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Does Cluster Policy Trigger R&D Activity? – Evidence from German Biotech Contests

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Abstract

This paper evaluates the R&D enhancing effects of two large public grant schemes for the German biotechnology industry (BioRegio, BioProfile). Both grant schemes are organized in the form of contents for cooperation with the goal to foster the performance of innovative firms by their organization in research clusters. We apply a Difference-in-Differences estimation technique in a generalized linear model framework, which allows us to control for different initial regional conditions in R&D activity of the biotech sector. Our econometric findings support the view that winners generally outperform non-winning participants during the treatment period, thus indicating that exclusive funding as well as the stimulating effect of being a "winner" have positive effects on R&D activity in the short-term. Apart from this direct winner effect, for the non-winning participants no beneficial indirect effect due to a mobilization of local actors during the application phase could be detected. Finally, first attempts in estimating the long-term effects of the contests for cooperation approach on the winner regions' R&D activity in the post-treatment period show ambiguous results.

JEL Classification: O38, C23

Keywords: Biotechnology; R&D policies; cluster; difference-in-differences estimation

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1 *Dirk Engel, University of Applied Science Stralsund; Timo Mitze, RWI, Ruhr-Universität Bochum; Roberto Patuelli, University of Bologna, The Rimini Centre for Economic Analysis (RCEA); Janina Reinkowski, ifo Munich.* *– An earlier version of this working paper circulated as: "Does the Support of Innovative Clusters Sustainably Foster R&D Activity? Evidence from the German BioRegio and BioProfile Contests", Quaderni della facoltà di Scienze economiche dell'Università di Lugano, No. 1105-2010. Previous versions of this paper have been presented at the GfR Summer Conference 2010 in Hannover, the RWI Therapy Summer Seminar 2010 and the IWH/University Jena Joint International Workshop on "Which regions benefit from emerging new industries? Evidence from photovoltaic and other high-tech industries". The authors wish to thank Uwe Cantner, Dirk Fornahl, Joel Stiebale, Christoph M. Schmidt and participants of the above events for helpful comments and advices. Also special thanks to Björn Alecke for providing some of the data used for this research, as well as Karl-Heinz Herlitschke for his efforts to extract and prepare information from the ESPACE database.* *– All correspondence to: Timo Mitze, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, E-Mail: timo.mitze@rwi-essen.de.*

1. Introduction

Throughout the 1990s, the design of the German national research and development (R&D) policy experienced a paradigmatic shift from standard grant schemes to a competition-based and regionally focused R&D policy, which provided public funding mainly to regions with a high expected social return on public funding. Among the first programmes implementing a competitive spirit in German R&D policy were the BioRegio and BioProfile contests starting in 1997 and 1999, respectively. Both programmes aimed at fostering the commercialization in biotechnology and at pushing Germany towards the international technological frontier. Since the programmes operated on a competitive basis, they were also labeled as "contests of cooperation" (see Eickelpasch and Fritsch 2005).

Although there exists a huge stock of theoretical and empirical contributions on the effects of geographical concentration among its main actors in regional and/or sectoral innovation systems (e.g., Marshall 1890, Jaffe et al. 1993, Porter 2003), hardly anything is known about the effects of policies aiming at the stimulation of R&D activity in selected regions through such contests for cooperation. Thus, in this paper we evaluate the research performance of winners compared to participating (but non-winning) and non-participating regions in the BioRegio and BioProfile contests, both for the periods during (treatment) and after funding (post-treatment). As outcome variables, we use the regions' patenting activity and their ability to raise public R&D funds due to the status of being a winner in the respective contest.[3] Our database covers 426 German NUTS-3 districts (*Kreise*) for the period 1991 to 2007.

From a methodological point of view, we use a Difference-in-Differences (DiD) estimation framework based on (zero inflated) Poisson regressions, where the latter account for excessive zeros in the outcome variables: the number of biotech research projects raised through public funding, as well as the number of biotech patent applications for all German NUTS-3 districts. The remainder of the paper is structured as follows. In section 2, we briefly discuss the theoretical background of cluster-oriented R&D policy. Section 3 presents the data and several descriptive findings, followed by a brief summary of the estimation strategy in Section 4. In this section we also discuss our estimation results. Section 5 concludes the paper.

2. The regionalization of R&D policy

2.1. Rationales

The competition- and contest-based regionalization of R&D policy described above fits quite closely to the theoretical expectation that the extent of externalities, technological change and commercialization of innovative ideas are all positively affected by the geographical concentration of public and private research actors who share interests in similar fields of technology. The idea of positive effects of local agglomeration has its roots in Marshall's (1890) externalities based on specialized labour pools, input sharing and knowledge spillover

[3] Using data on patenting activity, we explicitly account for the fact that patent applications are typically made with a time lag relative to the received funding.

as well as Porter's (2003) view of an enhanced competition in clusters.[4] While the positive effects of local agglomeration on knowledge intensive industries might be clear from a theoretical point of view, it is not easy to identify empirically the causal effect of geographical proximity on R&D activity. Starting from the influential work of Acs et al. (1993), Jaffe et al. (1993), Audretsch and Feldman (1996) and Anselin et al. (1997), there is a growing literature identifying the transmission channels from clustered firms to enhanced R&D, innovation activity and finally productivity growth. Acs et al. (1993), for instance, estimate production functions for US data and find that, beside standard input factors, the geographical position in a cluster matters strongly.

Jaffe et al. (1993) find that the probability of an inventor to be cited in a patent application is larger if the actors are located in geographical proximity. Likewise, Baptista and Swann (1998), based on UK micro data, show that firms in sectors that show a geographical concentration indeed exhibit, on average, more intensive research activities. In a further study, Baptista (2000) shows that firms adopt technical innovations particularly in those regions which are characterized by a high share of firms having implemented the same innovations already. With respect to Germany, Dauth (2010) reports evidence that compared to regions without industrial agglomeration, the existence of industrial agglomeration is significantly correlated with higher regional employment growth rates. Finally, Grimpe and Patuelli (2011) show the importance of co-location among firms (private R&D) and public research institutes (public R&D) for the case of nanomaterials innovation in German regions.

The main question remains how to interpret such findings. For example, Baptista (2000, p. 529) states: "*...[o]ne can, therefore, claim that there are significant learning effects arising from the geographical proximity to previous adopters*". In fact, it is quite likely that learning effects are higher in local agglomerations due to the existence of firms with higher knowledge competencies and absorptive capacities. One may then assume that local agglomerations are characterized by a "selection of the fittest", that is, actors with research activities and knowledge competencies above average prefer geographical proximity to actors with similar skills. Studies by Zucker et al. (2006) and Klepper (2007) clearly support this view. Klepper (2007), for instance, argues that better-performing firms will have more and better spinoffs, and these spinoffs will generally locate close to their parents. Zucker et al. (2006) show that scientific stars become more geographically concentrated over time because of relocations from areas with relatively few peers to those with many actors in their field of expertise.

These insights are essential for understanding any potential effect stemming from a regionalized, cluster-oriented R&D policy. The funding of projects in such leading-edge local agglomerations might have larger effects due to the additional acquisition of outside money, and higher effectiveness based on the selection of the fittest and the geographical proximity between well-performing actors.

[4] However, Dohse (2000, p. 1111) points out that the implementation of regionalized technology policy in Germany was not purely intended to be a "*...carbon-copy of the ideas proposed in the theoretical literature*".

2.2. Cluster-oriented R&D policy and its evaluation

The BioRegio contest (BRC) marks a major milestone of the German Federal Government's policy to stimulate the transfer of new knowledge into new products, and thereby narrows the gap between Germany and those countries leading in the application of biotechnological knowledge, i.e. the USA and Great Britain. The BRC was initiated by the Federal Ministry of Education and Research (BMBF) in 1995, and encouraged regions to apply for subsidies to be used for the establishment of biotech industry in the region (Dohse 2000). The funding concept aimed at developing a new holistic approach for R&D and innovation policy, and was planned to integrate biotechnological capacities and scientific, economic and administrative activities. The main governmental purpose of funding biotechnology was to catch up with the high international standard of performance. From the political perspective, R&D funding via contests should ideally lead to two effects: First, a direct output and reputation effect for winners, as well as, second, an indirect mobilization effect of the contest. The latter is expected to arise if regions, which have organized themselves and formulated a common strategy, can use these efforts as future assets even without the receipt of direct financial benefits.

In sum, 17 BioRegions were formed and participated in the BRC. An independent jury selected four winning regions (Rhineland, Rhine-Neckar, Munich, and Jena with a special vote) out of a total of 17 participant “meso”-regions (exceeding the size of NUTS-3 districts). Major criteria were based on “hard” facts like the existence of a critical mass of biotech firms and research facilities within the region, regarding the absolute number of firms, the average firm size, and the firms’ R&D and economic performance (for details, see Dohse, 2000). Each winning region received a total amount of public grants of about €25 Mio. (exception Jena: €15 Mio.) to run R&D-projects. Additionally, winning regions were favored in terms of getting access to the standard R&D-grant schemes of the BMBF. The total amount of these grants was about €750 Mio. for the time span 1997–2001.

The follow-up BioProfile contest (BPC) started in 1999, and a total of 30 regions participated in this contest. Three winning BPC “clusters” (Potsdam-Berlin; Braunschweig-Göttingen-Hannover; Stuttgart-Tübingen-Esslingen-Reutlingen-Neckar-Alb) were awarded funding by the jury in May 2001. Public subsidies with a maximum of €50 Mio. have been provided by the Federal Government for each of the three clusters between 2001 and 2007. Participation in the BRC and BPC was thus generally attractive in order to receive additional subsidies and to attract actors within and outside the region for participation in biotech-related research projects. It also offered access to different valuable resources increasing knowledge competencies and accelerating the commercialization of biotechnology-related products.

Despite its growing political importance, only very few quantitative studies measure the success of cluster-oriented R&D policies. Only recently, Martin et al. (2011) were among the first scholars to apply a quantitative (DiD) approach to the evaluation of economic effects of the French “Local Productivity System” (LPS) cluster programme. A further analysis for the subsequent French Policy of “Competitiveness Clusters” has been conducted by Fontagne et al. (2010), mainly finding that the policy was effective in picking the winners. With respect to German data, Falck et al. (2010) use a similar estimation strategy in order to analyse a

regional innovative cluster policy for Bavaria. While Martin et al. (2010) do not find evidence of productivity advantages of the specific cluster policy, Falck et al. (2010) conclude that the Bavarian state-wide cluster policy led to a significant increase in the probability of being innovative for Bavarian targeted sectors relative to non-Bavarian targeted sectors and Bavarian non-targeted sectors (two comparison groups).[5]

With respect to the biotechnology sector, different studies have analysed both the general role of clustering and the impact of public funding. Using a global dataset for 59 consolidated biotechnological firms, Lecocq et al. (2011) report evidence for a positive relationship between the number of technology clusters in which a firm is present, and its overall measured patent performance. Similar results are also reported in Fornahl et al. (2009) for a sample of German biotech firms in the period 1997–2004. Wolf et al. (2010) analyse the determinants of transition from nascent into real entrepreneurship for German biotechnology firms. The authors confirm the role of regional factors and the entrepreneurial environment, which are both typical for clusters and relevant for the success in the start-up activity of biotechnology firms.

Focusing on policy effects, Cooke et al. (2007) compared several measures as indicators for the success of policy support in the biotechnology sector (e.g., number of biotech firms, products in pipeline, etc.). The authors find that BRC and BPC winners perform better than non-funded biotech regions. However, the authors do not differentiate between non-winning participants and non-participants within the group of non-funded biotech regions. In doing so, Engel and Heneric (2008) find that non-winning participants of BRC outperform winning and non-participants regions of BRC with respect to the change in the number of newly founded biotech-firms between 1995–98 and 1999–2003. Thus, the authors conclude that the certification as a winner and exclusive financial support do not matter in attracting new biotech firms, compared to other participants.

A shortcoming of both studies is that the authors do not address the evolution of BRC winning regions after the funding period. Using actual data for the total amount of public R&D funds raised, we take up this research question explicitly. While many studies point out that a firm's public funding implies higher R&D activity, we are explicitly interested to know whether path dependence matters for the acquisition of public R&D funding. Furthermore, we will provide empirical evidence on whether BRC and BPC winning regions were more successful in terms of patent applications during the funding period.

3. Data and stylized facts

In the following, we give a short description of the variables used to analyse the effects of the BRC and BPC at the level of 426 German NUTS-3 districts. Several databases are needed to analyse the regional structure of Federal support for biotechnology projects and its determinants. In detail, we link the following data sources:

[5] In fact, the Bavarian State Government provided an amount of €1.45 billion for R&D projects to Bavarian firms and research institutes, which comes close to typical funding schemes at the Federal government level.

- Federal Government Project Funding Information Database (PROFI),
- Patent data from the European Patent Office (EPO), namely "ESPACE" Bulletin,
- Socio-Economic data from various sources including Federal Agency for Labour, ZEW Foundation Panel, as well as the Federal Statistical Office.

The PROFI database covers the civilian R&D funding of the German Federal Government. For the purpose of this paper, we focus on direct funding of biotechnology-related projects. The database contains information on the number of projects, expenditures, name and address of recipients, type of project (individual versus collaborative projects), and so on.[6] Based on the "ESPACE" Bulletin, we extract information regarding patenting behavior. Patent applications are the most important measure of innovative capacity (for comprehensive discussions on the informative value of patents, see, e.g., Griliches, 1990). We measure patent applications in the technology field "biotechnology" (see Table A.2 in Appendix) at the location of inventors, and sum up the number of patent application per county when at least one inventor comes from this county.

Acquisition of public funding and patent applications as outcome variables are determined by the innovative capacity in the region. In order to minimize any bias stemming from time-varying omitted variables, our set of explanatory variables considers several aspects of the districts' innovative capacity, which are extracted from several databases. Among others, R&D employment data, defined as the share of employees trained in mathematics, engineering and natural sciences relative to total employment, and obtained from the Federal Employment Agency, are used to extract measures regarding the innovative capacity of counties.

We add further measures for research activity, such as firm-specific information in the manufacturing sector (export share, firm size, etc.) and start-up activity in high-tech industries. The latter variable measures the entrepreneurial climate, and thus the potential to commercialize innovative ideas via the channel of business creation. Finally, we also include proxies for the regional patterns in sectoral specialization and agglomeration in general. The latter variable is measured in terms of employment in sectors with a high Ellison-Glaeser-Index (>0.005) relative to total employment in the region.[7] This measure, in turn, may provide general information about the Marshallian forces at work at the NUTS-3 level (i.e., forward-backward linkages, labour market pooling and knowledge spillovers). A detailed description of the data definitions is given in Table 1.

[6] We thank Mr. Günter Krauss from the Federal Ministry of Education and Research – Department Z 22 'Information technology' – for his effort in extracting related information from the PROFI database. In order to minimize the potential endogeneity problem stemming from the fact that winning the contests is directly associated with financial benefits for the respective regions, we use the number of raised research projects rather than the financial volume. The correlation of both indicators is reasonably high (Pearson's correlation coefficient is 0.87 for all projects and 0.91 for cooperative R&D projects), so that the number of projects serve as a good substitute for the financial volume. This strategy also avoids putting strong assumptions on the annual streams of funding over the project period.

[7] The threshold level of 0.005 was chosen in line with the empirical literature (see, e.g., Alecke et al. 2006).

Table 1: Variable description and data source

Variable	Source	Description
Government funding	PROFI database	Direct funding of biotechnology-related R&D projects by Federal government (number of projects and volume of expenditures)
Patents	European Patent Office (EPO)	Non-weighted number of patent applications in biotechnology (for a definition of the Biotech sector based on IPC classes, see Appendix)
Number of Firms	German Statistical Office	Number of firms in manufacturing sector
Average Firm size	German Statistical Office	Average number of employees per firm in manufacturing sector
Export share	German Statistical Office	Share of foreign turnover in manufacturing sector relative to total turnover in manufacturing sector
MINT Employment	Bundesagentur für Arbeit (Federal Employment Agency)	Share of employees trained in mathematics, informatics, natural sciences and technology relative to total employment
Start-up	ZEW Foundation Panel	Number of overall start-ups relative to total employment
Start-up (High-Tech)	ZEW Foundation Panel	Number of start-ups in high-tech industries relative to MINT employees
Population Density	German Statistical Office	Number of inhabitants per area
Sectoral Specialization	Alecke et al. (2006)	Sum of squared deviations of regional average employment shares for NACE3 sectors from national average
Ellison-Glaeser Index	Alecke et al. (2006)	Employment in sectors with high Ellison-Glaeser Index (>0.005) relative to total employment in the region
Dummy BioRegio Winner	Dohse (2000)	Binary dummy for winner districts in the BioRegio contest (for complete list, see Appendix)
Dummy BioRegio Participant	Dohse (2000)	Binary dummy for non-winning districts in the BioRegio contest (for complete list, see Appendix)
Dummy BioProfile	Cooke et al. (2007)	Binary dummy for winner districts in the BioProfile contest (for complete list, see Appendix)

For our empirical analysis, we collapse the yearly observations from our sample data into three periods: 1.) pre-treatment period, 2.) treatment period and 3.) post-treatment period. The time span of each period differs for BRC and BPC due to the fact that BPC ran two years after BRC (see Table 2). Therefore, we prepare two samples, one for the evaluation of BRC and the other one for the evaluation of BPC. The first BRC sample contains BRC winners, non-winning participants and non-participants.[8] While non-winning participants are needed as a comparison group to assess the expected direct effects of funding, non-participating regions serve as second comparison group (both relative to winners and non-winners) in order to give a first quantification of the possible indirect effects of funding as outlined above. We exclude BPC winners from the group of non-winning participants in this sample in order to avoid the problem that BPC winners – due to the overlap of both contests – also received funding during the BRC.

[8] A total of 55 NUTS3 regions participated in the BRC (see Table A.1 in the appendix for details). Although the BioRegio contest was officially set up on a five-year basis, between 1997 and 2001, we include an additional year as treatment period in order to account for the usual funding practice according to an *N+1* period, where *N* stands for the nominal time span of a specific project.

This sample reduction, however, might be critical given that the BPC winners can be seen as an ideal comparison group for BRC winners since the problem of selection into the treatment given unobserved regional characteristics should be less prevailing. In other words: Both groups should only differ with respect to the timing of exclusive funding. Therefore, we use a second shorter BRC sample (labeled BRC2) that – as comparison unit – also contains BPC winner regions prior to the BPC contest. To guarantee the comparability between the analysed groups the period of observation ends as the BPC starts. This approach thus has the advantage of an appropriate comparison group on the one hand, while it faces the disadvantage of shortening the investigation period on the other hand. However, while many R&D projects started immediately after the announcement of "BRC winner", we believe that losing two years does not fundamentally affect the precision of our estimates in the BRC2 sample. Descriptive statistics of the samples according to Table 2 are given in the Appendix.

Table 2: Sample periods under investigation

	Outcome variable	Pre-treatment period (before funding)	Treatment period (exclusive funding)	Post-treatment period (after funding)
BRC1[a]	Funding	1991–996	1997–2002	2003–2007
	Patents	1991–1997	1998–2006	n.a.
BRC2[b]	Funding	1991–1996	1997–2000	n.a.
	Patents	1991–1997	1998–2002	n.a.
BPC[c]	Funding	1991–2000	2001–2007	n.a.
	Patents	1991–2000	2002–2006[d]	n.a.

Notes: We assume that patent applications based on funding are earliest declared one year after the beginning of exclusive funding and latest one year after the exclusive funding is closed. [a] The sample *BRC1* contains BRC winners, non-winning BRC participants (without BPC winners) and non-participants. [b] In addition to sample BRC1, the sample BRC2 contains BPC winners. [c] The sample BPC contains BPC winners, non-winning BRC participants and non-participants of BRC. [d] Due to limitations in patent data, we can only consider five years instead of seven years in the ideal case.

Although collapsing the annual observations into three time periods results in a loss of information, there are statistical reasons that advocate carrying out the DiD-estimation strategy this way. Bertrand et al. (2004), for instance, propose to collapse data with a long sample range into just two periods (one before and one after the policy intervention) in order to minimize the risk of obtaining underestimated standard errors due to serially correlated errors when unobservable factors are present over time. In doing so, we also circumvent the problem that certain variables such as start-up activity are only available at longer time intervals. For the outcome variables, we sum up the number of patents and publicly funded projects observed for each region for the time intervals defined in Table 2. For the set of explanatory variables, we use sample averages for each respective time period.

Table 3 shows that both the number of directly funded projects and the sum of allocated grants in the field of biotechnology increased significantly between 1991 and 2007. In

particular, we observe a take-off between the periods 1991–96 and 1997–2002, which may give a first indication of the boost in Biotech funds throughout the BRC competition. Compared to this, for the period 2003–07 we observe a consolidation phase of public R&D spending in biotechnology. The apparent time trend faced by the whole industry makes it thus important to compare the performance of winning regions not only over time, but also relative to the other actors, in order not to erroneously allot the positive industry trend to the causal impact of BRC (and BPC) funding.

Table 3: Directly funded biotechnology related R&D projects

	Pre-treatment 1991–96	**Treatment 1997–2002**	**Post-treatment 2003–07**
Number of directly funded projects	3,692	4,482	4,603
Total amounts of directly funded projects (in €1000)	723,995	1,055,159	1,331,133

Source: PROFI, own calculation.

Tables 4 and 5 show the allocation of federal funds with respect to the different regions and the share of cooperative R&D projects, respectively. Table 4 points out that BRC winners could further increase their relative share of the total funding during the treatment period from 1997 to 2002. However, for the post-treatment period we see a significant decline in the regional share of total direct project funds. By contrast, especially BPC winners and non-winning BRC participants were able to increase their share in this latter period. Regarding the distribution of funds among the four groups, the table shows that all parties have received a fairly similar share of funding, indicating that they may serve as homogeneous comparison groups with respect to the outcome variable of publicly funded R&D projects.

Table 5 further highlights that, for all regions, the share of cooperative R&D projects increased over time. It seems that exclusive funding for "winners" correlates with the extension of collaborative projects. BRC and BPC winners show a significant increase in the share of collaborative projects during the treatment period (1997–2002 for BRC and 2001–07 for BPC). Most interestingly, the importance of collaborative projects (as share of overall projects) reduces for BRC winners in the post-treatment period. In the result, the change in the collaborative share for the winning and non-winning regions of BRC is very similar over the periods.

Table 4: Allocation of direct project funding to biotechnology programs (percentage)

Participation State	Pre-treatment 1991–96	Treatment 1997–2002	Post-treatment 2003–07
BRC winner	32.1	33.8	27.3
Non winning BRC participants	17.1	15.0	18.6
BPC winner	24.1	24.5	26.6
Other NUTS-3 districts	26.6	26.7	27.5
Sum (Germany)	100.0	100.0	100.0

Source: PROFI, own calculation.

Table 5: Percentage of cooperative R&D projects relative to overall funding per group

Participation State	Pre-treatment 1991–96	Treatment 1997–2002	Post-treatment 2003–07
BRC winner	20.4	36.9	29.0
BPC winner	32.3	42.9	49.6
Non winning BRC participants	31.6	39.0	40.3
Other NUTS-3 districts	26.4	42.9	42.9

Source: PROFI, own calculation.

Given the fact that patenting activity inherently exhibits a time lag in the transmission process from R&D funds to R&D activity and finally to R&D outcome, we are only able, at this point, to compare the treatment effect relative to the pre-treatment period for winning regions of the BRC/BPC with the specific comparison groups. Due to restrictions in patent data publication, as well as to time lags in the transmission from R&D inputs to outputs, we cannot construct a sufficiently long post-treatment period. Thus, for patent applications, we set the treatment and pre-treatment periods as follows: from 1991 to 1997, we assume that there is – by definition – no significant patent application activity as a result of the BRC. Instead, for the period 1998 to 2006, we assume that patent applications are directly influenced by the BRC (2002–06 for the BPC).

As Table 6 shows, BRC winning regions significantly increased their number of patents in the treatment period. The growth rate was about +183 per cent. However, BPC winners showed a significant boost in their patenting activity as well (+281 per cent), showing the strongest growth performance among all four groups. Table 6 shows that, compared to BRC winners, BPC winners were initially smaller in absolute size, but showed a convergence to the BRC level throughout the sample period. For the non-winning participants and all remaining NUTS-3 districts, the number of patent applications showed a smaller increase (+93 per cent and +168 per cent, respectively). Finally, compared to public R&D spending from Table 6, we also see that here the inter-group heterogeneity is much higher, indicating that in particular

the comparison between winning and participant regions is expected to yield the utmost reliable results in the estimation approach, trying to minimizing any possible self-selection bias. We turn to the model set-up in the following.

Table 6: Total number of biotech patent applications (Average per NUTS-3 district for each category)

	Pre-treatment 1991–97	Treatment 1998–2006	Growth rate
BRC winner	83.6	236.6	+183.0%
Non winning BRC participants (excluding BPC winner)	49.2	95.1	+93.3%
BPC winner	55.7	212.3	+281.1%
Other NUTS-3 districts	9.2	24.7	+168.4%

Source: EPO, own calculation.

4. Econometric approach and estimation results

4.1 Model set-up

In order to analyse the effects of funding on private R&D activity, we have to estimate a set of models which differ by the design of the treatment versus the comparison group and the time period employed, as shown in Table 2. The econometric literature offers different approaches to estimate treatment effects. Here we apply a Difference-in-Differences (DiD) technique, which aims at isolating the policy effect related to changes in the outcome variable $Y_{i,t}$ for a group of treated individuals (i, in our case: NUTS-3 regions) over time (t, in our case: limited to two consecutive periods) relative to a comparison group. The underlying identification assumption of this approach is that the difference between treatment and comparison groups would have been constant over time if the treatment group had not received the subsidy. Since we are dealing with three groups (winners, participants and non-participants), our model specification has the following general form

$$(1) \qquad Y_{i,t} = \alpha + \beta_1 D_i^1 + \beta_2 D_i^2 + \gamma T_t + \delta_1 (D_i^1 \times T_t) + \delta_2 (D_i^2 \times T_t) + \omega' \mathbf{X}_{i,t} + u_{i,t},$$

where D_i^1 and D_i^2 are defined as binary variables with values

$$D_i^1 = \begin{cases} 1 & \text{if region } i \text{ belongs to the group of contest winners,} \\ 0 & \text{otherwise.} \end{cases}$$

$$D_i^2 = \begin{cases} 1 & \text{if region } i \text{ belongs to the group of non-winning participants,} \\ 0 & \text{otherwise.} \end{cases}$$

The third group of non-participating regions serves as reference group. Statistically significant positive parameters for D_i^1 and D_i^2 indicate level differences among the groups for the outcome variable. In addition to these dummy variables, we include a common time period indicator *T*, which takes either a value of zero (pre-treatment period) or one (treatment or post-treatment period respectively). The crucial parameters of interest are the two DiD-terms, which are calculated as interaction effects between the common time trend and the individual group dummies as $(D_i^1 \times T_t)$ and $(D_i^2 \times T_t)$. Both terms measure the difference between the expected outcome for treated regions before and after treatment, net of the outcome difference of the comparison or reference group during the treatment.

Statistically significant parameters δ_1 and δ_2 indicate a treatment effect for each subgroup relative to the benchmark case of non-participant regions. Specifically, δ_i measures the change in expected outcome variable *E[Y]* for treated (*D=1*) and non-treated individuals (*D=0*) between the treatment (*t=1*) and pre-treatment (*t=0*) periods as

$$(2) \qquad \delta_i = (E[Y \mid D = 1, t = 1] - E[Y \mid D = 1, t = 0]) - (E[Y \mid D = 0, t = 1] - E[Y \mid D = 0, t = 0]).$$

They can be interpreted as the combined direct and indirect effects of funding, respectively. By testing for parameter restrictions in terms of $\delta_3 = (\delta_1 - \delta_2)$, we are finally able to identify the treatment effect of winners versus non-winners within a common regression exercise, which allows us to isolate the direct treatment effect of funding "on the fly". In other words, the latter effect can be defined as a further Difference in the Difference-in-Differences parameters (DiDiD).

By the inclusion of the group-specific binary variables we are able to control for time-invariant omitted variables, however, the model may still be sensitive to temporary fluctuations that influence the performance of the treatment and control groups differently. The latter problem can be handled by including a set of time-varying control variables (**X**) for further regional characteristics, like the number of firms, new firm formations, international competiveness, share of MINT employees, sectoral specialization and agglomeration. Finally, $u_{i,t}$ is the error term of the model, and α, β_1, β_2, γ and ω are further regression coefficients.

Since patent applications and R&D grants are count data that exhibit a high share of zeros, the underlying distribution of the outcome variables may be neither normal-distributed nor conforming to a regular or overdispersed Poisson. A common solution to this problem is to rely on a so-called zero-inflated Poisson (ZIP) model.[9] Another crucial point for our empirical policy analysis is whether the estimated DiD-parameters in the (non-linear) ZIP model can be interpreted in the usual (linear) fashion. For the case of the Poisson model, the answer is straightforward, since the latter is just a flexible generalization of the ordinary least squares regression. In other words, we are still in the linear case and the usual assumptions hold. Since

[9] For our estimation approach, we explicitly test for the appropriateness of the ZIP specification versus the standard Poisson model by means of standard post-estimation tests.

the Poisson model uses the logarithm as the link function, we can obtain the marginal effect for the DiD-parameter as $[exp(\delta_i) - 1]$.[10]

4.2. Results

In this section, we estimate different ZIP models for the samples designed according to Table 2. Statistical inference for the two DiD-terms is made directly from the regression output, and significance of the DiDiD term is tested ex-post based on the so-called delta method (for details, see Greene 2003). The main empirical results regarding the parameter of the DiD term for different sample designs are given in Table 7. Full regression outputs are reported in Tables 8–11.

As Panel A.1 in Table 7 (for the BRC) shows, we detect a positive and statistically significant higher number of patent application and raised R&D projects for BRC winners compared to non-participants, throughout the treatment period. Likewise, the result holds for all R&D projects, as well as for the subgroup of collaborative R&D projects. These findings clearly support the existence of direct treatment effects of funding, and suggest that the label "winner" signals an above-average R&D performance and it may contribute positively to a better innovative performance in biotechnology. However, we do not find evidence of indirect effects of funding when comparing non-winning participants with non-participants (others).

One drawback for the approach in Panel A.1 is that one may still argue that BRC winners differ from remaining regions with respect to adjustments due to environmental changes.[11] For instance, the implementation of the "Neuer Markt" in April 1997, Germany's equivalent to the United States' NASDAQ, and its rapid growth measured by the number of listed companies and market capitalization, marks a remarkable change and may be an alternative source for increased patent activity.[12] However, comparing BRC winners with BPC winners (as a comparison group in BRC2) may be seen as an effective strategy to eliminate some of above-mentioned unobservable differences. In fact, the share of venture capital-financed firms does not differ remarkably between BRC and BPC winners (see Engel and Heneric 2005).

In Panel A.2, we report the estimation results of the BRC2 sample, where we compare the relative performance of BRC winners against the one of non-winning participants, including BPC winners, prior to the starting date of the BPC competition. The results for patent applications show that BRC winners again show a better track record compared to the remaining full candidate set for the treatment period (1998–2002), both in terms of patent

[10] We do not include the DiD terms in the non-linear Probit part of the model since both the BRC and BPC aim to improve the track record of promising biotech regions rather than initiating a regime switch from non-innovators to innovators.

[11] Additionally, we have to keep in mind that the group of non-winning participants is defined as net of the winning regions from the BPC contest, and thus has been subject to a dual selection mechanism, leaving only poor candidates within this group.

[12] While highly profitable exit opportunities are offered to investors in non-listed firms, venture capital investments in biotechnology went up by a factor of six between 1997 and 2001 (see OECD 2006: 119). According to the "selection of the fittest" hypothesis, firms and scientists in BRC winning regions are more stimulated by the rapid growth of the venture capital market. As a result, inventions could be better protected by patent applications to secure a unique selling proposition in the commercialization process of innovative ideas.

applications and of the number of raised R&D projects. However, if we split the latter candidate set into BPC winners and remaining participants, we see that the obtained positive direct treatment effect of BRC winners for patent applications stems mainly for the relative superiority of winners relative to non-winners (net of BPC winners). Compared to them, BPC winners show a better patent performance, while they clearly fall behind in terms of raising R&D funds relative to BRC regions.

Table 7: Estimated elasticity for the DiD-interaction term for different subsamples

Elasticity of DiD term	Patents	R&D Projects (total)	R&D Projects (collaborative)
Panel A.1. Treatment Period for BRC1: Period 2 versus Period 1			
Winner / Non-Winner	0.72***	0.37***	0.41***
Winner / Others	0.59***	0.43***	0.49***
Non-Winner / Others	–0.07**	0.04	0.06
Panel A.2. Treatment Period for BRC2: Period 2 versus Period 1			
Winner / Non-Winner (All)	0.15***	0.46***	0.55***
Winner / Non-Winner (Only BPC)	–0.28***	0.52***	0.61***
Winner / Non-Winner (Rest)	0.61***	0.41***	0.49***
Panel B. Post Treatment Period for BRC1: Period 3 versus Period 1			
Winner / Non-Winner	n.a.	0.24***	0.09
Winner / Others	n.a.	0.09	0.25**
Non-Winner / Others	n.a.	–0.11*	0.14
Panel C. Treatment Period for BPC: Period 2 versus Period 1			
Winner / Non-Winner	0.42***	0.32***	0.36***
Winner / Others	–0.04	0.07*	0.38***
Non-Winner / Others	–0.33***	–0.18***	0.02

Notes: ***,**,* indicate statistical significance at the 1, 5 and 10 per cent level. The reported elasticities are calculated as $[exp(\delta_i) - 1]$, where δ_i is based on the DiD- and DiDiD-parameters of the full regression outputs given in Tables 8 to 11.

Given the absence of direct effects (or even negative ones) for patent activity between BRC and BPC winners, one may thus ask whether the selection mechanism in the BRC competition was operating poorly. In order to answer such a question, one has to recall that the goal of the programme was to push the technological competitiveness of German biotechnology towards an international dimension. As the regression parameters for the treatment variables (D_i) in Table 8 (column BRC2) show, the (initial) level of patent applications of BRC winners was more than twice as large as the one of the reference group (calculated as exp[0.745] – 1 =

+1.1), while BPC winners were only 1.3 times larger (as exp[0.261] – 1 = +0.3) in terms of patent applications. Thus, among the positively performing candidates, the jury in the BRC picked the heavyweights, and put a focus on dynamically growing – but smaller – "rising stars" in the BPC. This finding provides further empirical evidence that both the BRC and BPC are a sequential result of "picking the winners", as argued, for example, by Dohse (2000).

When it comes to the long-term effects of BRC participation and exclusive funding, Panel B of Figure 7 shows the findings for the R&D performance of BRC winners and both comparison groups in the post-treatment period. This may give an indication of which new equilibrium levels will be reached after the extensive funding by the BRC. On the one hand, we may expect that the receipt of additional public funding leads firms to acquire competences, and thus, positive path dependence should matter. On the other hand, the number of raised public R&D grants may actually follow different motives than allocating R&D sources to the most successful region (e.g., distributive rather than allocative arguments from a policy perspective). As the results in Table 7 show that, in comparison with the short-term effects in the treatment period, statistical evidence for long-term effects of funding is indeed much weaker. Although BRC winners still tend to outperform non-winners with respect to raised public R&D funds, there is no evidence of an overall better performance compared to non-participating regions, and non-winners even appear to fall behind the reference group of non-participating regions.

Compared to non-participating regions, the only significant difference of BRC winners is their ability to raise more collaborative projects. This result hints at the successful ability to create networks. We do not find statistically significant long-term effects when comparing non-winning participants and other regions. This latter result may point to the fact that the number of biotech regions and, subsequently, their ability and success in acquiring R&D grants have grown over time. BRC non-winners and non-participants have significantly improved their position relative to BRC winners. As a matter of fact, ten more biotech-regions were formed by 2005 (for details, see Engel and Heneric 2005). In addition to the efforts of the Federal Government, many Federal States governments promote these biotech-regions within state programmes. At this stage, we cannot conclude that regionalized technological policy lacks efficiency in the long term. We believe that improvements in non-participant regions are the key explanation for the absence of long-term effects of BRC.

Finally, with regard to the evaluation of the BPC, Panel C of Figure 7 shows the findings for BPC winners and the two comparison groups. Consistently with the findings discussed above, here we obtain fairly small effects when comparing winning regions and the others, as the winners only appear to perform better in terms of raising collaborative R&D projects. Nevertheless, the "selection of the fittest" also seems to works in both stages of the competitions, since the BPC winners also perform significantly better than non-winning participants (during the treatment period) for the latter contest. The estimated elasticity of the DiD-term is about the same size as the effect identified for the BRC. This is an important finding, since one might expect the performance of the winners at the second stage to be characterized by lower differences with the non-winners. The smaller treatment effects found

for BPC winners relative to non-participants may be partly due the consolidation phase going on in the industry throughout the second half of the last decade. Although we control for a common time trend among all groups, which turns out to be significantly negative according to Table 7, throughout this consolidation period the chances to realize excess returns may have been limited for funded regions as well.

We finally report some details of the full regression outputs shown in Table 8 to Table 11. Regarding the appropriate functional form, in most specifications the ZIP model is favored over the Poisson model based on model information criteria (AIC, BIC) as well as on the Vuong (1989) non-nested test between the Poisson and ZIP models. As a key explanatory variable in the Probit specification, we use the share of regional high-tech startups indicating an innovative climate for a region that either supports R&D or not. In all specifications, this variable turns out to be statistically significant and of the expected sign. Also, the remaining variables in the Poisson part of the model mostly reflect our ex-ante expectations, that is, both the share of MINT employees and the export share have a positive impact on R&D activity. Moreover, the total number of firms, the variables measuring general agglomeration (e.g., population density), and sectoral concentration indices (and their squared values) are statistically significant. As a robustness check, we also controlled for the likely role of spatial dependence in the variables. Though positive spatial autocorrelation was found to be present for patent applications (no statistically significant spatial autocorrelation in the case of public R&D funding), the inclusion of spatial filters to control for unobserved spatial heterogeneity did not alter the key conclusions from the DiD-estimation approach.[13]

[13] Detailed results can be obtained from the authors upon request and are reported in an earlier version of this paper ("*Does the Support of Innovative Clusters Sustainably Foster R&D Activity? Evidence from the German BioRegio and BioProfile Contests*", Quaderni della facoltà di Scienze economiche dell'Università di Lugano, No. 1105-2010).

Table 8: Estimation Results for Patent Applications (Treatment Period)

Sample	BRC1		BRC2		BPC	
D^1	0.682***	(0.0375)	0.745***	(0.0376)	0.879***	(0.0315)
D^2	0.521***	(0.3577)	0.542***	(0.0358)	0.580***	(0.0267)
D^3			0.261***	(0.0486)		
T	0.727***	(0.0207)	0.520***	(0.0211)	–0.733***	(0.0197)
(D^1xT)	0.465***	(0.0383)	0.378***	(0.0400)	–0.046	(0.0420)
(D^2xT)	–0.079**	(0.0398)	–0.099**	(0.0419)	–0.401***	(0.0421)
(D^3xT)			0.706***	(0.0502)		
Number of Firms	0.002***	(0.0001)	0.003***	(0.0001)	0.002***	(0.0001)
Average Firm size	0.001***	(0.0001)	0.001***	(0.0002)	–0.001***	(0.0002)
Export Share	0.008***	(0.0008)	0.007***	(0.0006)	0.011***	(0.0007)
MINT Employment	0.064***	(0.0061)	0.018***	(0.0063)	0.006	(0.0074)
Population Density	0.072***	(0.0113)	0.041***	(0.0118)	0.167***	(0.0116)
Sectoral Specialization Manu	0.191	(0.1683)	–0.434**	(0.1781)	–0.569***	(0.1898)
Sectoral Specialization Serv1	–1.222***	(0.1432)	–0.386**	(0.1643)	–0.585***	(0.1520)
Sectoral Specialization Serv2	0.166	(0.1024)	–0.183*	(0.1054)	0.066	(0.1103)
(Sectoral Specialization Manu)^2	–0.032**	(0.0133)	0.019	(0.0141)	0.028*	(0.0150)
(Sectoral Specialization Serv1)^2	0.128***	(0.0133)	0.055***	(0.0152)	0.068***	(0.0143)
(Sectoral Specialization Serv2)^2	–0.012	(0.0109)	0.033***	(0.0111)	–0.001	(0.0118)
Ellison-Glaeser Manu	0.059***	(0.0034)	0.049***	(0.0035)	0.078***	(0.0042)
Ellison-Glaeser Serv1	0.151***	(0.0097)	0.100***	(0.0105)	0.093***	(0.0104)
Ellison-Glaeser Serv2	0.019	(0.0123)	0.101***	(0.0131)	0.071***	(0.0128)
(Ellison-Glaeser Manu)^2	–0.001***	(0.0001)	–0.001***	(0.0001)	–0.002***	(0.0001)
(Ellison-Glaeser Serv1)^2	–0.003***	(0.0003)	–0.002***	(0.0003)	–0.001***	(0.0003)
(Ellison-Glaeser Serv2)^2	–0.001**	(0.0006)	–0.004***	(0.0007)	–0.002***	(0.0007)
Probit (ZIP)						
Start-up (High-Tech)	0.569**	(0.2225)	1.078***	(0.3473)	0.989**	(0.3929)
Start-up (all)	–0.045**	(0.0164)	–0.095***	(0.0274)	–0.125***	(0.0346)
$DiDiD_1 = (D^1xT) – (D^2xT)$	0.545***	(0.0047)	0.478***	(0.0498)	0.355***	(0.0531)
$DiDiD_2 = (D^1xT) – (D^3xT)$			–0.327***	(0.0570)		
diff(BIC)	3768.5	(ZIP)	4062.0	(ZIP)	3741.1	(ZIP)
diff(AIC)	4.62	(ZIP)	4.87	(ZIP)	4.62	(ZIP)
Vuong test (p-value)	5.87	(0.00)	7.26	(0.00)	6.44	(0.00)
No. of obs.	818 [a]		836		812 [a]	

Notes: ***,**,* indicate statistical significance at the 1, 5 and 10% level. Standard errors in brackets. Specialization and Ellison-Glaeser indices: *Manu* = manufacturing, *Serv1* = business-related services, *Serv2* = household-related services. Dummy variables: D^1 = winners, D^2 = participants (in the BRC2 sample: D^2 = participants net of BPC winner, D^3 = BPC winner). (D^1xT) to (D^3xT) indicate the DiD-interaction terms calculated as the product of the level dummies and the common time period indicator T. [a] BPC winners dropped in sample BRC1, BRC winners dropped in sample BPC. For *diff(BIC)* and *diff(AIC)*, the expression in brackets indicates the preferred model as either ZIP or PRM.

Table 9: Estimation Results for all R&D Projects (Treatment Period)

Sample	BRC1		BRC2		BPC	
D^1	1.099***	(0.0617)	1.186***	(0.0598)	1.650***	(0.0441)
D^2	0.656***	(0.0543)	0.677***	(0.0538)	0.779***	(0.0420)
D^3			1.526***	(0.0542)		
T	0.228***	(0.0407)	–0.121**	(0.0493)	0.127***	(0.0331)
(D^1xT)	0.357***	(0.0615)	0.173**	(0.0718)	0.076	(0.473)
(D^2xT)	0.041	(0.0624)	–0.176**	(0.0740)	–0.204***	(0.0510)
(D^3xT)			–0.245***	(0.0706)		
Number of Firms	0.002***	(0.0001)	0.002***	(0.0001)	0.002***	(0.0001)
Average Firm size	–0.002***	(0.0003)	–0.001***	(0.0003)	–0.003***	(0.0004)
Export Share	0.018***	(0.0017)	0.007***	(0.0008)	0.010***	(0.0008)
MINT Employment	0.086***	(0.0111)	0.089***	(0.0114)	0.108***	(0.0100)
Population Density	0.237***	(0.0244)	0.293***	(0.0237)	0.246***	(0.0186)
Sectoral Specialization Manu	–1.038**	(0.3965)	–2.427***	(0.4196)	–4.258***	(0.3185)
Sectoral Specialization Serv1	–2.379***	(0.2771)	–1.947***	(0.3227)	–1.958***	(0.2767)
Sectoral Specialization Serv2	1.099***	(0.2137)	0.920***	(0.2296)	1.022***	(0.1875)
(Sectoral Specialization Manu)^2	0.072**	(0.0311)	0.177***	(0.0332)	0.318***	(0.0254)
(Sectoral Specialization Serv1)^2	0.219***	(0.0265)	0.181***	(0.0308)	0.148***	(0.0274)
(Sectoral Specialization Serv2)^2	–0.058***	(0.0218)	–0.052**	(0.0233)	–0.071***	(0.0195)
Ellison-Glaeser Manu	–0.065***	(0.0066)	–0.019***	(0.0062)	0.036***	(0.0065)
Ellison-Glaeser Serv1	–0.202***	(0.0203)	–0.236***	(0.0231)	–0.231***	(0.0198)
Ellison-Glaeser Serv2	0.225***	(0.0264)	0.289***	(0.0273)	0.318***	(0.0224)
(Ellison-Glaeser Manu)^2	0.001***	(0.0001)	–0.0002	(0.0001)	–0.001***	(0.0001)
(Ellison-Glaeser Serv1)^2	0.005***	(0.0006)	0.005***	(0.0007)	0.006***	(0.0006)
(Ellison-Glaeser Serv2)^2	–0.005***	(0.0011)	–0.007***	(0.0012)	–0.008***	(0.0011)
Probit (ZIP)						
Start-up (High-Tech)	1.104***	(0.2107)	1.025***	(0.2076)	1.113***	(0.2242)
Start-up (all)	–0.051***	(0.0153)	–0.053***	(0.0150)	–0.084***	(0.0182)
$DiDiD_1 = (D^1xT) – (D^2xT)$	0.316***	(0.0676)	0.349***	(0.0772)	0.280***	(0.0524)
$DiDiD_2 = (D^1xT) – (D^3xT)$			0.419***	(0.0745)		
diff(BIC)	2677.1	(ZIP)	2212.1	(ZIP)	3173.9	(ZIP)
diff(AIC)	3.31	(ZIP)	2.67	(ZIP)	3.92	(ZIP)
Vuong test (p-value)	8.41	(0.00)	8.27	(0.00)	8.16	(0.00)
No. of obs.	812 [a]		834		812 [a]	

Notes: ***,**,* indicate statistical significance at the 1, 5 and 10% level. Standard errors in brackets. Specialization and Ellison-Glaeser indices: *Manu* = manufacturing, *Serv1* = business-related services, *Serv2* = household-related services. Dummy variables: D^1 = winners, D^2 = participants (in the BRC2 sample: D^2 = participants net of BPC winner, D^3 = BPC winner). (D^1xT) to (D^3xT) indicate the DiD-interaction terms calculated as the product of the level dummies and the common time period indicator T. [a] BPC winners dropped in sample BRC1, BRC winners dropped in sample BPC. For *diff(BIC)* and *diff(AIC)*, the expression in brackets indicates the preferred model as either ZIP or PRM.

Table 10: Estimation Results for collaborative R&D Projects (Treatment Period)

Sample	BRC1		BRC2		BPC	
D^1	0.731***	(0.0962)	0.897***	(0.0950)	1.173***	(0.0644)
D^2	0.318***	(0.0872)	0.352***	(0.0866)	0.431***	(0.0605)
D^3			1.128***	(0.0879)		
T	0.554***	(0.0647)	0.114*	(0.0708)	0.257***	(0.0450)
(D^1xT)	0.399***	(0.0929)	0.360***	(0.0865)	0.328***	(0.0654)
(D^2xT)	0.054	(0.0962)	–0.043	(0.1085)	0.022	(0.0699)
(D^3xT)			–0.116	(0.1036)		
Number of Firms	0.003***	(0.0002)	0.003***	(0.0002)	0.002***	(0.0001)
Average Firm size	0.0006	(0.0004)	0.001*	(0.0005)	–0.002***	(0.0005)
Export Share	0.019***	(0.0025)	0.002*	(0.0012)	0.009***	(0.0012)
MINT Employment	0.041***	(0.0153)	0.036**	(0.0163)	0.082***	(0.0130)
Population Density	0.022	(0.0354)	0.068**	(0.0349)	0.101***	(0.0254)
Sectoral Specialization Manu	0.796	(0.5570)	–0.485	(0.620)	–4.111***	(0.4407)
Sectoral Specialization Serv1	–1.818***	(0.3806)	–1.294***	(0.4367)	–0.750*	(0.3826)
Sectoral Specialization Serv2	0.854***	(0.3148)	0.469	(0.3517)	0.095***	(0.2632)
(Sectoral Specialization Manu)^2	–0.074*	(0.0436)	0.027	(0.0491)	0.031***	(0.0354)
(Sectoral Specialization Serv1)^2	0.154***	(0.0371)	0.114**	(0.0448)	0.020	(0.0383)
(Sectoral Specialization Serv2)^2	–0.028	(0.0323)	–0.001	(0.0357)	0.060*	(0.0275)
Ellison-Glaeser Manu	–0.055***	(0.0094)	–0.006	(0.0094)	0.056***	(0.0092)
Ellison-Glaeser Serv1	–0.221***	(0.0281)	–0.265***	(0.0329)	–0.165***	(0.0261)
Ellison-Glaeser Serv2	0.311***	(0.0364)	0.334***	(0.0388)	0.259***	(0.0288)
(Ellison-Glaeser Manu)^2	0.001**	(0.0002)	–0.0005**	(0.0003)	–0.002***	(0.0002)
(Ellison-Glaeser Serv1)^2	0.004***	(0.0008)	0.005***	(0.0010)	0.004***	(0.0008)
(Ellison-Glaeser Serv2)^2	–0.007***	(0.0016)	–0.007***	(0.0017)	–0.003**	(0.001)
Probit (ZIP)						
Start-up (High-Tech)	1.194***	(0.2430)	1.249***	(0.2399)	1.131***	(0.2370)
Start-up (all)	–0.033**	(0.0166)	–0.033**	(0.0161)	–0.062***	(0.0186)
$DiDiD_1 = (D^1xT) – (D^2xT)$	0.345***	(0.0995)	0.403***	(0.1109)	0.307***	(0.0722)
$DiDiD_2 = (D^1xT) – (D^3xT)$			0.475***	(0.1068)		
diff(BIC)	2017.8	(ZIP)	1472.3	(ZIP)	2551.7	(ZIP)
diff(AIC)	2.50	(ZIP)	1.78	(ZIP)	3.16	(ZIP)
Vuong test (p-value)	7.80	(0.00)	7.19	(0.00)	7.98	(0.00)
No. of obs.	812 [a]		834		812 [a]	

Notes: ***,**,* indicate statistical significance at the 1, 5 and 10% level. Standard errors in brackets. Specialization and Ellison-Glaeser indices: *Manu* = manufacturing, *Serv1* = business-related services, *Serv2* = household-related services. Dummy variables: D^1 = winners, D^2 = participants (in the BRC2 sample: D^2 = participants net of BPC winner, D^3 = BPC winner). (D^1xT) to (D^3xT) indicate the DiD-interaction terms calculated as the product of the level dummies and the common time period indicator T. [a] BPC winners dropped in sample BRC1, BRC winners dropped in sample BPC. For *diff(BIC)* and *diff(AIC)*, the expression in brackets indicates the preferred model as either ZIP or PRM.

Table 11: BRC1-Estimation Results for R&D Projects (Post-Treatment Period)

Sample: BRC1	**All Projects**		**Collaborative**	
D^1	1.037***	(0.0618)	0.644***	(0.0962)
D^2	0.607***	(0.0543)	0.223**	(0.0881)
T	0.244***	(0.0443)	0.504***	(0.0688)
(D^1xT)	0.094	(0.0638)	0.224**	(0.0959)
(D^2xT)	–0.117*	(0.0638)	0.134	(0.0969)
Number of Firms	0.003***	(0.0001)	0.003***	(0.0002)
Average Firm size	0.0001	(0.0002)	0.002***	(0.0004)
Export Share	0.013***	(0.0016)	0.015***	(0.0022)
MINT Employment	0.087***	(0.0115)	0.035**	(0.0159)
Population Density	0.232***	(0.0245)	0.082**	(0.0366)
Sectoral Specialization Manu	–1.616***	(0.4112)	–1.177**	(0.5699)
Sectoral Specialization Serv1	–1.7199***	(0.2883)	–1.885***	(0.4011)
Sectoral Specialization Serv2	1.094***	(0.2239)	0.0033	(0.3227)
$(Sectoral\ Specialization\ Manu)^2$	0.0995***	(0.0322)	0.065***	(0.0446)
$(Sectoral\ Specialization\ Serv1)^2$	0.152***	(0.0277)	0.160***	(0.0393)
$(Sectoral\ Specialization\ Serv2)^2$	–0.051**	(0.0229)	0.068**	(0.0329)
Ellison-Glaeser Manu	–0.047***	(0.0065)	–0.027***	(0.0093)
Ellison-Glaeser Serv1	–0.262***	(0.0225)	–0.223***	(0.0304)
Ellison-Glaeser Serv2	0.358***	(0.0287)	0.347***	(0.0385)
$(Ellison\text{-}Glaeser\ Manu)^2$	0.001	(0.0013)	–0.0003*	(0.0001)
$(Ellison\text{-}Glaeser\ Serv1)^2$	0.005***	(0.0007)	0.004***	(0.0009)
$(Ellison\text{-}Glaeser\ Serv2)^2$	–0.010***	(0.0013)	–0.008***	(0.0017)
Probit (ZIP)				
Start-up (High-Tech)	1.099***	(0.2165)	1.557***	(0.2655)
Start-up (all)	–0.057***	(0.0151)	–0.040**	(0.0167)
$DiDiD = (D^1xT) - (D^2xT)$	0.212***	(0.0707)	0.091	(0.1015)
diff(BIC)	2708.9	(ZIP)	1821.4	(ZIP)
diff(AIC)	3.379	(ZIP)	2.27	(ZIP)
Vuong test (p-value)	8.17	(0.00)	7.64	(0.00)
No. of obs.	806 [a]		806 [a]	

Notes: ***,**,* indicate statistical significance at the 1, 5 and 10% level. Standard errors in brackets. Specialization and Ellison-Glaeser indices: *Manu* = manufacturing, *Serv1* = business-related services, *Serv2* = household-related services. Dummy variables: D^1 = winners, D^2 = participants. (D^1xT) to (D^2xT) indicate the DiD-interaction terms calculated as the product of the level dummies and the common time trend T. [a] BPC winners dropped. For *diff(BIC)* and *diff(AIC)* the expression in brackets indicates the preferred model as either ZIP or PRM.

5. Conclusions

In this paper, we have analysed the performance of winning regions for Germany's well-known BioRegio and BioProfile contests. These contests marked a milestone in the attempt to allocate public R&D funds in a competitive way, which strongly emphasizes the role of geographic proximity in knowledge creation, and to push collaborative R&D projects in leading biotechnology clusters. Although the BioRegio contest was one of the major attempts of the German Federal Government to narrow the gap between Germany and those countries leading in the application of biotechnological knowledge, little is known so far about its innovation and economic impact during the treatment period and in the post-treatment period. We tackled this issue by analysing two measures of R&D performance, namely the number of biotech patent applications and the number of raised public R&D projects. Using a Difference-in-Differences estimation strategy with data for 426 German NUTS-3 districts, our estimation strategy controls for observable and time-invariant unobservable differences in the pre-funding period, which also drive R&D performance in the treatment and post-treatment periods.

In first place, we compare the research outcomes of winning regions against non-winning participants. The choice of this comparison is motivated by the need to reduce any potential self-selection bias stemming from a non-random selection into treatment. Our results show that BRC winners and (to a lesser extent) BPC winners outperform non-winning participants during the treatment period. Exclusive funding, as well as stimulating effects of the "winner" label, seem to work for them in the short run. Given the sequential starting dates of the BioRegio and BioProfile contests, we are also able to compare the performance of BRC and BPC winners during a common (but temporally truncated) treatment period. In this case, the results highlight two facts: on the on hand, after being selected, the BRC winners significantly increased their relative performance in raising public R&D projects; on the other hand, they did not outperform BPC winners in terms of patent applications during the treatment period, although both groups show a significant positive effect compared to non-winning participants. The catching up of BPC winners to BRC winners can be explained by their smaller absolute size in terms of the number of patent applications prior to treatment. Thus, among the candidates in the BRC, the jury clearly selected heavyweights, rather than dynamically growing, but smaller "rising stars". The latter were selected in the second competition, the BPC. This finding provides further empirical evidence that the outcome of both the BRC and BPC are the result of "picking the winners", as argued, for example, by Dohse (2000).

In contrast with these positive effects during the treatment period, we do not find significant outcome effects of public R&D grants for BRC winners in the post-treatment period. This result is striking, and may indicate that the success of the BRC seems to be only of a temporary manner. Still, there is some evidence of positive long-term effects for collaborative R&D projects. It should be pointed out that our findings may be limited by the quality of the indicator used: in fact, we are only able to compare the number of raised public R&D grants, which may actually follow different allocation guidelines than the one of serving the most successful regions (e.g., distributive arguments). Finally, the absence of long-term effects of BRC may also driven by the fact that non-winning regions have increased their efforts to

establish networks between biotech-related firms and research units, that is, ten more biotech-regions were formed by 2005 after the BioRegio contest, and several Federal States have promoted strongly the emergence of BioRegions locally. However, it is very difficult to quantify these indirect effects. Future analyses will thus be needed to consider additional measures for the assessment of R&D performance (e.g., the share of turnover with new biotech products, or employment in biotechnology-related firms).

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Appendix

Table A.1: List of regions in the BioRegio and BioProfile contests

ID	Name	BioRegio Winner	BioRegio Non-Winner	BioProfile Winner
1002	Kiel (KS)	0	1	0
1003	Lübeck (KS)	0	1	0
2000	Hamburg (KS)	0	1	0
13003	Rostock (KS)	0	1	0
13001	Greifswald (KS)	0	1	0
3405	Wilhelmshaven (KS)	0	1	0
3403	Oldenburg (KS)	0	1	0
4011	Bremen (KS)	0	1	0
4012	Bremerhaven	0	1	0
3241	Region Hannover	0	1	1
3201	Hannover (KS)	0	1	1
3101	Braunschweig (KS)	0	1	1
3152	Göttingen	0	1	1
5124	Wuppertal (KS)	1	0	0
5111	Düsseldorf (KS)	1	0	0
5315	Köln (KS)	1	0	0
5313	Aachen (KS)	1	0	0
5316	Leverkusen (KS)	1	0	0
5354	Aachen	1	0	0
5358	Düren	1	0	0
5314	Bonn (KS)	1	0	0
6534	Marburg-Biedenkopf	0	1	0
6531	Gießen	0	1	0
6414	Wiesbaden (KS)	0	1	0
6412	Frankfurt (KS)	0	1	0
7315	Mainz (KS)	0	1	0
6411	Darmstadt (KS)	0	1	0
6413	Offenbach (KS)	0	1	0
6436	Main-Taunus	0	1	0
6438	Offenbach	0	1	0
7314	Ludwigshafen (KS)	1	0	0
7316	Neustadt a. d. W. (KS)	1	0	0
8111	Stuttgart (KS)	0	1	1
8116	Esslingen	0	1	1
8221	Heidelberg (KS)	1	0	0
8222	Mannheim (KS)	1	0	0
8416	Tübingen	0	1	1
8415	Reutlingen	0	1	1
8417	Zollernalbkreis	0	1	1
8311	Freiburg (KS)	0	1	0
8421	Ulm (KS)	0	1	0
9162	München (KS)	1	0	0
9188	Starnberg	1	0	0
9362	Regensburg (KS)	0	1	0
16053	Jena (KS)	1	0	0
15202	Halle (KS)	0	1	0
14365	Leipzig (KS)	0	1	0
15261	Merseburg-Querfurt	0	1	0
15265	Saalkreis	0	1	0
15154	Bitterfeld	0	1	0
11000	Berlin (KS)	0	1	1
12065	Oberhavel	0	1	1
12069	Potsdam-Mittelmark	0	1	1
12072	Teltow-Fläming	0	1	1
12054	Potsdam (KS)	0	1	1

Table A.2: Definition of the Biotech sector based on IPC classes

Patent class	Title
A01H 1/00	Processes for modifying genotypes
A01H 4/00	Plant reproduction by tissue culture techniques
A61K 38/00	Medicinal preparations containing peptides
A61K 39/00	Medicinal preparations containing antigens or antibodies
A61K 48/00	Medicinal preparations containing genetic material which is inserted into cells of the living body to treat genetic diseases; Gene therapy
C02F 3/34	Biological treatment of water, waste water, or sewage: characterized by the micro-organisms used
C07G 11/00	Compounds of unknown constitution: antibiotics
C07G 13/00	Compounds of unknown constitution: vitamins
C07G 15/00	Compounds of unknown constitution: hormones
C07K 4/00	Peptides having up to 20 amino acids in an undefined or only partially defined sequence; Derivatives thereof
C07K 14/00	Peptides having more than 20 amino acids; Gastrins; Somatostatins; Melanotropins; Derivatives thereof
C07K 16/00	Immunoglobulins, e.g. monoclonal or polyclonal antibodies
C07K 17/00	Carrier-bound or immobilized peptides; Preparation thereof
C07K 19/00	Hybrid peptides
C12M	Apparatus for enzymology or microbiology
C12N	Micro-organisms or enzymes; compositions thereof
C12P	Fermentation or enzyme-using processes to synthesize a desired chemical compound or composition or to separate optical isomers from a racemic mixture
C12Q	Measuring or testing processes involving enzymes or micro-organisms; compositions or test papers therefore; processes of preparing such compositions; condition-responsive control in microbiological or enzymological processes
C12S	Processes using enzymes or micro-organisms to liberate, separate or purify a pre-existing compound or composition processes using enzymes or micro-organisms to treat textiles or to clean solid surfaces of materials
G01N 27/327	Investigating or analysing materials by the use of electric, electro-chemical, or magnetic means: biochemical electrodes
G01N 33/53*	Investigating or analysing materials by specific methods not covered by the preceding groups: immunoassay; biospecific binding assay; materials therefore

Table A.2 (continued): Definition of the Biotech sector based on IPC classes

G01N 33/54*	Investigating or analysing materials by specific methods not covered by the preceding groups: double or second antibody: with steric inhibition or signal modification: with an insoluble carrier for immobilizing immunochemicals: the carrier being organic: synthetic resin: as water suspendable particles: with antigen or antibody attached to the carrier via a bridging agent: Carbohydrates: with antigen or antibody entrapped within the carrier
G01N 33/55*	Investigating or analysing materials by specific methods not covered by the preceding groups: the carrier being inorganic: Glass or silica: Metal or metal coated: the carrier being a biological cell or cell fragment: Red blood cell: Fixed or stabilized red blood cell: using kinetic measurement: using diffusion or migration of antigen or antibody: through a gel
G01N 33/57*	Investigating or analysing materials by specific methods not covered by the preceding groups: for venereal disease: for enzymes or isoenzymes: for cancer: for hepatitis: involving monoclonal antibodies: involving limulus lysate
G01N 33/68	Investigating or analysing materials by specific methods not covered by the preceding groups: involving proteins, peptides or amino acids
G01N 33/74	Investigating or analysing materials by specific methods not covered by the preceding groups: involving hormones
G01N 33/76	Investigating or analysing materials by specific methods not covered by the preceding groups: human chorionic gonadotropin
G01N 33/78	Investigating or analysing materials by specific methods not covered by the preceding groups: thyroid gland hormones
G01N 33/88	Investigating or analysing materials by specific methods not covered by the preceding groups: involving prostaglandins
G01N 33/92	Investigating or analysing materials by specific methods not covered by the preceding groups: involving lipids, e.g. cholesterol

Source: OECD (2005), p.32.
Notes: * = Those IPC codes also include subgroups up to one digit (0 or 1 digit). For example, in addition to the code G01N 33/53, the codes G01N 33/531, GO1N 33/532, etc. are included.

Table A.3: Biotech categories in PROFI database

Code: Biotechnology	**Technology field**
K	Biotechnology
I19080	Molecular Bioinformatics

Notes: Own definition according to the technology field classification of the *Leistungsplansystematik des Bundes*. - The following activities have not been considered; "Projektstabskosten" (Code XX XX 90), "Projektbegleiter" (Code XX XX 91), "Beratungsgremien" (Code XX XX 92), "Programmevaluation" (Code XX XX 95).

Table A.4: Descriptive statistics for total sample (Pre-, Treatment, Post-Treatment period)

Variable	N	Mean	Std. Dev.	Min	Max
Patents	1317	20.722	63.124	0	1099
Projects (all)	1317	10.845	40.491	0	673
Projects (collaborative)	1317	6.008	22.881	0	445
Number of Firms	1317	109.369	95.156	12	1071.5
Average Firm Size	1317	131.899	112.608	37.47	1816.60
Export Share	1257	27.334	13.233	0.15	96.19
R&D Employment	1317	2.206	1.305	0.40	13.55
Population Density	1317	5.606	1.085	3.68	8.30
Sectoral Specialization Manu	1311	6.257	0.682	4.97	9.00
Sectoral Specialization Serv1	1311	5.375	0.549	3.67	7.98
Sectoral Specialization Serv2	1311	4.634	0.677	2.97	6.41
Ellison-Glaeser Manu	1311	21.301	10.671	2.075	68.631
Ellison-Glaeser Serv1	1311	6.362	3.847	1.205	2.933
Ellison-Glaeser Serv2	1311	3.231	2.703	0.273	21.630
Start-up (High-Tech)	1317	0.401	0.267	0.03	2.04
Start-up (all)	1317	9.974	3.597	2.36	35.44

Notes: For variable definition, see text. Population Density and Sectoral Specialization are in log-levels. Specialization and Ellison-Glaeser indices: Manu = manufacturing, Serv1 = business-related services, Serv2 = household-related services.