as the dependent variable in the subsequently discussed difference in differences (DiD) approach.

Betweenness centrality measures the number of times that a node is in the shortest path between two other nodes in the knowledge space. Thereby, it captures the importance of a node for the overall connectedness of the network. A node with a high intensity relation to only one other node could score high on degree centrality even though it is unconnected to the rest of the network (Basilico & Graf, 2020). Betweenness centrality takes all indirect relations into account and if a node with high betweenness disappears, the knowledge space would be less connected. We therefore consider it more meaningful in the context of this analysis. Betweenness centrality of node i is defined by:

$$B_i^C = \sum_{j<k} \frac{g_{jik}}{g_{jk}}, \forall i \neq j, k \tag{2}$$

With i, j, k as distinct nodes, g_{jk} is the number of geodesics between j and k and g_{jik} is the number of geodesics between j and k passing through i (Wassermann & Faust, 1994)[3]. We use a weighted version of betweenness so that edges with high relatedness are shorter than edges with low relatedness (Basilico & Graf, 2020). Since we are interested in nodes that are important for the regional knowledge space, we only included the ones that have at least a score of 1, meaning that they are at least once on the shortest path between two other nodes.

[3]We calculate the node betweenness centrality with the igraph package for R (R Core Team, 2018; Csardi & Nepusz, 2006).

For the econometric analysis, we take the logarithm of betweenness centrality since the raw measure is highly skewed to the right (meaning there are many nodes with low betweenness and few with high so that the mean is shifted to the right of the distribution).

5.2 Estimation strategy

The difference-in-differences (DiD) approach is widely used in the literature to assess the impact of the introduction of a policy on some performance indicators. Our approach is based on two different regression models. In the first one, we assume that biotech was treated by the policy while other technologies have not, i.e., we assess if biotechnology became more embedded in the knowledge space of the winning regions relative to other fields. In this case, we compare betweenness among the biotech IPC4 classes with all non-biotech IPC4 classes. This analysis is performed only among the winning regions. The linear model is the following (the time index is dropped for readability):

$$\log B^C_{i,r\in W} = \beta_0 + \beta_1 Time + \beta_2 Bio_{i,r} + \beta_3 (Time \times Bio_{i,r}) + \gamma_i + \delta_r + \mu \qquad (3)$$

where $\log B^C_{i,r\in W}$ is the natural logarithm of betweenness centrality calculated for each IPC4 class (i) in all winning regions ($r \in W$), $Time$ is a dummy variable that takes value zero in the pre-treatment period (1990-1996) and value 1 in the post-treatment period (two different regressions for the time during and after BioRegio), Bio takes the value zero if the IPC4 class is not identified as biotechnology while it takes value one if it is, γ and δ are the control variables on the technology and regional level and μ represents the residuals.

In the second model, we assume that the policy treatment took place on the level of the region. Therefore, we compare betweenness of biotechnology classes within winning regions with betweenness in non-winning regions. With this regression, it is possible to understand if any trend of increased embeddedness of biotechnology identified by the model 1 is also present in other regions. If this should be the case, BioRegio would not have affected the transformation of the knowledge space of the winning regions, but there is rather a more general trend of higher bridging of biotechnology. The second model is the following:

$$\log B^C_{i\in B,r} = \beta_0 + \beta_1 Time + \beta_2 Winning_{i,r} + \beta_3 (Time \times Winning_{i,r}) + \gamma_i + \delta_r + \mu \qquad (4)$$

where $\log B^C_{i\in B,r}$ is the natural logarithm of betweeennes centrality calculated only on the IPC4 classes identified as biotechnology ($i \in B$) in all regions (r), $Time$ is a dummy variable that distinguishes between the pre-treatment period (before BioRegio) and the post-treatment period (for the time during and after BioRegio was running), $Winning$ is a dummy variable which is zero IPC4 classes in the non-winning regions and one for those that won the competition, γ and δ are controls and μ are the residuals.

In both models, a treatment effect is observed by the coefficient of the interaction term. By differentiating between policy effects during and after funding, we capture four different effects: biotech compared to non-biotech within winning regions and biotech in winning as compared to non-winning regions, each in the short and in the long run. As noted above, our dependent variable is calculated on a knowledge space based on patent applications during a five-year period. By using moving windows for smoothing, our approach might not be best suited to identify immediate policy effects. However, given the nature of the knowledge space and the policy, we think that this a more conservative and therefore appropriate approach.

Using patent data as described in section 4.1, we generate several variables for the whole period (1990-2014) at the level of the single IPC4 class in each region. Table 1 contains all variables used for the regressions along with short descriptions. Tables 2 and 3 present descriptive statistics of the subsets of these variables used in the respective regressions. Correlations are presented in tables 8 and 9 in appendix A.

5.3 Control variables

We control for several variables that might affect the position of a technology within the knowledge space. The first one is the log of the number of patents in an IPC4 class in one region in a specific period (*Log patents*). This variable is used to control for potentially disturbing effects of IPC4 classes with high patenting activity on the betweenness measure. Since there is a positive correlation between betweenness and the number of patents (0.59 in table 8 and 0.47 in table 9), the possibility that a node with more patents is central in the knowledge space is higher, but we are interested in the structural embeddedness induced by the policy beyond the size effect.

Avg Team Size measures the average number of inventors in each IPC4 class. For each patent, we calculate the number of inventors and take the average for each IPC4 class. There is a constant, general increase in the division of labor, which shows in more and larger teams in science and research (Wuchty et al., 2007). This trend might affect the number of interactions between different technologies since, with increasing the team size, there is more interaction among people with potentially different backgrounds. This could impact the structure of the knowledge space, with an increased number of interactions between different technological fields due only to a physiological increase in the team size and not due to the BioRegio program itself.

The third control variable is a dummy variable that distinguishes between regions located in East and West Germany (*East*). It takes value 1 for all observations from the East and 0 otherwise. This is important since, especially in the period after reunification, there was a big difference between patenting activities in the Eastern and Western part of Germany. West Germany had a higher research intensity and patented more than the East, and even though there are some high-patenting regions in the East, the process of catching-up is still ongoing. Since we cover the period right after reunification (1990-1996) as our pre-treatment period, we have to control for these structural differences.

The *Neighbour* dummy is one for all observations from non-winning regions that are neighbors of regions that won the contest. The regions that won the contest could have influenced indirectly other neighboring areas in their biotech patent production. Because of such spillovers, we should consider the possibility that an increasing betweenness centrality in one of the non-winning regions is due to funding in a neighboring area. In the literature, there is evidence that when a cluster is supported by a policy, then automatically the neighbors also indirectly increase the number of their relationships within the cluster (Delgado et al., 2014). This is mainly evidenced in the inventor/applicant clusters, but if there are more relationships and more patents on this level, then the technological space might also be influenced. For the nature of this variable, it

Table 1: Variables used in the regressions

Variable Name	Description	Regressions
	Dependent Variable	
Log Betweenness Centrality	Betweenness centrality logarithm measured on each node in the regional technological space	Both
	Independent Variables	
Time During BioRegio	Dummy variable that takes value one when the year is between 1997 and 2005	Both
Time After BioRegio	Dummy variable that takes value one when the year is between 2006 and 2014	Both
BioTech	Dummy variable that takes value one when the IPC class is a biotechnology according to OECD classification	First
Winning region	Dummy variable that takes value one when the node is from a winning region	Second
Interaction Term During BioRegio	Interaction term used for the DiD approach, takes value one only for the treatment group in the period between 1997 and 2005	Both
Interaction Term After BioRegio	Interaction term used for the DiD approach, takes value one only for the treatment group in the period between 2006 and 2015	Both
	Control Variables	
Log Number of Patents	Logarithm of the number of patents for each IPC class	Both
Avg Team Size	Average team size calculated for each IPC class	Both
East	Dummy variable that takes value one when the node is from a region in the former German Democratic Republic (GDR)	Both
Neighbor	Dummy variable that takes value one when the node is from a region sharing a common border with a winning cluster	Second

Table 2: Descriptive statistics for model 1 (table 5)

Variable Name	N	Mean	SD	Min	Max
	Dependent Variable				
Log Betweenness Centrality	28302	5.226	1.728	0.000	9.292
	Independent Variables				
Time During BioRegio	28302	0.378	0.485	0.000	1.000
Time After BioRegio	28302	0.374	0.484	0.000	1.000
BioTech	28302	0.028	0.164	0.000	1.000
	Control Variables				
Log Number of Patents	28302	2.810	1.284	0.000	7.336
East	28302	0.055	0.227	0.000	1.000
Avg Team Size	28302	1.693	0.617	1.000	9.167

is only used in model 2 where non-winning regions are present.

6 Results

6.1 Biotechnology compared to other technologies in winning regions

Figure 7 shows the total number of patents in the winner regions for each of the two groups considered as treatment (biotech IPC4 classes) and control (non-biotech IPC4 classes) groups in model 1 (table 5). It becomes apparent that both groups experienced an increase in the number of patents during the period when BioRegio was running. In the period after BioRegio, the number of filed patents declined for both groups. However, as pointed out above, to assess the policy effects on the knowledge space it is not sufficient to simply count the number of patents. It is not the amount of the innovative activity that determines the quality of a system. Instead,

Table 3: Descriptive statistics for model 2 (table 7)

Variable.Name	N	Mean	SD	Min	Max
	Dependent Variable				
Log Betweenness Centrality	2872	5.765	2.020	0.000	9.292
	Independent Variables				
Time During BioRegio	2872	0.380	0.485	0.000	1.000
Time After BioRegio	2872	0.365	0.482	0.000	1.000
Winning region	2872	0.273	0.446	0.000	1.000
	Control Variables				
Log Number of Patents	2872	3.698	1.510	0.000	7.602
East	2872	0.210	0.407	0.000	1.000
Neighbor	2872	0.191	0.393	0.000	1.000
Avg Team Size	2872	1.894	0.551	1.000	5.200

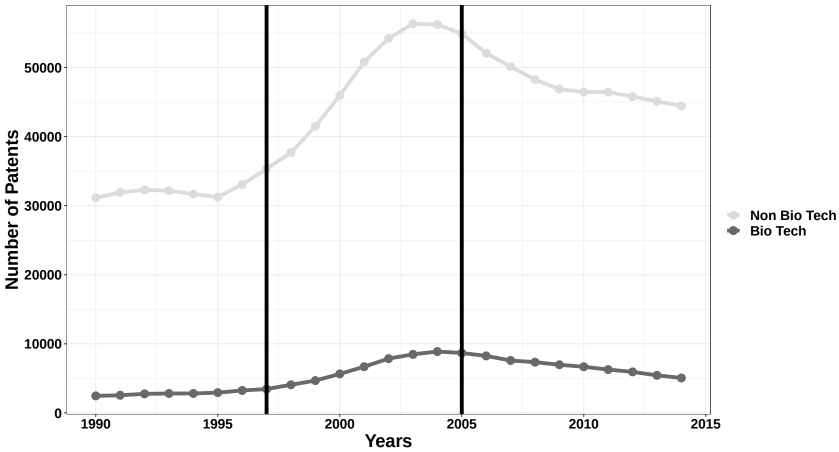


Figure 7: Number of patents (model 1 (table 5) for Biotech (treatment) and non-biotech (control) IPC4 classes)

it is the number and the quality of interactions among the elements of this network. Therefore, it is necessary to use measures able to evaluate the changes on the structure of the knowledge space over time.

Table 4 shows a mean comparison of the log betweenness centrality for the two considered groups. In addition to the means of both groups, their difference, the significance and the standard errors are shown for each considered year. It is important to note that the hypothesis of parallel trends in the pre-treatment period (fundamental condition for the DiD approach) cannot be rejected. The difference between both groups in the period before funding is marginal and not significant. However, a difference between the two groups starts to develop while BioRegio was running. The gap widens by the end of the considered period when it also becomes statistically significant.

Figure 8 shows the predicted values of log betweenness for treatment and control groups from the base-line model (considering only log $B^C_{i,r\in W}$ and $\beta_2 Bio_{i,r}$) for model 1. The graph adds support to the hypothesis of parallel trends in the pre-treatment period observed in table 4. The visual representation helps us to understand how the predicted values change over time, and we observe an increasing difference between the dashed (treatment group) and the solid (control group) lines. This indicates that BioRegio had a positive influence on the embeddedness of biotechnological classes in the knowledge spaces of the winning regions. In the post-treatment period, both curves show an increase in betweenness centrality. Since this might be related

Table 4: Mean comparison of log betweenness centrality. Treatment and control groups as in model 1 (table 5)

Year	Non-Biotech Mean	Biotech Mean	Difference	SE
		Pre-Treatment		
1990	5.344	5.341	-0.003	0.443
1991	5.277	5.253	-0.025	0.444
1992	5.293	5.252	-0.042	0.404
1993	5.281	5.394	0.114	0.415
1994	5.299	5.291	-0.008	0.424
1995	5.347	5.393	0.046	0.429
1996	5.320	5.081	-0.239	0.479
		During-Treatment		
1997	5.263	5.330	0.067	0.442
1998	5.248	5.453	0.205	0.340
1999	5.253	5.406	0.153	0.344
2000	5.104	5.528	0.424	0.325
2001	5.092	5.447	0.355	0.376
2002	5.047	5.378	0.331	0.382
2003	5.030	5.383	0.353	0.400
2004	5.053	5.531	0.478	0.406
2005	5.084	5.412	0.328	0.390
		Post-Treatment		
2006	5.179	5.718	0.54	0.368
2007	5.229	5.697	0.468	0.425
2008	5.227	5.822	0.595	0.415
2009	5.269	5.988	0.719.	0.379
2010	5.289	5.931	0.642.	0.377
2011	5.259	5.991	0.732*	0.328
2012	5.269	5.871	0.601.	0.330
2013	5.218	6.174	0.955**	0.348
2014	5.277	6.229	0.952*	0.381

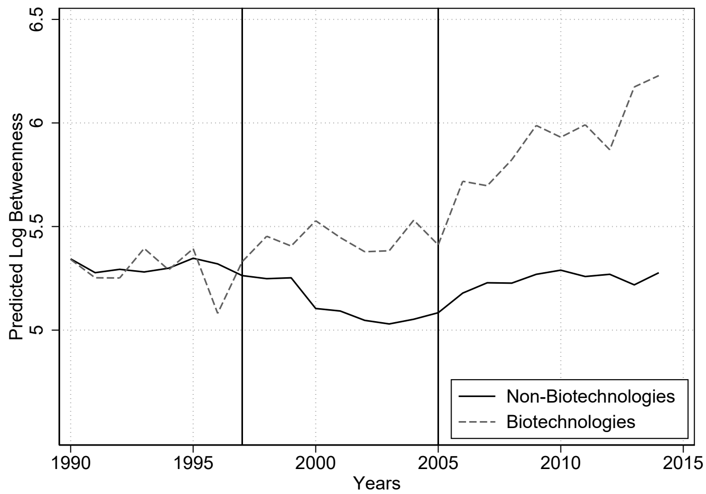


Figure 8: Fitted trends comparison for model 1

to the simultaneous decrease in the total number of patents, it is necessary to control for the number of patents in the subsequent regressions.

To test the influence of BioRegio on biotechnology embeddedness, we performed a classical DiD regression, i.e., a simple OLS with clustered standard errors over time with regional fixed effects (table 5). The first column (model 1a) shows the results for the period in which the policy was running. Here, the interaction term is negative and significant. This indicates that the policy in this time frame was not effective in better connecting biotechnology with other classes in the winning regions. As such, it did not contribute to an increased connectedness and density in the knowledge spaces beyond its positive impact on the number of patents in biotechnology.

In model 1b, we test if there are effects in the period after BioRegio funding. Here, the interaction term becomes positive and significant. This means that the biotechnology classes become more important and more connected in the knowledge space of the winning regions compared to other technologies in the post-treatment period[4]. One possible interpretation of these results is that during the initial stages of the program, research was focused on incremental and refined what was already known. Later in the funding period, research shifted and started to connect biotechnology with other, distant fields. Due to the time lag between funding and patentable output, which might also differ between incremental and more radical innovations, an exact attribution of these changes is difficult. Nevertheless, our findings indicate that BioRegio was a trigger to allow exploration of different capabilities that were not accessible inside the regions before.

6.2 Biotechnology in winner and non-winner regions

Figure 9 shows the evolution of the average number of biotechnology patents in the treatment (winner regions) and control (non-winner regions) groups for model 2. Since in this case we

[4]As explained by Basilico & Graf (2020) the usage of a different methodology to map the knowledge space can change the results when calculating centrality measures. Using a simple co-occurrence matrix instead of a relatedness matrix, the results on the calculated betweenness centrality do not vary.

Table 5: Comparing structural embeddedness between biotech and non-biotech classes in winning regions (DiD regression, robust standard errors and regional fixed effects)

	Dependent variable:	
	Log Betweenness Centrality	
	Model during funding	Model after funding
	(1a)	(1b)
Time During BioRegio	-0.453^{***}	
	(0.060)	
Time After BioRegio		-0.172^{***}
		(0.057)
BioTech	-0.778^{***}	-0.997^{***}
	(0.077)	(0.082)
Interaction Term During BioRegio	-0.243^{*}	
	(0.128)	
Interaction Term After BioRegio		0.352^{***}
		(0.121)
Log Number of Patents	0.879^{***}	0.878^{***}
	(0.007)	(0.007)
East	0.630^{***}	0.629^{***}
	(0.042)	(0.042)
Avg Team Size	-0.232^{***}	-0.231^{***}
	(0.011)	(0.011)
Observations	28,304	28,304
R^2	0.382	0.382
Adjusted R^2	0.382	0.382
Residual Std. Error (df = 28274)	1.359	1.359
F Statistic (df = 29; 28274)	603.578^{***}	603.912^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

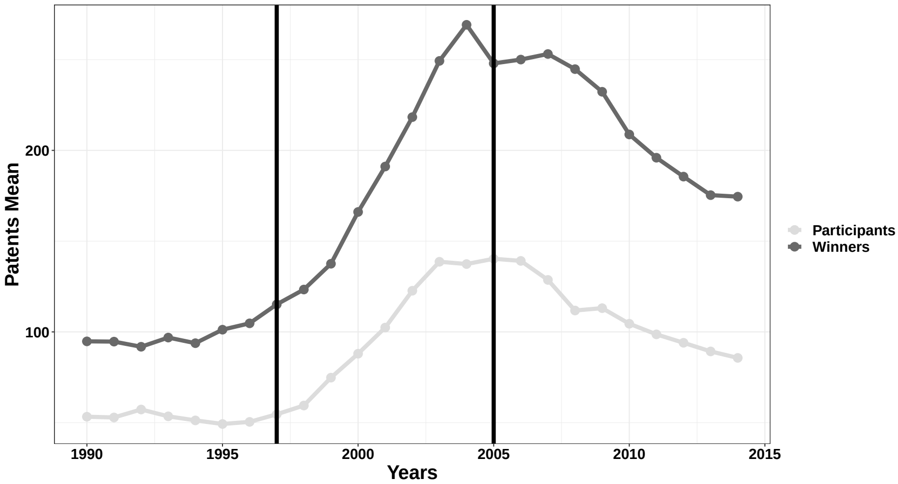


Figure 9: Number of patents over time (model 2 (table 7) treatment and control groups)

use the same number of classes (only from biotechnology) among different knowledge spaces, it is possible to compare them by their averages. We observe that both curves have a similar development. Biotech classes both in winning and non-winning regions have a rather low average number of patents in the period before the funding, while in the period during funding, there is the peak for both groups and then finally a decrease in the period when funding ceased. This means that even if the curve for the winners is higher, there is no big difference in relative changes in patenting activity when comparing biotechnological classes in winning and non-winning regions. Nevertheless, as stated above, the number of patents it is not sufficient to assess if there was an increased interaction among the nodes in the knowledge space.

Table 6 shows the means of log betweenness, their differences and standard errors for control and treatment groups in model 2 for each year. The control group is mainly above the treatment group in terms of betweenness centrality. This situation changes only in the post-treatment period. In fact, here the gap is lower, and in some years, the treatment group is above the control group. This result gives already some insights on what to expect from the DiD regressions. Moreover, the difference in means in the pre-funding period is never significant. So, the assumption of parallel trends, which is important for the DiD approach, cannot be rejected.

Figure 10 represents the DiD approach for model 2 using a base-line model without controls. Here, the result shown in table 6 become even clearer. Betweenness centrality increases steadily in both groups after the start of BioRegio. Before and during treatment, biotechnology in the control group (solid line) is structurally more embedded than in the treatment group. However, in the post-treatment period, biotechnology embeddedness in the two groups becomes more similar. The relatively lower embeddedness in the winning regions can be explained by their strength in several other fields so that initial embeddedness of biotech was lower despite absolute strength in terms of the number of patents. The sharper increase, in particular after funding, indicates long term changes in the knowledge space which might be induced by the policy.

To test this, in table 7, we present the results for models 2a and b. Model 2a evaluates if BioRegio had a significant impact on biotechnology embeddedness in the period when the policy was running, while model 2b evaluates the significance for the post-treatment period. For both models, it holds that winning regions show a significantly lower betweenness centrality than the

Table 6: Mean comparison of log betweenness centrality. Treatment and control groups as in model 2 (table 7)

Year	Participating Mean (Control group)	Winning Mean (Treatment group)	Difference	SE
		Pre-Treatment		
1990	5.755	5.341	-0.413	0.494
1991	5.789	5.253	-0.536	0.495
1992	6.082	5.252		0.444
1993	5.877	5.394	-0.483	0.467
1994	5.725	5.291	-0.434	0.481
1995	5.696	5.393	-0.303	0.477
1996	5.720	5.081	-0.639	0.515
		During-Treatment		
1997	5.822	5.330	-0.492	0.481
1998	5.561	5.453	-0.108	0.400
1999	5.664	5.406	-0.259	0.405
2000	5.702	5.528	-0.174	0.390
2001	5.752	5.447	-0.305	0.427
2002	5.806	5.378	-0.427	0.434
2003	5.694	5.383	-0.311	0.454
2004	5.606	5.531	-0.075	0.464
2005	5.636	5.412	-0.225	0.456
		Post-Treatment		
2006	5.686	5.718	0.032	0.441
2007	5.932	5.697	-0.235	0.475
2008	5.768	5.822	0.054	0.471
2009	6.035	5.988	-0.047	0.430
2010	6.139	5.931	-0.208	0.418
2011	6.142	5.991	-0.151	0.378
2012	6.073	5.871	-0.202	0.380
2013	6.130	6.174	0.044	0.398
2014	6.202	6.229	0.026	0.418

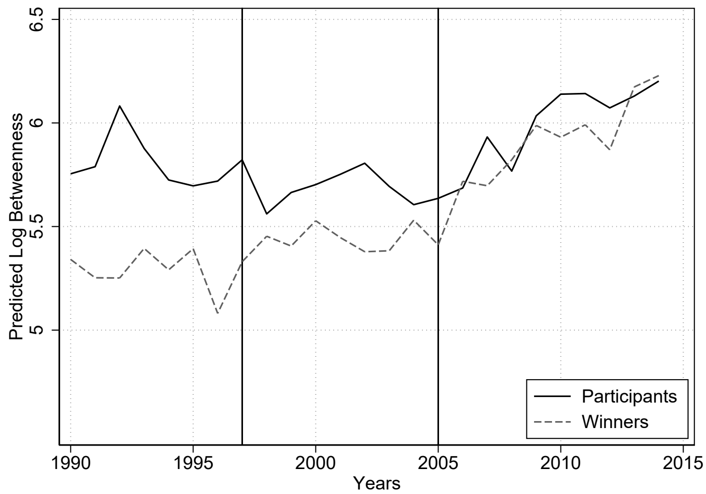


Figure 10: Fitted trends comparison for model 2

control regions. With respect to period differences, the first model (2a) shows that betweenness centrality in the time during BioRegio is significantly lower than in the other periods. The second model (2b) delivers that for the time after BioRegio, there is no significant difference in betweenness centrality to the periods before. The interaction of time during BioRegio and winning region is positive but not significant. However, in the post-treatment period, the interaction term turns out positive and significant. This means that the biotech classes in the winning regions become more important than their corresponding classes in the non-winning regions. This result is quite important because it shows that when comparing biotech classes among regions (some affected by the policy and some not), the positive effect on betweenness is larger in the regions that won the contest. As such, winning regions have a knowledge space with better embedded biotechnological classes by the end of the considered period[5].

7 Conclusion

Innovation oriented cluster policies, such as the German BioRegio contest, have the potential to change the behavior of actors in terms of increased innovation activities and interaction (Engel et al., 2013; Graf & Broekel, 2020). Such effects, measured on the individual (firm) level, find substantial support in the literature (Nishimura & Okamuro, 2011; Mar & Massard, 2021). In that respect, they do not differ much from other types of innovation policies, such as general R&D subsidies. However, the ambition of cluster policies goes beyond increased innovation and interaction, and it also aims at more ample structural effects in terms of specific technologies pursued and links to other technologies intensified or newly created. For the purpose of evaluation of such policy targets, there is a need to identify respective policy impacts in a causal way. Since targeted structural effects might not show up in the short term, such evaluation studies need to focus, in particular, on long term effects. Complementing research on

[5]These results are robust to the selection of regions. We performed the same analyses with a more homogeneous subsample of regions. For each winning region, we manually select the most similar non-winning region in terms of the number of biotechnology patents during the pre-funding period and ran models 2a and b. Since the results do not change much (slightly higher model fit), we refrain from presenting them here. Tables are available upon request.

Table 7: Comparing structural embeddedness of biotech classes between winning and non-winning regions (DiD regression, robust standard errors and regional fixed effects)

	Dependent variable:	
	Log Betweenness Centrality	
	Model during funding	Model after funding
	(2a)	(2b)
Time During BioRegio	-0.496^{**}	
	(0.245)	
Time After BioRegio		0.263
		(0.225)
Winning region	-0.820^{***}	-0.899^{***}
	(0.093)	(0.100)
Interaction Term During BioRegio	0.022	
	(0.152)	
Interaction Term After BioRegio		0.241^{*}
		(0.144)
Log Number of Patents	0.727^{***}	0.727^{***}
	(0.020)	(0.020)
East	0.043	0.042
	(0.085)	(0.085)
Neighbour	−0.033	−0.033
	(0.083)	(0.083)
Avg Team Size	-0.252^{***}	-0.249^{***}
	(0.048)	(0.048)
Observations	2,872	2,872
R^2	0.278	0.279
Adjusted R^2	0.271	0.271
Residual Std. Error (df = 2841)	1.726	1.725
F Statistic (df = 30; 2841)	36.507^{***}	36.623^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

policy effects on the structure of actor networks (Graf & Broekel, 2020; N'Ghauran & Autant-Bernard, 2020), we investigated their impact on the regional knowledge space. As an interesting case, we took biotechnology and the BioRegio program in Germany. We studied changes in the embeddedness of biotechnology in regional knowledge spaces and how this was affected by BioRegio.

We argue that supported fields of activity, in our case biotechnology, should increase their visibility and importance within the knowledge space by either creating and/or intensifying links within the field itself (along existing trajectories) or by creating links with previously unrelated fields (cross-fertilization). Our descriptive analysis shows that in the four winning regions, biotechnology was connected with many other fields in the knowledge space during funding. However, we also observed a decrease in those inter-technological linkages in the periods after the funding. In connecting biotechnology with other fields, all four winner regions showed distinct patterns of specialization. In Jena, for example, many links were established with medical technology, while in Rhineland, novel combinations with textiles and paper machines were developed. In general, many of the new combinations were with classes in the broader field of chemistry.

We complemented this dyad-based analysis with an econometric approach to assess the policy impact on the embeddedness of biotechnology within the knowledge space of supported regions. To measure embeddedness, we used betweenness centrality of IPC4 classes in the regional knowledge spaces and implemented it as the dependent variable in two sets of diff-in-diff estimations. In the first set, we compared biotech with non-biotech IPC4 classes in winning regions and find a positive effect of the policy on the embeddedness of the biotech classes only after the funding period. By focusing only on winning regions, this setting did not allow us to unambiguously identify policy effects, since increasing biotechnology embeddedness could also have been a result of a general technological trend. Therefore, in a second set of regressions, we compared biotechnology in winning and non-winning regions. Again, our results indicate a positive policy effect on the knowledge space integration of biotechnology only after the funding period. Given that patent applications increase substantially during the funding period but drop afterwards, this finding is somewhat startling. One reasonable interpretation would be that research during initial stages of BioRegio was concerned with incremental progress along the lines of existing research, while public funding via the BioRegio program allowed for research that was more risky and connected biotechnology with more distant technological fields. That type of research takes more time to develop, which might explain why such a transformative effect of the policy shows up only after the funding period.

Compared with other evaluations of the BioRegio program, our research implies that long term effects of cluster policies can be manifold. While neither Engel et al. (2013) nor Graf & Broekel (2020) find evidence for long term effects on innovation outputs or actor network structures, our findings show that the direction of the search process was shaped by the policy. We have to acknowledge, though, that our research approach did not allow for a comparison with other, simultaneous policy measures.

A generalization of our findings has limitations due to the nature of the analysis. First, like several other studies on the knowledge space, we rely on patents which limits our analyses to inventions that can be patented. As such, we miss many non-patentable inventions like advances in software and services. Second, our analysis relies on the patent classification system which implies that the patents classified within each class are assumed to be similar but substantially different from others. Since this classification is done by the patent offices for other reasons than this type of analysis, this might not hold true. Third, measuring treatment effects with moving windows is also subject to limitations. Immediate policy effects might be blurred since periods overlap. Fourth, since we do not control for other policies that support biotechnology, we cannot exclude that they had effects on the knowledge space as well. Generalizing the results to other cluster policies seems challenging, as each policy has its own objectives, characteristics and design features.

Future research should focus on the effects of these induced changes in the structure of the knowledge space on regional innovative and economic performance. This is fundamental, since the usage of performance indicators can really capture if a policy had an effect on the innovative activity of a region, whereas, the creation of new technological combinations cannot be directly translated to an increase in more and better innovations in the region.

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A Correlation Tables

Table 8: Correlation table for models 1a and b (table 5)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Log Betweenness Centrality	-	-0.04***	0.02***	0.03***	0.59***	-0.07***	0.03***
(2) Time During BioRegio		-	-0.60***	0.00	0.02***	0.01***	0.02***
(3) Time After BioRegio			-	-0.01	0.05***	0.06***	-0.01***
(4) BioTech				-	0.20***	0.09***	0.11***
(5) Log Number of Patents					-	-0.16***	0.29***
(6) East						-	0.13***
(7) Avg Team Size							-

Note: *p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01

Table 9: Correlation table for models 2a and b (table 7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Log Betweenness Centrality	-	-0.06***	0.08***	-0.06***	0.47***	-0.09***	0.02	0.02
(2) Time During BioRegio		-	-0.59***	0.01	0.08***	0.02	-0.01	0.03
(3) Time After BioRegio			-	-0.01	0.08***	0.02	0.01	-0.08***
(4) Winning region				-	0.24***	-0.05***	-0.30***	0.23***
(5) Log Number of Patents					-	-0.15***	-0.04***	0.41***
(6) East						-	0.16***	0.19***
(7) Neighbour							-	0.07***
(8) Avg Team Size								-

Note: *p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01

References

Andersson, M. & Karlsson, C. (2006). *Regional Innovation Systems in Small and Medium-Sized Regions*, (pp. 55–81). Springer Berlin Heidelberg: Berlin, Heidelberg. https://doi.org/10.1007/3-540-34488-8_4".

Audretsch, D. B. & Feldman, M. P. (1996). Innovative clusters and the industry life cycle. *Review of Industrial Organization*, 11(2), 253–273. https://doi.org/10.1007/bf00157670.

Balland, P.-A., Boschma, R., Crespo, J., & Rigby, D. L. (2019). Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Regional Studies*, 53(9), 1252–1268. https://doi.org/10.1080/00343404.2018.1437900.

Balland, P.-A., Rigby, D., & Boschma, R. (2015). The technological resilience of US cities. *Cambridge Journal of Regions, Economy and Society*, 8(2), 167–184. https://doi.org/10.1093/cjres/rsv007.

Baptista, R. & Swann, P. (1998). Do firms in clusters innovate more? *Research Policy*, 27(5), 525–540. https://doi.org/10.1016/s0048-7333(98)00065-1.

Basilico, S. & Graf, H. (2020). *Bridging Technologies in the Regional Knowledge Space: Measurement, Evolution and Determinants*. Working Paper 12, Friedrich Schiller University Jena.

Beaudry, C. & Breschi, S. (2003). Are firms in clusters really more innovative? *Economics of Innovation and New Technology*, 12(4), 325–342. https://doi.org/10.1080/10438590290020197.

Belleflamme, P., Picard, P., & Thisse, J. F. (2000). An Economic Theory of Regional Clusters. *Journal of Urban Economics*, 48(1), 158–184. https://doi.org/10.1006/juec.1999.2161.

Boschma, R. (2005). Proximity and innovation: a critical assessment. *Regional studies*, 39(1), 61–74. https://doi.org/10.1080/0034340052000320887.

Boschma, R., Balland, P.-A., & Kogler, D. F. (2014). Relatedness and technological change in cities: the rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and corporate change*, 24(1), 223–250. https://doi.org/10.1093/icc/dtu012.

Boschma, R., Minondo, A., & Navarro, M. (2012). Related variety and regional growth in Spain. *Papers in Regional Science*, 91(2), 241–256. https://doi.org/10.1111/j.1435-5957.2011.00387.x.

Boschma, R. A. & ter Wal, A. L. J. (2007). Knowledge networks and innovative performance in an industrial district: The case of a footwear district in the south of italy. *Industry and Innovation*, 14(2), 177–199. https://doi.org/10.1080/13662710701253441.

Breschi, S. & Lenzi, C. (2016). Co-invention networks and inventive productivity in US cities. *Journal of Urban Economics*, 92, 66–75.

Breschi, S., Lissoni, F., & Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. *Research policy*, 32(1), 69–87. https://doi.org/10.1016/s0048-7333(02)00004-5.

Broekel, T. (2012). Collaboration intensity and regional innovation efficiency in germany—a conditional efficiency approach. *Industry and Innovation*, 19(2), 155–179.

Broekel, T., Fornahl, D., & Morrison, A. (2015). Another cluster premium: Innovation subsidies and r&d collaboration networks. *Research policy*, 44(8), 1431–1444. https://doi.org/10.1016/j.respol.2015.05.002.

Broekel, T. & Graf, H. (2012). Public research intensity and the structure of german R&D networks: a comparison of 10 technologies. *Economics of Innovation and New Technology*, 21(4), 345–372.

Cantner, U. & Graf, H. (2006). The network of innovators in Jena: An application of social network analysis. *Research Policy*, 35(4), 463–480.

Cantner, U., Meder, A., & Wolf, T. (2011). Success and failure of firms' innovation co-operations: The role of intermediaries and reciprocity. *Papers in Regional Science*, 90(2), 313–329.

Cantner, U. & Vannuccini, S. (2018). Elements of a schumpeterian catalytic research and innovation policy. *Industrial and Corporate Change*, 27(5), 833–850.

Carlsson, B. & Stankiewicz, R. (1991). On the nature, function and composition of technological systems. *Journal of Evolutionary Economics*, 1(2), 93–118. https://doi.org/10.1007/BF01224915.

Champenois, C. (2012). How can a cluster policy enhance entrepreneurship? Evidence from the German 'BioRegio' case. *Environment and Planning C: Government and Policy*, 30(5), 796–815. https://doi.org/10.1068/c1180.

Cooke, P. (2001). New economy innovation systems: biotechnology in europe and the USA. *Industry and Innovation*, 8(3), 267–289. https://doi.org/10.1080/13662710120104583.

Csardi, G. & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal*, Complex Systems, 1695. Available at http://igraph.org.

Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy*, 43(10), 1785–1799. http://dx.doi.org/10.1016/j.respol.2014.05.007.

Dohse, D. (2000). Technology policy and the regions—the case of the BioRegio contest. *Research Policy*, 29(9), 1111–1133. https://doi.org/10.1016/s0048-7333(99)00077-3.

Dohse, D. & Staehler, T. (2008). *BioRegio, BioProfile and the rise of the German biotech industry*. Kiel Working Paper 1456, Kiel Institute for the World Economy.

Duranton, G. (2011). California Dreamin': The Feeble Case for Cluster Policies. *Review of Economic Analysis*, 3(1), 3–45. https://openjournals.uwaterloo.ca/index.php/rofea/article/view/1375.

EFI (2017). *Report on research, innovation and technological performance in Germany 2017*, volume 127. Berlin: EFI - Commission of Experts for Research and Innovation.

Eickelpasch, A. & Fritsch, M. (2005). Contests for cooperation - A new approach in German innovation policy. *Research Policy*, 34(8), 1269–1282. https://doi.org/10.1016/j.respol.2005.02.009.

Engel, D. & Heneric, O. (2008). Legal frameworks and public support in the biotechnology industry. In H. Patzelt & T. Brenner (Eds.), *Handbook of Bioentrepreneurship* (pp. 249–274). New York: Springer US.

Engel, D., Mitze, T., Patuelli, R., & Reinkowski, J. (2013). Does Cluster Policy Trigger R&D Activity? Evidence from German Biotech Contests. *European Planning Studies*, 21(11), 1735–1759. https://doi.org/10.1080/09654313.2012.753689.

Fornahl, D., Broekel, T., & Boschma, R. (2011). What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location. *Papers in Regional Science*, 90(2), 395–418.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social Networks*, 1(3), 215–239.

Giuliani, E. & Bell, M. (2005). The micro-determinants of meso-level learning and innovation: Evidence from a Chilean wine cluster. *Research Policy*, 34(1), 47–68.

Giuliani, E. & Bell, M. (2008). Industrial clusters and the evolution of their knowledge networks: revisiting a Chilean case. *IV Globelics Conference*, 44(2005), 1–25.

Giuliani, E., Matta, A., & Pietrobelli, C. (2016). Networks, cluster development programs, and performance: the electronics cluster in córdoba, argentina. *The Impact Evaluation of Cluster Development Programs: Methods and Practices*, (pp. 117–150).

Graf, H. (2017). *Regional innovator networks: A review and an application with R*. Technical report, Jena Economic Research Papers. http://www2.wiwi.uni-jena.de/Papers/jerp2017/wp_2017_016.pdf.

Graf, H. & Broekel, T. (2020). A shot in the dark? Policy influence on cluster networks. *Research Policy*, 49(3), 103920. https://doi.org/10.1016/j.respol.2019.103920.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, 28(4), 1661.

Hausmann, R. & Klinger, B. (2007). The structure of the product space and the evolution of comparative advantage. *CID Working Paper Series*.

Hidalgo, C. A., Klinger, B., Barabasi, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, 317(5837), 482–487. https://doi.org/10.1126/science.1144581.

Hospers, G.-J. & Beugelsdijk, S. (2002). Regional cluster policies: Learning by comparing? *Kyklos*, 55(3), 381–402.

Jaffe, A. B. (1989). Characterizing the "technological position" of firms, with application to quantifying technological opportunity and research spillovers. *Research Policy*, 18(2), 87–97. https://doi.org/10.1016/0048-7333(89)90007-3.

Kaiser, R. & Prange, H. (2004). The reconfiguration of National Innovation Systems - The example of German biotechnology. *Research Policy*, 33(3), 395–408. https://doi.org/10.1016/j.respol.2003.09.001.

Kattel, R. & Mazzucato, M. (2018). Mission-oriented innovation policy and dynamic capabilities in the public sector. *Industrial and Corporate Change*, 27(5), 787–801.

Kiese, M. (2019). Regional cluster policies in Germany: challenges, impacts and evaluation practices. *Journal of Technology Transfer*, 44(6), 1698–1719. https://doi.org/10.1007/s10961-017-9589-5.

Kogler, D. F., Rigby, D. L., & Tucker, I. (2013). Mapping knowledge space and technological relatedness in US cities. *European Planning Studies*, 21(9), 1374–1391. https://doi.org/10.1080/09654313.2012.755832.

Koo, J. (2005). Technology spillovers, agglomeration, and regional economic development. *Journal of Planning Literature*, 20(2), 99–115. = https://doi.org/10.1177/0885412205279796 .

Krauss, G. & Stahlecker, T. (2001). New Biotechnology Firms in Germany: Heidelberg and the BioRegion Rhine-Neckar Triangle. *Small Business Economics*, 17(1-2), 143–153. https://doi.org/10.1023/A:1011145615243.

Lucena-Piquero, D. & Vicente, J. (2019). The visible hand of cluster policy makers: An analysis of aerospace valley (2006-2015) using a place-based network methodology. *Research Policy*, 48(3), 830–842.

Malmberg, A. & Maskell, P. (1997). Towards an explanation of regional specialization and industry agglomeration. *European planning studies*, 5(1), 25–41.

Mar, M. & Massard, N. (2021). Animate the cluster or subsidize collaborative R&D? A multiple overlapping treatments approach to assess the impacts of the French cluster policy. *Industrial and Corporate Change*. https://doi.org/10.1093/icc/dtab002.

Markusen, A. (1996). Sticky places in slippery space: A typology of industrial districts. *Economic Geography*, 72(3), 293–313. https://doi.org/10.2307/144402.

Marshall, A. (1890). *Principles of Economics*. London: Macmillan.

Martin, R. & Sunley, P. (1996). Paul Krugman's geographical economics and its implications for regional development theory: A critical assessment. *Economic Geography*, 72(3), 259–292.

Martin, R. & Sunley, P. (2003). Deconstructing clusters: Chaotic concept or policy panacea? *Journal of Economic Geography*, 3(1), 5–35. https://doi.org/10.1093/jeg/3.1.5.

Müller, C. (2002). The evolution of the biotechnology industry in Germany. *Trends in Biotechnology*, 20(7), 287–290. https://doi.org/10.1016/S0167-7799(02)01966-2.

Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, 87(3), 237–265. https://doi.org/10.1111/j.1944-8287.2011.01121.x.

Nishimura, J. & Okamuro, H. (2011). R&D productivity and the organization of cluster policy: An empirical evaluation of the Industrial Cluster Project in Japan. *The Journal of Technology Transfer*, 36(2), 117–144. https://doi.org/10.1007/s10961-009-9148-9.

N'Ghauran, K. A. & Autant-Bernard, C. (2020). Effects of cluster policies on regional innovation networks: Evidence from France. Available at SSRN https://ssrn.com/abstract=3540169.

Ochiai, A. (1957). Zoogeographical studies on the soleoid fishes found in Japan and its neighbouring regions-i. *Bulletin of the Japanese Society for the Science of Fish*, 22, 522–525.

Pavitt, K. (1984). Sectoral patterns of technical change: towards a taxonomy and a theory. *Research policy*, 13(6), 343–373. https://doi.org/10.1016/0048-7333(84)90018-0.

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, 68(2), 73–93.

Porter, M. E. (1998). Clusters and the new economics of competition. *Harvard Business Review*, 76(6). https://hbr.org/1998/11/clusters-and-the-new-economics-of-competition.

Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly*, 14(1), 15–34. https://doi.org/10.1177/089124240001400105.

Quatraro, F. (2010). Knowledge coherence, variety and economic growth: Manufacturing evidence from Italian regions. *Research Policy*, 39(10), 1289–1302. https://doi.org/10.1016/j.respol.2010.09.005.

R Core Team (2018). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. Available online at https://www.R-project.org/.

Rosenberg, N. & Frischtak, C. R. (1983). Long waves and economic growth: A critical appraisal. *American Economic Review*, 73(2), 146–151. http://www.jstor.org/stable/1816830.

Rothgang, M., Cantner, U., Dehio, J., Engel, D., Fertig, M., Graf, H., Hinzmann, S., Linshalm, E., Ploder, M., Scholz, A. M., & Töpfer, S. (2017). Cluster policy: insights from the German leading edge cluster competition. *Journal of Open Innovation: Technology, Market, and Complexity*, 3(1). https://doi.org/10.1186/s40852-017-0064-1.

Rothgang, M., Lageman, B., & Scholz, A.-M. (2021). Why are there so few hard facts about the impact of cluster policies in Germany? A critical review of evaluation studies. *Review of Evolutionary Political Economy*, 2, 105–139.

Schmoch, U. (2008). Concept of a technology classification for country comparisons. *Final report to the world intellectual property organisation (wipo), WIPO*. http://www.wipo.int/export/sites/www/ipstats/en/statistics/patents/pdf/wipo_ipc_technology.pdf.

Sonn, J. W. & Storper, M. (2008). The increasing importance of geographical proximity in knowledge production: an analysis of us patent citations, 1975–1997. *Environment and Planning a*, 40(5), 1020–1039.

Staehler, T., Dohse, D., & Cooke, P. (2007). *Evaluation der Fördermaßnahmen BioRegio und BioProfile*. BMBF.

Sternberg, R., Kiese, M., & Stockinger, D. (2010). Cluster policies in the US and Germany: Varieties of capitalism perspective on two high-tech states. *Environment and Planning C: Government and Policy*, 28(6), 1063–1082.

Teece, D. J., Rumelt, R., Dosi, G., & Winter, S. (1994). Understanding corporate coherence: Theory and evidence. *Journal of economic behavior & organization*, 23(1), 1–30. https://doi.org/10.1016/0167-2681(94)90094-9.

Töpfer, S., Cantner, U., & Graf, H. (2019). Structural dynamics of innovation networks in German Leading-Edge Clusters. *Journal of Technology Transfer*, 44(6), 1816–1839. https://doi.org/10.1007/s10961-017-9642-4.

Toth, G., Elekes, Z., Whittle, A., Lee, C., & Kogler, D. (2020). *Technology network structure conditions the economic resilience of regions*. Papers in Evolutionary Economic Geography (PEEG) 2048, Utrecht University, Department of Human Geography and Spatial Planning, Group Economic Geography.

Uyarra, E. & Ramlogan, R. (2012). The effects of cluster policy on innovation. *Compendium of Evidence on the Effectiveness of Innovation Policy Intervention, Manchester Institute of Innovation Research*. https://doi.org/10.22163/fteval.2012.88.

Van Beuzekom, B. & Arundel, A. (2009). *OECD Biotechnology statistics 2009*. Technical report, OECD. https://www.oecd-ilibrary.org/oecd-biotechnology-statistics-2009_5ksf4fzb0xf0.pdf.

Wanzenböck, I., Scherngell, T., & Fischer, M. M. (2013). How do firm characteristics affect behavioural additionalities of public R&D subsidies? Evidence for the Austrian transport sector. *Technovation*, 33(2–3), 66–77.

Wassermann, S. & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511815478.

Whittle, A. & Kogler, D. F. (2019). Related to what? reviewing the literature on technological relatedness: Where we are now and where can we go? *Papers in Regional Science*, 99(1), 97–113.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, 316(5827), 1036–1039.