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Subsidizing R&D in Germany: Direct and spillover effects

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Abstract

This study estimates the effects of research and development (R&D) funding on firm performance and innovation activity in Germany for the period of 2000 to 2020. Since R&D collaborations between funded and non-funded firms can lead to positive externalities, our study accounts not only for the direct effects of the policy on funded firms but also for indirect (spillover) effects on non-funded firms. We use multiple databases (DAFNE, PATSTAT, Förderkatalog) and conduct empirical estimations on both firm and cluster levels. Our findings suggest that, in general, R&D funding has a positive impact on both funded and non-funded firms, which varies with the share of funded firms in the cluster. Interestingly, the indirect impact on innovation is larger than the direct impact. The latter finding points out the advantages of this broad type of R&D funding (no sectoral or regional concentration) in enforcing innovation spillovers, but also highlights its limitation in generating stronger direct effects.

Keywords: R&D funding, Spillover Effects, Policy Evaluation, Regional Innovation, Patent Data

JEL Classification: O33, O38

1 Introduction

Recently, considerable effort has been made for the development of R&D and innovation policies worldwide. This growing trend is justified by the positive effects of private sector R&D on sustainable growth (Aghion and Howitt 2009; Doraszelski and Jaumandreu 2013; Griliches 1979; Grossman and Helpman 1994), innovation (increased number of patent applications and new products) (Czarnitzki and Delanote 2015; Czarnitzki and Hottenrott 2011; Czarnitzki and Licht 2006; David et al. 2000; Howell 2017), and additional R&D expenses (Aerts and Schmidt 2008; Almus and Czarnitzki 2003; Czarnitzki and Hussinger 2004; Czarnitzki et al. 2007; Czarnitzki and Fier 2002; Hussinger 2008). However, R&D funding can also lead to the crowding out of private investments by public funding (Montmartin and Herrera 2015; Wallsten 2000). R&D funding can affect firms from two perspectives: it will either stimulate firms to increase innovation activity due to the enhanced capability to afford innovation costs or it will give them a possibility to use the R&D subsidy for their own funding because they would have implemented their R&D projects anyway.

The paper contributes to the existing debate on the effects of R&D funding by studying the causal impact of R&D funding on the performance and innovation outcomes of German firms over the period of 2000-2020. The main research questions are (1) whether R&D funding improves firm performance and innovative output and (2) whether there are any spillovers for non-funded firms due to the presence of funded firms. The latter question is inspired by the work of earlier scholars, who claim that the presence of FDI firms (Girma et al. 2015) can generate positive externalities via collaboration.

For the first time, the study integrates multiple datasets by leveraging the comprehensive German Förderkatalog dataset (includes information on all R&D projects funded in Germany) and linking it with the DAFNE database and the EPO Worldwide Patent Statistical Database (PATSTAT). Our empirical strategy includes several steps. First of all, to address the selection problem implying that the firms with certain characteristics were selected for the funding, we implement matching on several covariates (fixed assets, number of employees, firm age, and industry dummy) at the firm as well as the cluster level. We define clusters as unique industry-region combinations (by using German NUTS1 regions (16 Bundesländer) and NACE1 industry classification (9 broad industries)) resulting in 144 unique clusters. Then, we perform firm- and cluster-level estimations to obtain the direct, indirect, and total effects of funding for different proportions of funded firms in the cluster following Girma et al. (2015).

Although there is a broader literature on R&D policy evaluations, most of the papers analyzing the effect of R&D subsidies either focus on the general effect of funding on the funded firms or collaboration and spillover effects without disentangling the direct from the indirect effects. With this paper, we want to add more insights to the existing literature by making a clear distinction between direct and indirect (spillover) effects of R&D funding on the firms' financial and innovation outcomes, and understanding what drives the overall effect. To the best of our knowledge, only the study by Czarnitzki et al. (2007) looks at both effects by regressing innovation activity on collaboration and separately on R&D funding. Their results suggest that there is no direct effect of R&D funding on private R&D. In contrast, they find that collaboration increases the firms' R&D activity and might generate positive spillovers for other non-funded firms, which drives the overall positive effects of R&D funding on innovation. However, the latter study does not explore how the effect of R&D varies when we have different shares of treated firms in the cluster. Our key contribution lies in using the share of funded firms as a mechanism to identify spillovers, thereby uncovering insights into the role of the share of funded actors and potential nonlinearities in spillover effects.

The remainder of the paper is structured as follows. Section 2 presents the existing literature. Section 3 presents the data and the main descriptive statistics. The empirical estimation strategy is explained in Section 4. The main findings are discussed in Section 5. Section 6 concludes.

2 Literature Review

Traditionally, economists ascribe economic growth to technological progress, which can be stimulated via research and development (R&D) funding (Romer 1990). The latter one is very important, because it develops a systematic approach towards innovation and stimulates the diffusion of knowledge and interactive learning among different public and private actors (Clausen 2009).

Another justification for public funding of R&D is the existence of two types of market failures. The first one is related to the classical market failure argument by Arrow (1962) which states that firms have fewer incentives to invest in R&D. The main reason is the existence of knowledge externalities and incomplete appropriability, which makes it difficult to claim ownership rights and allows free-riding by competitors. The second type of market failure implies that due to very high costs of external capital, firms do not have sufficient incentives to invest in R&D from the societal point of view; thus, some innovations will not be developed. This problem is particularly severe for small, young, and cash-limited firms (Hall 2002a; Hall 2002b).

To fill this gap between private and social return rates to R&D investments, governments design different R&D initiatives, which usually offer either direct funding or a tax incentive (Hall 2002a; Hall 2002b) by stimulating private R&D investments (Jaffe 2002). Existing research analyzes the impact of R&D funding from two different perspectives by concentrating on the direct and spillover effects. The overwhelming majority of studies tackling the direct effects of R&D policies focus on input additionally. Some of them claim that R&D funding increases R&D expenditures of funded firms (Almus and Czarnitzki 2003; Czarnitzki and Licht 2006; Czarnitzki and Fier 2002; Duguet 2004; González et al. 2005; Hud and Hussinger 2015; Hussinger 2008; Li and Bosworth 2018) by supporting the R&D complementarity hypothesis, while the others argue that it leads to the crowding out of R&D spending of funded firms (Montmartin and Herrera 2015; Wallsten 2000). Another strain of research concentrates on output additionality and provides positive evidence of R&D subsidies on innovation (Aschhoff 2009; Bronzini and Piselli 2016; Czarnitzki and Hussinger 2004; Czarnitzki and Licht 2006; Czarnitzki and Fier 2002; Czarnitzki and Hussinger 2018; Czarnitzki and Lopes Bento 2012; Kleine et al. 2022) and collaboration (Czarnitzki et al. 2007; Kleine et al. 2022). Particularly, the importance of R&D collaboration raised tremendously, which is seen by the firms as a possibility to access new resources, and knowledge (Badillo and Moreno 2015; Kaiser 2002; Li and Bosworth 2018), and share the risks and costs of R&D projects (Antonioli et al. 2016; Belderbos et al. 2004) by leading to the improvement of firm-level outcomes (Falk 2010; Hall et al. 2010; Lerner 1999). The formation of such collaborations, however, depends on the characteristics of the participating partners. Examining FP7-funded research teams, Coad et al. (2017) show that greater diversity in organizational form, nationality, or funding shares is often accompanied by greater similarity on other dimensions.

However, R&D collaborations do not necessarily occur between the firms funded within the same scope of certain R&D policies but can be established between different non-funded actors, thus generating positive spillovers and indirect effects of the funding for non-funded firms. This brings us to the second strain of recent literature concentrating on the spillover effects of R&D policies.

In general, inter-firm spillovers are the result of knowledge exchange between scientists (Jaffe 1986). Due to the limited mobility of scientists (Breschi and Lissoni 2009), knowledge exchange is more likely to be stimulated and successfully transferred at a close distance (Audretsch and Feldman 1996; Jong and Freel 2010; Spithoven et al. 2019) by generating geographical spillovers. The latter is the most studied direction in the spillover literature and is found to lead to positive externalities (Acemoglu et al. 2016; Breschi and Lissoni 2005; Petruzzelli 2011). For instance, Petruzzelli (2011) asserts that R&D collaboration at a close geographic distance leads to more innovation.

However, proximity is not only constrained to a spatial context. There is a higher probability of knowledge exchange not only in geographic proximity but also in the same (Bernstein and Nadiri 1989) or more related industries (Jaffe et al. 1993). Similar patterns emerge in publicly funded R&D networks: Amoroso et al. (2018) find that FP7 collaborations are persistent and concentrated primarily among geographically close and technologically similar regions. Technological connectedness can, in turn, generate stronger spillovers and higher social returns to R&D

(Bloom et al. 2013), although these effects are weaker for small firms operating in technological niches. Li and Bosworth (2018) further show that own-sector R&D spillovers have the strongest effect on labor productivity among British firms. More broadly, Amoroso et al. (2023) emphasize that the benefits of technological relatedness and knowledge diffusion depend on firms' absorptive capacity as well as regional capabilities, development trajectories, and networking capacity.

Consistent with this view, studies of agglomeration economies suggest that region–industry clusters can support the growth of innovative firms through economies of scale and knowledge spillovers (Akcigit et al. 2018, March; Breschi and Lissoni 2009; Crass et al. 2017; Engel et al. 2017; Nishimura and Okamuro 2010; Uyarra and Ramlogan 2016).

Finally, the study by Czarnitzki et al. (2007) looks both at the direct and indirect (spillover) effects of R&D funding. They argue that R&D collaborations have a more pronounced impact on firms' R&D activity through positive spillovers than direct funding itself.

3 Data

The final dataset results from linking three types of data sources on the firm level. Firm financial information is taken from the DAFNE database (extracted in September 2020). It is geo-referenced data, which provides information on firm location, sector, financial outcomes (e.g., fixed assets, employment costs, sales, revenue, etc.), legal entity details, corporate structures, ownership, etc. The analysis concentrates on the sub-sample of German firms (around 2 million firms) over the period of 2000–2020.

DAFNE data is linked to the EPO Worldwide Patent Statistical Database (PATSTAT), which contains detailed information on all patented innovations, including the names and addresses of applicants and inventors, priority year, patent families, the title and abstract of patent applications, citation links, and patent classification by technology class. We restrict PATSTAT data also to the patent applications by German firms.

Finally, the information on the direct R&D funding of firms by the German Federal Government is taken from the Förderkatalog (funding catalog) database, which is jointly created by the Federal Ministry of Education and Research (BMBF) and the Federal Ministry of Economics and Technology (BMWi). The Förderkatalog is a comprehensive, unique data that contains detailed information (i.e., funding type, amount, duration, area, recipient groups, responsible institutions/federal states/countries) on 90,000 individual R&D projects that have been funded since 1970. The growing number of funding recipients from 1970 to 2020 led to 28,013 firms with a total budget of 44 bn € (BMBF (2023)). It's noteworthy that this extensive dataset, encompassing all R&D-funded projects in Germany, has not been previously utilized.

Dependent variables: Firm-level outcomes are divided into the firm's fixed assets and employment (number of employees). Assessing innovation outcomes often relies on measuring patents, but this poses challenges as patents vary in their commercial value and technological impact. Research suggests that while most patents hold little value, a select few represent significant technological breakthroughs (Gambardella et al. 2008). When explicit value information is lacking, citation-based measures offer the best approximation of patent quality (Gambardella et al. 2008; Reitzig 2004). Patents that are frequently cited by subsequent patents are generally considered higher quality, provided that differences in citation propensity are controlled for (Harhoff et al. 1999; Jaffe and de Rassenfosse 2017; Trajtenberg 1990).

However, comparing citation counts across countries has limitations. For one, applicants tend to protect more valuable patents abroad (due to the elevated expenses associated with filing and translating patents), making direct comparisons between domestic and foreign applications less informative (Harhoff et al. 2003). Additionally, variations in examination practices across national patent offices result in significant differences in citation counts. Furthermore, patent examiners commonly demonstrate a tendency to favor citing patents from their native country (Michel and Bettels 2001). To address these challenges, we adopt a patent quality measure proposed by Boeing and Mueller (2016) that enables technology-specific cross-country comparisons and incorporates forward citations.

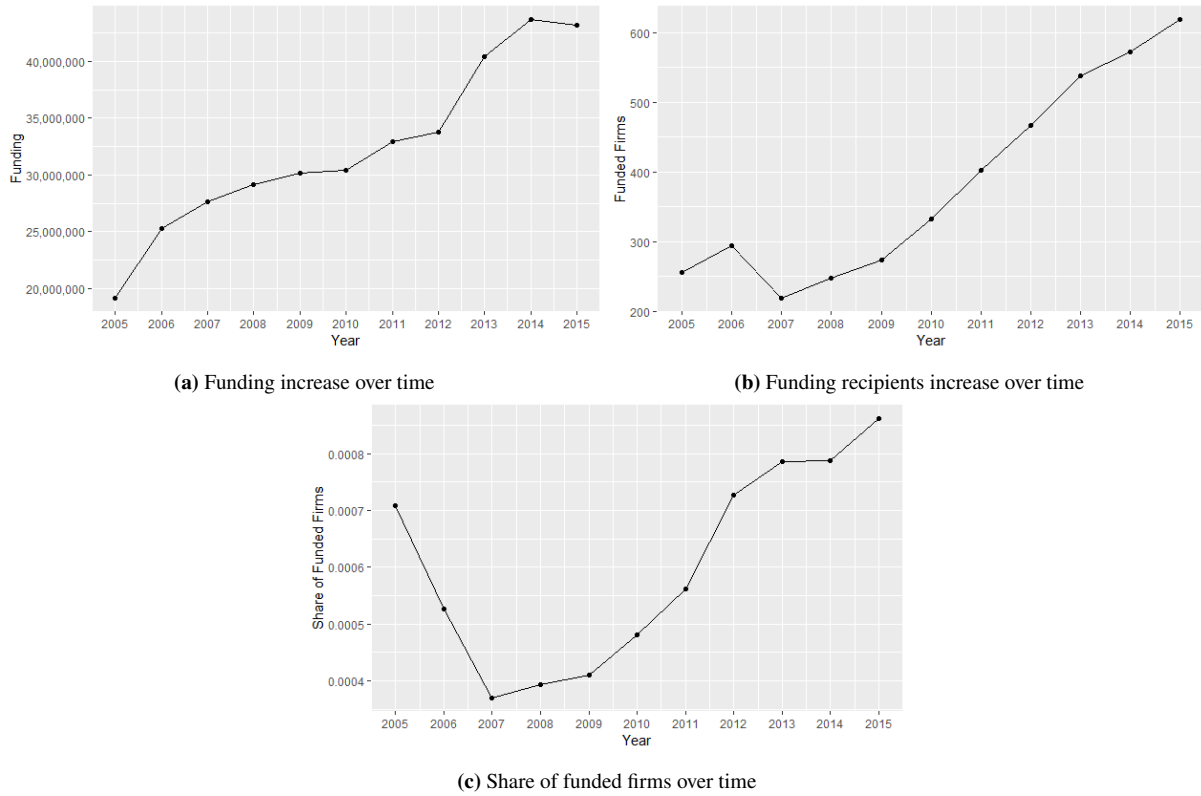


Fig. 1 Development of R&D funding and funding recipients over time

This measure accounts for factors such as the number of technology classes, family size (number of countries in which a patent application was filed), and the number of forward citations received by the patent.

Figure 1 shows summarising graphs for funding. Both funding (a) as well as funding recipients¹ (b) increased over the years of observation. The funding programs were widened and R&D funding increased in general. Graph (c) shows the decrease in the share of funding recipients/funded firms from 2005 to 2007 due to a slight decrease in funding recipients and an increase in the total number of firms.

Table 1: Summary statistics on firm-level characteristics

	Funded (N=207164)	Non-Funded (N=12498684)	Overall (N=12705848)
Firm age	27.2 (31.6)	17.7 (22.3)	17.9 (22.5)
Firm size	2.22 (1.74)	0.805 (0.972)	0.834 (1.01)
Patent (simple)	19.8 (170)	5.42 (85.1)	9.12 (113)
Patent (adjusted)	52.0 (457)	14.1 (214)	23.8 (296)
Fixed assets	107 (1560)	6.12 (303)	8.17 (373)
Total assets	170 (2320)	9.99 (448)	13.2 (554)
Turnover	270 (2420)	20.5 (536)	27.7 (670)
Sales	259 (2430)	23.5 (465)	33.7 (682)
Number of employees	442 (4430)	30.9 (726)	39.1 (953)
Labor costs	46.6 (390)	7.67 (330)	10.9 (336)

Notes: This table reports summary statistics for firm-level characteristics by funding status. Means are reported with standard deviations in parentheses. Firm age is measured in years; firm size is the logarithm of total assets. Patent (simple) denotes the number of patent applications, while Patent (adjusted) is citation-weighted. Fixed assets, total assets, turnover, sales, and labor costs are expressed in million euros. Sample sizes are shown in column headers.

Table 1 presents summary statistics for variables of interest categorized by R&D funding status. The first column illustrates the average outcomes of funded firms, the second column - the average outcomes of non-funded firms, and the third column - the average overall outcome from 1970 to 2020. Firm-level metrics encompass firm

¹A funding recipient means the firm that received the funding.

age (computed as the difference between the current year and the year of incorporation), firm size (log of total assets), simple and quality-adjusted number of patents, fixed and total assets, turnover, sales, number of employees, and labor costs. Significantly, substantial discrepancies emerge between R&D-funded and non-funded firms, underscoring the necessity of adopting a treatment effects evaluation framework. The raw data indicates that, on average, funded firms are approximately 10 years older and twice as large as non-funded firms. Funded firms also boast around four times more patents and greater firm capital and labor. Regarding industry distribution, funded firms tend to dominate in knowledge-intensive sectors such as Education, Professional, Scientific and Technical Activities, Information and Communication, etc. (refer to Table 2).

Table 2: Summary statistics on industry characteristics

Industry	Funded (N=207164)	Non-Funded (N=12498684)	Overall (N=12705848)
Accommodation and Food Service Activities	897 (0.4%)	138562 (1.1%)	139459 (1.1%)
Administrative and Support Service Activities	914 (0.4%)	136456 (1.1%)	137370 (1.1%)
Arts, Entertainment and Recreation	1042 (0.5%)	46172 (0.4%)	47214 (0.4%)
Construction of Buildings	1932 (0.9%)	417631 (3.3%)	419563 (3.3%)
Education	5019 (2.4%)	97475 (0.8%)	102494 (0.8%)
Financial and Insurance Activities	509 (0.2%)	182500 (1.5%)	183009 (1.4%)
Human Health and Social Work Activities	2729 (1.3%)	84619 (0.7%)	87348 (0.7%)
Information and Communication	3067 (1.5%)	91675 (0.7%)	94742 (0.7%)
Manufacturing	3118 (1.5%)	62820 (0.5%)	65938 (0.5%)
Other Service Activities	2870 (1.4%)	129965 (1.0%)	132835 (1.0%)
Professional, Scientific and Technical Activities	4677 (2.3%)	350926 (2.8%)	355603 (2.8%)
Public Administration and Defense: Compulsory Social Security	1569 (0.8%)	17802 (0.1%)	19371 (0.2%)
Real Estate Activities	3450 (1.7%)	1060267 (8.5%)	1063717 (8.4%)
Transportation and Storage	1668 (0.8%)	84346 (0.7%)	86014 (0.7%)
Water Supply	862 (0.4%)	18567 (0.1%)	19429 (0.2%)
Wholesale and Retail Trade	5749 (2.8%)	819881 (6.6%)	825630 (6.5%)
Activities of households as employers	0 (0%)	290 (0.0%)	290 (0.0%)

Notes: The table reports the distribution of firms across industries by funding status. Entries show the number of firms in each industry, with percentages in parentheses. Industries are classified according to the NACE Rev. 2 classification. Sample sizes are reported in column headers.

As will be discussed in detail in the next section, our identification strategy relies on the partial interference assumption, where firm interaction is freely allowed within well-defined clusters. In this study, we categorize firms into clusters based on 16 geographic areas and 9 broadly defined industries (detailed explanation provided in section 4 and the list of regions and industries in Appendix A). This classification yields 144 clusters, each comprising an average of 1438 funded firms. Table 3 presents summary statistics of cluster-level variables. The average proportion of funded firms within a cluster is approximately 2.5 percent. Moreover, it is evident from the various measures of dispersion presented in Table 3 that clusters exhibit considerable heterogeneity in terms of average characteristics. Table 4 showcases the number of funded firms and the proportion of funded (treated) firms by cluster, indicating substantial heterogeneity across clusters.

Table 3: Summary statistics on some cluster-level characteristics

	Mean	SD
Number of funded firms	1438	1905
Proportion of funded firms	0.025	0.022
Average firm age	17.8	22.4
Average firm size	0.83	1.01
Average patents (simple)	9.11	113.4
Average patents (adjusted)	23.8	296.2
Fixed assets	8.16	373.3
Total assets	13.2	553.5
Turnover	27.7	670.4
Sales	33.7	681.8
Number of employees	39.1	953.4
Labor costs	10.9	335.76

Notes: The table reports summary statistics for cluster-level characteristics. Cluster-level variables are constructed as averages or totals of firm-level characteristics within each cluster. Monetary variables (fixed and total assets, turnover, sales, and labor costs) are expressed in million euros. The sample comprises 144 clusters.

Table 4: The number and the proportion of funded (treated) firms by clusters

C	NF	PF	C	NF	PF	C	NF	PF	C	NF	PF
1	12	0.002	37	2619	0.035	73	1242	0.0098079	109	2968	0.054
2	12090	0.055	38	317	0.016	74	763	0.0241609	110	2110	0.006
3	2270	0.021	39	303	0.009	75	523	0.0537623	111	461	0.09
4	330	0.017	40	3696	0.058	76	976	0.0100608	112	310	0.022
5	126	0.013	41	339	0.005	77	1807	0.0219408	113	2086	0.011
6	652	0.017	42	1189	0.014	78	1022	0.0053821	114	565	0.004
7	1219	0.05	43	1008	0.006	79	269	0.0149769	115	349	0.017
8	349	0.021	44	899	0.029	80	1653	0.0834469	116	322	0.014
9	1108	0.06	45	3453	0.008	81	371	0.0237683	117	449	0.009
10	174	0.014	46	1126	0.023	82	4341	0.0089880	118	101	0.01
11	207	0.012	47	332	0.017	83	51	0.0124299	119	504	0.03
12	1246	0.021	48	378	0.008	84	447	0.0247152	120	3968	0.045
13	453	0.006	49	504	0.025	85	3522	0.0141429	121	503	0.014
14	4904	0.01	50	738	0.024	86	996	0.0299405	122	71	0.006
15	674	0.036	51	1111	0.008	87	1104	0.0287134	123	1032	0.021
16	860	0.024	52	404	0.02	88	615	0.0217437	124	534	0.021
17	2130	0.054	53	4507	0.014	89	361	0.0384124	125	718	0.074
18	446	0.007	54	794	0.032	90	313	0.0110445	126	805	0.008
19	2550	0.034	55	955	0.008	91	1710	0.0103238	127	1210	0.0143984
20	711	0.009	56	298	0.005	92	6288	0.0068924	128	475	0.0063220
21	284	0.027	57	577	0.019	93	634	0.0372350	129	5478	0.1264134
22	211	0.008	58	8083	0.057	94	912	0.0805938	130	2588	0.0110198
23	295	0.01	59	206	0.02	95	596	0.0417425	131	3799	0.0549195
24	11547	0.071	60	1163	0.015	96	1573	0.0105336	132	867	0.0149550
25	239	0.044	61	739	0.004	97	2715	0.0073573	133	5198	0.0076556
26	948	0.02	62	1645	0.094	98	468	0.0207898	134	228	0.0244530
27	3182	0.115	63	205	0.008	99	72	0.0089186	135	2877	0.0212318
28	121	0.009	64	1414	0.053	100	229	0.0126394	136	762	0.0603803
29	759	0.016	65	823	0.018	101	387	0.0148395	137	1509	0.0292187
30	670	0.048	66	321	0.031	102	401	0.0309318	138	160	0.0306279
31	458	0.041	67	356	0.075	103	779	0.0123749	139	4313	0.0091855
32	6516	0.01	68	702	0.006	104	1546	0.0216739	140	246	0.0109362
33	511	0.005	69	107	0.039	105	2207	0.0097025	141	2152	0.0259437
34	4231	0.021	70	1292	0.058	106	1434	0.0197360	142	2660	0.0194057
35	481	0.006	71	1828	0.03	107	1264	0.0061842	143	347	0.0070236
36	646	0.007	72	2345	0.014	108	262	0.0198050	144	200	0.0075259

Notes: C denotes the cluster (region–sector) identifier. NF is the number of funded (treated) firms in the cluster, and PF is the proportion of funded (treated) firms relative to the total number of firms in the cluster.

4 Empirical Framework

4.1 Identification Strategy

The estimation of direct and spillover effects has an inherent identification problem. The Stable Unit Treatment Value Assumption (SUTVA) is violated by construction. For the assumption to be reasonable, the outcome of units must be independent of the treatment status of the other units. If we now consider spillover effects, such that the firms benefit from other firms' increased R&D activity in response to the funding, then SUTVA is violated. Additionally, the funding of firms strengthens their position in a competitive market with other funded and non-funded firms, causing changes in the competition of the firms due to the funding. Therefore, for SUTVA to hold, we can only compare firms that do not have any innovation spillovers and that do not compete with each other in a common market.

Second, public policy programs usually target certain firms which raises a selection problem in the identification. In this case, there is selection on two levels. The authority deciding who receives the funding might be more interested in specific regions or in specific industries. This might be due to future expectations about the economic

outcomes in the industry or region or due to personal preference. Furthermore, the firm selection into the treatment is not random but the result of a decision process. It is a decision both from the firm side to apply for funding and from the side of a policymaker to choose a specific firm. The third identification problem comes from region-industry-specific effects. Industry-specific productivity shocks can affect productivity and the innovation outcomes from innovation inputs such as R&D expenditure. This might lead to treatment as a response to the shock and biased estimates.

Since standard approaches are not able to tackle the aforementioned issues, we introduce a non-standard approach by combining the methods suggested by Fong et al. (2018), Girma et al. (2015), and Hudgens and Halloran (2008). First of all, to consistently estimate both direct and spillover effects, we relax the SUTVA assumption as suggested by the recent econometric literature (Baird et al. 2018; Ferracci et al. 2014; Girma et al. 2015; Hudgens and Halloran 2008; Rosenbaum 2007). As per this literature, treatment externalities, also known as spillovers, occur when an individual's potential outcome is influenced by the treatment status of others within a group. As the effect of the funding is not limited to funded firms, the treatment pollutes the control units. As the funding does not affect all control units, but only groups of them, we refer to partial interference. In contrast to standard methods controlling for the funding of neighboring firms, we can form groups in the spatial dimension as well as the industry dimension to also control for the effect of funding on technologically close non-treated firms. This is important to capture knowledge spillovers and effects on competition in markets as two potential sources of spillover effects. Furthermore, defining clusters and allowing the firms within clusters to interact enables us to perform matching on an additional level, the cluster level. Following the approach outlined by Hudgens and Halloran (2008), we utilize the proportion of treated firms within a group as a metric for interaction among individual firms. Consequently, potential outcomes are modeled as a function of the firm's treatment status and the fraction of R&D-funded firms within a specific group or cluster.

Following Girma et al. (2015), we conduct estimations at two distinct levels: the firm level and the cluster level, with clusters defined as unique region-industry combinations. Our main identification assumption is the Partial Interference Assumption, where we posit that the SUTVA holds across clusters but not within clusters. This implies that the potential outcomes of an observed unit are unaffected by the treatment status of other units in other clusters. To satisfy this assumption, we require a cluster definition that provides a sufficient number of clusters with substantial variation to facilitate estimation while ensuring diverse levels of interaction within the clusters. On the other hand, it's essential to minimize interaction in innovative activity and competition across the clusters as much as possible. For this purpose, we utilize region-industry combinations with German NUTS 1 regions (Bundesländer) and the broad NACE 1 industry classification. Our Partial Interference Assumption dictates that interactions occur solely between firms within the same industry and region. This approach aligns with findings in the literature on innovative spillovers, which indicate a sharp spatial decay and limited interactions within broader industries (Acemoglu et al. 2016; Breschi and Lissoni 2005; Glaeser et al. 1992). Moreover, this definition, rather than relying solely on industry classification or regions, offers a sufficiently broad range of clusters. The 9 NACE 1 industries and 16 NUTS 1 regions in Germany give us 144 unique combinations of broad industries and regions. An illustrative example of a cluster could be the manufacturing industry in North Rhine-Westphalia (NRW) or the Information and Communication industry in Bavaria.

4.2 Estimation Strategy

We use the empirical methodology suggested by the literature on causal estimands under partial interference that was introduced by Hudgens and Halloran (2008) and shifted to infinite populations by Baird et al. (2018). As suggested by Girma et al. (2015), we perform the first part of the analysis separately for each cluster and then shift the analysis to the cluster level. To give a brief overview, the methodology we use involves the following steps:

Steps on the firm level (separately for each cluster):

1. Firm-Level Matching

We obtain inverse probability weights by regressing the binary treatment variable (1 if a firm was funded, 0 otherwise) on pre-treatment firm characteristics.

2. Computing cluster-specific treatment effects

We regress the firm-level outcome (quality-adjusted patents, fixed assets, and number of employees) on the binary treatment variable and control variables.

3. Computing potential outcomes

We obtain the potential outcomes based on the estimated coefficients from step 2 and the corresponding observations for those variables. We calculate cluster-average potential outcomes for treated and non-treated units.

Steps on the cluster level:

4. Aggregating the variables

We compute the cluster-means for the firm-specific control variables and the binary treatment variable.

5. Generalized Propensity Scores

We compute Generalized Propensity Scores following Fong et al. (2018) by regressing the average binary treatment variable in a cluster on the average firm characteristics in a cluster.

6. Computing coefficients for the treatment intensity and the GPS

We regress the cluster-average potential outcomes across treated firms and across non-treated firms on the Generalized Propensity Scores and the treatment intensity.

7. Computing Cluster-potential outcomes

Based on the coefficients obtained from step 6, we compute the cluster-level potential outcomes for different levels of treatment intensities.

8. Treatment effect calculation

We compute the direct, indirect, and overall treatment effects by comparing the cluster-level potential outcomes.

We start with the analysis on the firm level. Addressing the effectiveness of R&D funding poses several challenges, primarily stemming from the selective nature of such funding initiatives. Comparing funded and non-funded firms is inherently complex due to existing disparities in outcomes. These disparities give rise to various identification issues. Firstly, the endogeneity of treatment arises as firms may self-select into receiving R&D funding based on unobservable traits that also influence their outcomes. This self-selection introduces bias into estimates of the causal impact of R&D funding on firm performance and innovation outcomes.

Secondly, sample selection bias emerges as the sample of funded firms may not accurately represent the broader population of firms. This discrepancy can lead to biased estimates if treated and untreated groups differ systematically in ways that influence the outcomes of interest.

The latter can be observed in Table 5 which summarizes the means of the main variables for the treated firms and the non-treated firms before the first observed treatment. The outcome variables and covariates differ across treated firms and non-treated firms. Treated firms are larger in terms of number of employees and fixed assets. Also, they are slightly older (3 years) and the innovation outcomes (quality-adjusted patents) were already higher before the funding programs were rolled out. We conclude from differences in means between the treatment and control group that firms are non-randomly selected into treatment based on pre-treatment characteristics.

Finally, the heterogeneous treatment effects add another layer of complexity as the impact of R&D funding may vary across firms based on diverse characteristics such as size, industry, and age. Failing to consider these differences can result in biased estimates of the average treatment effect.

Table 5: Pre-treatment differences between treated and non-treated firms

Variables	Treated	Non-treated
Firm age	30	27
Yearly Patents (adjusted)	2.49	0.16
Fixed assets	69036	8012
Number of employees	332	38

Notes: The table reports mean pre-treatment characteristics of treated and non-treated firms prior to matching. Yearly patents (adjusted) refer to citation-weighted patent counts. Fixed assets are expressed in thousand euros.

To overcome these identification issues on the firm level, we perform inverse probability weighting on pre-treatment firm-level characteristics. This approach relies on the assumption of unconfoundedness, which states that conditional on the observed covariates, treatment assignment is independent of potential outcomes. Additionally, matching methods assume common support, which means that there are units in both the treatment and control groups with propensity scores overlapping across the entire range. These assumptions help ensure that the weighted samples are comparable, allowing for a more credible estimation of treatment effects (Hill and Su 2013; Huber 2013).

Treatment dummy d_{ict} is defined on the firm level that takes the value of 1 if firm i in cluster c received funding in year t , and 0 otherwise. To compute the inverse probability weights, we perform the logistic regression from equation (1) for each cluster separately. We regress the treatment dummy d_{ict} on a vector X_{ict} of firm-level covariates before treatment. Those covariates include firm age, number of employees, fixed assets, and a dummy indicating whether the firm is a low-tech, medium-tech, or high-tech firm. The dummy is based on the NACE 2 industry classification of the firm. We exclude the respective outcome variable from the firm covariates in the logistic regressions.

$$P(d_{ict} = 1) = \frac{1}{1 + e^{-b_0 + b_1 X_{ict}}} \quad (1)$$

We obtain the inverse probabilities by calculating $\frac{1}{d_{ict}}$ for treated firms and $\frac{1}{1-d_{ict}}$ for non-treated firms. We use the generated propensity scores as inverse probability weights in the OLS regressions at the firm level.

Table 6: Determinants for selection into treatment

	Dependent variable:
	Treatment
Fixed Assets	0.169*** (0.011)
Number of Employees	0.398*** (0.016)
Firm Age	0.045 (0.034)
High-Tech	0.035 (0.080)
Low-Tech	-1.066*** (0.057)
Constant	-5.950*** (0.172)
Observations	39,595
Log Likelihood	-6,913.510
Akaike Inf. Crit.	13,839.020

*Notes: The table reports estimates from a logit model of selection into treatment. The dependent variable equals one if a firm receives treatment and zero otherwise. Fixed assets and number of employees are measured in logarithms. High-Tech and Low-Tech are indicator variables based on industry classification. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 6 shows the determinants of the treatment on the firm level. The size of the firm in terms of fixed assets and number of employees has a positive impact on selection into treatment, and low-tech firms are less likely to receive the treatment compared to medium- or high-tech firms.

Using the inverse-probability weights from the logistic regressions for each cluster separately, we regress the

outcomes on firm-level control variables X_{ict} and the treatment dummy d_{ict} ,

$$y_{ict} = \alpha + \beta d_{ict} + \delta X_{ict} + \epsilon_{ict}; \quad i = 1, \dots, N_{ct} \quad (2)$$

With y_{ict} being the firm-level (fixed assets, number of employees) and innovation (quality-adjusted number of patents) outcome of firm i in cluster c , X is the vector of firm-level covariates including firm age, number of employees, and fixed assets, and the error term ϵ . Here, we obtain separate estimates for the effect of receiving funding on the outcome.

In the third step, we calculate the potential outcomes separately for each cluster c and each year t . For that, we use the OLS estimates from equation (2) and the firm-level observations for control variables X_{ict} . We set the treatment dummy $d_{ict=1}$ for the potential outcome under treatment $\bar{y}_{ct}^1$ and $d_{ict=0}$ for the potential outcome under no treatment $\bar{y}_{ct}^0$. We aggregate those potential outcomes across the firms in a respective cluster to obtain the average potential outcomes for each cluster and year, for treated and untreated firms.

$$\bar{y}_{ct}^1 = \frac{1}{N_{ct}} \sum_{i=1}^{N_{ct}} \hat{\alpha} + \hat{\beta}_c + \hat{\delta}_c X_{ict} \quad \text{and} \quad \bar{y}_{ct}^0 = \frac{1}{N_c} \sum_{i=1}^N \hat{\alpha} + \hat{\delta}_c X_{ict} \quad (3)$$

After obtaining the potential outcomes for each cluster and year separately, we shift our methodology to the cluster level. To solve potential selection issues also on the cluster level, we again calculate propensity scores. The treatment variable now needs to be adapted, as we now do not observe the treatment of each firm individually, but the overall treatment intensity within each cluster. Therefore, we use the proportion of treated firms as suggested by Hudgens and Halloran (2008) in the cluster (p_c). Note that $p_c \in (0, 1)$ and is continuous. The proportion of treated firms in a cluster indicates the intensity of the funding within the cluster and, at the same time, it is a proxy for the probability of interaction of treated firms in a cluster.

$$p_{ct} = \frac{\sum_{i=1}^{N_{ct}} d_{ict}}{N_{ct}} \quad (4)$$

To check the validity of the SUTVA assumption on the cluster level, we observe the correlation between the share of treated firms in the cluster and other cluster-level variables (see Table 7). The clusters show heterogeneity regarding their firm composition, and the selection of funding is likely to be non-random but in parts driven by differences in cluster-level characteristics. To overcome a potential selection bias on observed cluster-level variables, we also match on the cluster-level.

Table 7: Correlation matrix of cluster-level variables

	% Treated Firms	No. Employees	Fixed Assets	Firm Age	Pot. Outcome
% Treated Firms	1.00***	0.06***	-0.00	-0.22***	0.14***
No. Employees	0.06***	1.00***	0.08***	0.25***	0.51***
Fixed Assets	-0.00	0.08***	1.00***	0.04***	0.18***
Firm Age	-0.22***	0.25***	0.04**	1.00**	0.41***
Pot. Outcome	0.14***	0.51***	0.18***	0.41***	1.00***

*Notes: The table reports pairwise Pearson correlation coefficients between cluster-level variables. % Treated Firms denotes the share of treated firms within a cluster. Pot. Outcome refers to the cluster-level potential outcome. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 8 shows the firm-level characteristics averaged over the cluster. We split by different treatment intensities p_{ct} . However, there are still observable differences in the characteristics between different levels of treatment. The clusters with a higher proportion of treated firms tend to be larger, with a larger number of employees and higher fixed assets. Additionally, they already had higher patent counts before the observed treatment. Also, they are slightly older. To account for those differences in the characteristics that increase the overall level of treatment in the cluster and at the same time increase average patent outcomes in the clusters, we perform matching also on the cluster level.

Table 8: Pre-treatment in clusters

Variables	25% quantile p_c	50% quantile p_c	75% quantile p_c
Firm age	37.0	37.6	37.9
Yearly Patents (adjusted)	25.28	31.13	36.81
Fixed assets	63947	63364	83366
Number of employees	430	464	585

Notes: The table reports pre-treatment cluster-level characteristics by quantiles of p_c , the cluster-level proportion of treated firms. Reported values are means within each quantile. Yearly patents (adjusted) refer to citation-weighted patent counts. Fixed assets are expressed in thousands euros.

Due to the treatment variable now being continuous, we calculate the conditional density of the treatment using the Covariate Balancing Generalized Propensity Score estimation procedure suggested by Fong et al. (2018). We use the same covariates as in the firm-level matching, but now we average them across the firms in the cluster. As we did on the firm-level, we again exclude the outcome variable from the cluster-level covariates. We fit different estimators of the Generalised Propensity Score and pick the one with the best Covariate Balancing. The Covariate Balancing Generalized Propensity Score is the one with the best Covariate Balancing properties. See Appendix C for more details on the generalized propensity score estimation procedure.

Figure 3 shows the covariate balancing statistics for the generalized propensity score estimations. We use the propensity scores from the Covariate Balancing Generalised Propensity Score (CBPS) estimation in the further procedure, as it minimizes the Correlation of the covariates considerably compared to Generalized Boosted Models and Maximum Likelihood (MLE). The non-parametric version of the CBPS (npCBPS) achieves similar, but slightly worse Covariate Balancing.

We use the estimates of the conditional density of the continuous treatment $G\hat{P}S_c$ and the proportion of treated firms within a cluster p_{ct} to approximate the expected values of the cluster-level potential outcomes under treatment and no treatment $\bar{y}_{ct}^d$ we generated in the firm-level estimation in equation 3. Following Hirano and Imbens (2004), we approximate the potential outcomes under treatment $d = 1$ and potential outcomes under no treatment $d = 0$. We use polynomial approximations of the second-order

$$\bar{y}_{ct}^d = \beta_0 + \beta_1 G\hat{P}S_{ct} + \beta_2 p_{ct} + \beta_3 G\hat{P}S_{ct}^2 + \beta_4 p_{ct}^2 + \beta_5 G\hat{P}S_{ct} p_{ct}. \quad (5)$$

The approximation in (5) gives us estimates $\hat{\beta}_1$ to $\hat{\beta}_5$ to calculate the average potential cluster outcomes for different levels of proportion of treated firms $\bar{y}_p^d$, where p is the proportion of treated firms.

In the final step, we use a grid of possible values of p_c over the range of treatment intensities considered in the analysis. For each of these values of the grid, we calculate the sample average potential outcomes across all clusters under treatment and no treatment. For this, we use the estimated coefficients from equation 5 and the conditional treatment density estimates $G\hat{P}S_c$. We follow

$$\bar{y}_p^d = \frac{1}{C} \sum_{r=1}^C (\hat{\beta}_0 + \hat{\beta}_1 G\hat{P}S_{ct} + \hat{\beta}_2 p_{ct} + \hat{\beta}_3 G\hat{P}S_{ct}^2 + \hat{\beta}_4 p_{ct}^2 + \hat{\beta}_5 G\hat{P}S_{ct} p_{ct}) \quad (6)$$

We obtain the cluster-level average potential outcomes from (6) for different levels of cluster-level treatment intensity. We then distinguish between the direct, spillover, and total effects of R&D funding.

The direct effect, $\bar{\gamma}_{pp}^{10}$, compares the average cluster-level potential outcomes under treatment and no treatment at the same proportion p of funded firms in the cluster. Holding cluster-level treatment intensity (p) constant and assuming no interaction across clusters, the outcomes differ only in the firm's own treatment status:

$$\bar{\gamma}_{pp}^{10} = \bar{y}_p^1 - \bar{y}_p^0, \quad (7)$$

where $\bar{y}_p^1$ is the average potential outcome under treatment for a cluster with the proportion of treated firms p , and $\bar{y}_p^0$ is the average potential outcome under no treatment for a cluster with the same proportion of treated firms

p .

For the spillover effect $\bar{\gamma}_{p0}^{00}$, we compare average cluster-level potential outcomes under no treatment at different levels of the proportion of funded firms in the cluster. Since treatment status is held constant, the outcomes differ only because of exposure to different proportions of funded firms within the cluster.

$$\bar{\gamma}_{p0}^{00} = \bar{y}_p^0 - \bar{y}_0^0, \quad (8)$$

where $\bar{y}_p^0$ is the average potential outcome under no treatment for a cluster with a proportion of treated firms p , and $\bar{y}_0^0$ is the average potential outcome under no treatment for a cluster without treated firms, i.e., the proportion of treated firms $p = 0$.

The total effect, $\bar{\gamma}_{p0}^{10}$, compares the average cluster-level potential outcomes under treatment intensity p with the average cluster-level potential outcomes in the absence of treatment:

$$\bar{\gamma}_{p0}^{10} = \bar{y}_p^1 - \bar{y}_0^0, \quad (9)$$

where $\bar{y}_p^1$ is the average potential outcome under treatment for a cluster with a proportion of treated firms p , and $\bar{y}_0^0$ is the average potential outcome under no treatment for a cluster without treated firms, i.e., the proportion of treated firms $p = 0$.

The total effect can be decomposed into the direct and spillover effects:

$$\bar{\gamma}_{p0}^{10} = \bar{\gamma}_{pp}^{10} + \bar{\gamma}_{p0}^{00} \quad (10)$$

5 Results

The main findings regarding the direct and spillover effects of R&D funding on the firm-level and innovation outcomes are depicted in Figure 2. The latter shows that the average treatment effect (i.e., the changes in firm financial and innovation outcomes due to the R&D subsidy) is highly dependent on the proportion of R&D funded firms in the cluster. For example, the direct effect of funding on the quality-adjusted number of patents is enhanced by around 3.5% when we increase the share of R&D funded firms up to 1.6 %.

When we further increase the share of R&D-funded firms to 1.7% and above, its direct effect on patents starts to decline. The picture is different when we observe the spillover effect of R&D funding on innovation, which will be around 10% and 30% when the proportions of R&D funded firms in the cluster are 1% and 2%. This might indicate that the R&D funding indirectly initiated new collaborations between funded and non-funded firms, thus leading to the generation of more patents. Analogous results regarding more pronounced indirect effects were observed by Czarnitzki et al. (2007) who identified no direct impact but rather significant indirect effects on private R&D stemming from positive spillovers facilitated by collaborations.

Further, we uncover a significant positive direct impact on the financial outcomes of treated firms. For example, the direct effects of R&D subsidy on fixed assets and the number of employees are 10% and 20% when the proportion of funded firms in the cluster is 1%. When we increase the share of funded firms up to 2%, the direct effect on fixed assets and the number of employees almost triples as well by reaching up to 30% and 20%, respectively. The positive trend holds for the spillover effects of R&D subsidy on fixed assets of non-funded firms. However, the indirect effect on the number of employees is negative and reduces by 25% when we increase the share of funded firms up to 2%. This can indicate that the R&D funding of single firms triggered negative competition effects for employment.

Our findings suggest that after the treatment, the funded firms increase their capital and labor. The non-funded firms increase their knowledge output, which can be seen from the increase in the number of quality-adjusted patents for non-funded firms with exposure to funded firms. One possible interpretation is that, if high-skilled labor for innovative activity is limited within the cluster, non-funded firms increase their innovative input by increasing

capital but face stronger competition from funded firms in the high-skilled labor market. Similar results regarding negative competition effects for labor are reported in the previous research on cutting-edge innovation clusters conducted by Lehmann and Menter (2017). While they observed positive impacts on innovation outcomes similar to our results, they also identified 'beggar-thy-neighbor' effects in sunrise regions affecting neighboring areas. They argue that focusing on 'winning' regions increases their capacity and the demand for highly skilled labor, causing neighboring regions to suffer more from the 'power of attraction' of these leading-edge clusters in comparison to non-neighboring regions.

Finally, we obtain the total effect by combining the direct and indirect effects together. We find that the total effects on both innovation (patents) and firm-level (fixed assets and employment) outcomes are uniformly positive and increasing with the share of funded firms in the cluster. However, for the number of employees and quality-adjusted number of patents, the total effect stabilizes when the proportion of funded firms in the cluster goes beyond 1.6%. Despite having negative spillovers from employment, here the direct effect dominates, and thus the total effect of R&D funding on the number of employees is positive.

These findings align with the broader consensus in the innovation literature, which suggests that R&D funding enhances innovation (Aschhoff 2009; Bronzini and Piselli 2016; Czarnitzki and Licht 2006; Czarnitzki and Fier 2002; Czarnitzki and Hussinger 2018; Czarnitzki and Lopes Bento 2012; Kleine et al. 2022) and firm-level outcomes (Falk 2010; Hall et al. 2010; Lerner 1999). They also support the ideas of Akcigit et al. (2018, March), Breschi and Lissoni (2009), Crass et al. (2017), Engel et al. (2017), Nishimura and Okamuro (2010), and Uyarra and Ramlogan (2016), who highlight the importance of agglomeration for firm-level development. Furthermore, the findings reinforce the spillover literature's arguments regarding the positive effects of spatial (Acemoglu et al. 2016; Breschi and Lissoni 2005; Petruzzelli 2011) and industrial (Bloom et al. 2013; Li and Bosworth 2018) proximity demonstrated by the unique region-industry clusters in our analysis. They also verify the findings of Girma et al. (2015) regarding FDI spillovers in innovation setup, as the prevalence of R&D funded firms suggests a greater propensity for positive externalities through increased collaboration.

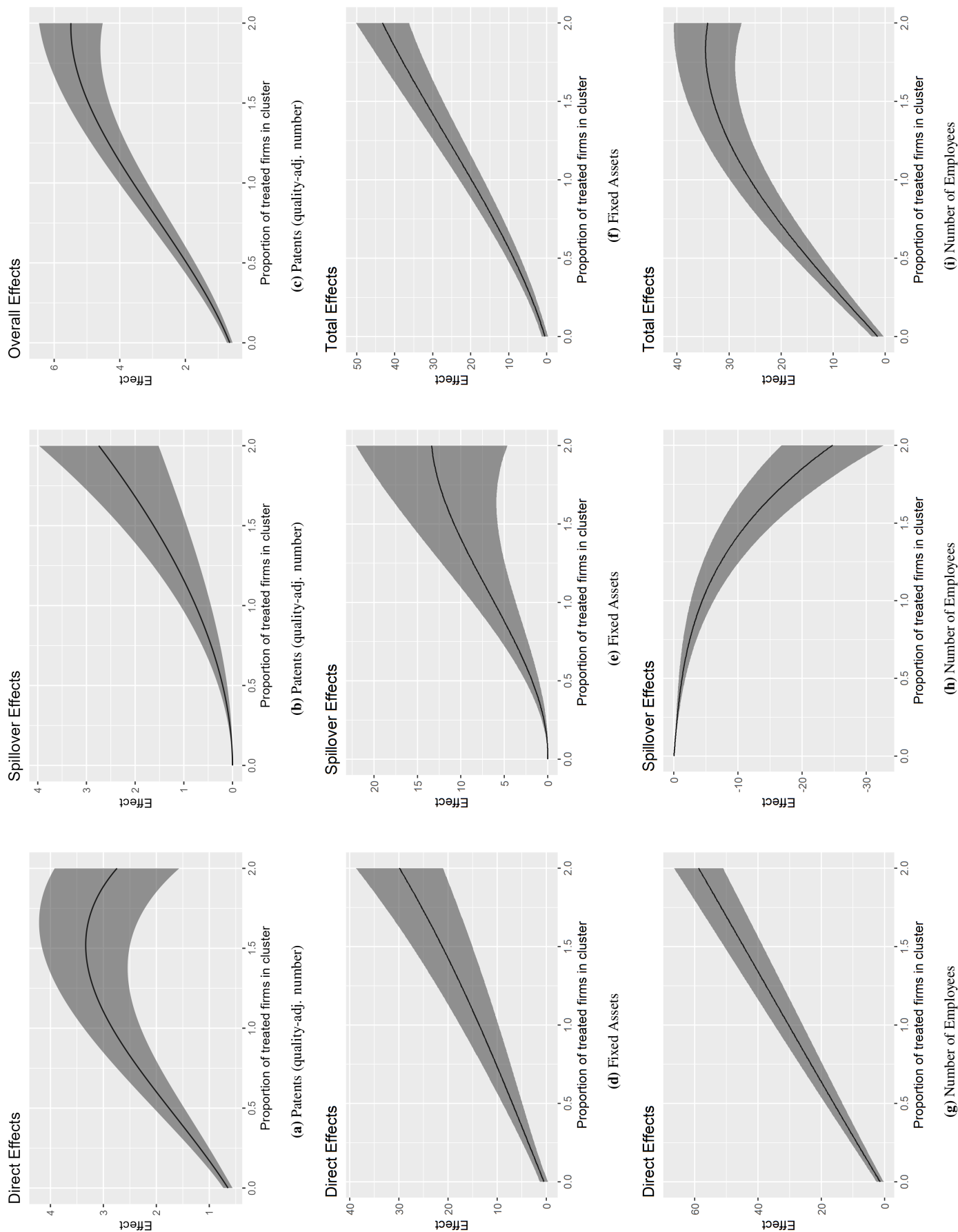


Fig. 2 Direct, indirect, and overall effects of R&D funding on innovation and firm performance

6 Conclusions

This research implements the causal analysis of the direct and spillover effects of R&D funding on firm-level performance and innovation activity of funded and non-funded firms. This study reveals a crucial insight: the effects of research and development (R&D) funding, both direct and spillover impact, exhibit variability contingent on the proportion of funded firms within the cluster. While we see a positive direct impact on firm capital and labor when we increase the proportion of funded firms, the direct effect on patents decreases when the share of funded firms exceeds 1.7%. For spillovers on non-funded firms, we find that they are positive for patents and fixed assets; however, they are negative for the number of employees. What is also interesting, the indirect effects for the quality-adjusted number of patents and fixed assets increase monotonically with the proportion of funded firms.

Another striking finding is that the direct effect of R&D funding on patents is less pronounced compared to the indirect effect: for the clusters with a higher proportion of treated firms, the indirect effect starts to dominate. This finding suggests potential advantages of funding several firms that are spatially or industry-wise close to each other, as such a policy design may facilitate both direct and indirect positive effects. One working example of the aforementioned policy setup can be the cluster type of funding, which, according to the existing literature (Acemoglu et al. 2016; Audretsch et al. 2018; Breschi and Lissoni 2005; Crass et al. 2017; Lehmann and Menter 2017), not only has a positive direct impact on the innovation activity of funded firms but also enforces positive spillovers for non-funded neighbor firms. Finally, the total effect is positive and significant for all outcome variables.

Generally, the results show that the estimation of both direct and indirect treatment effects provides a clearer understanding of different mechanisms through which the share of funded firms impacts the potential outcomes of funded and non-funded firms. In this way, our research significantly contributes to the policy debate regarding the benefits of R&D funding and optimal allocation from a regional development perspective and aligns well with the earlier studies reporting positive direct (Aschhoff 2009; Bronzini and Piselli 2016; Czarnitzki and Hussinger 2018; Falk 2010; Hall et al. 2010) and indirect effects (Czarnitzki et al. 2007).

However, our research also has some potential limitations. The results are obtained under the Partial Inference Assumption, assuming that SUTVA holds across the clusters but not within. There are scenarios where this might not be the case. A potential threat to the SUTVA assumption is the presence of ownership groups. Subsidiaries within these ownership groups are linked across different clusters and might interact as part of the same group, implying inter-firm interactions across clusters and potentially violating the SUTVA assumption. Additionally, input and output linkages might similarly challenge the validity of SUTVA.

Additionally, the assumption of random treatment assignments conditional on observable characteristics might not hold perfectly because, in an ideal scenario, we would require more detailed information about the firms to ensure genuine randomness. Relying only on observable characteristics means that unobserved variables could still affect treatment assignment, introducing potential biases. More comprehensive data on firm-specific attributes, such as internal capabilities and market conditions, would enhance the reliability and ensure a more accurate analysis of the causal effects. Hence, it might be interesting for future research to observe these linkages and utilize more detailed data to improve empirical validity.

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Appendix

A Cluster Definition

Table 9: Geographical classification used in this paper

NUTS1		Region	Share of funded firms
1	DE1	Baden-Württemberg	0.0208890
2	DE2	Bayern	0.0138296
3	DE3	Berlin	0.0170714
4	DE4	Brandenburg	0.0175150
5	DE5	Bremen	0.0233157
6	DE6	Hamburg	0.0107204
7	DE7	Hessen	0.0127690
8	DE8	Mecklenburg-Vorpommern	0.0203811
9	DE9	Niedersachsen	0.0148482
10	DEA	Nordrhein-Westfalen	0.0148137
11	DEB	Rheinland-Pfalz	0.0132487
12	DEC	Saarland	0.0187119
13	DED	Sachsen	0.0325534
14	DEE	Sachsen-Anhalt	0.0232295
15	DEF	Schleswig-Holstein	0.0106457
16	DEG	Thüringen	0.0302741

Notes: Regions are defined according to German NUTS 1 classification. The share of funded firms denotes the proportion of firms receiving treatment within each region.

Table 10: Industrial classification used in this paper

Industry		Share of funded firms
1	Manufacturing	0.0163587
2	Manufacturing	0.0663014
3	Manufacturing	0.0419899
4	Construction	0.0072075
5	Wholesale trade and retail	0.0093676
6	Transport and communication	0.0101057
7	Real estate activities	0.0129624
8	Education	0.0196599
9	Other service activities	0.0218824

Notes: Industries are defined according to the NACE Rev. 2 classification. The share of funded firms denotes the proportion of firms receiving treatment within each industry.

B Generating Inverse Probability Weights

On the firm level, we perform logistic regressions for each cluster separately. For each cluster, we use the same set of covariates with pre-treatment values. The set of covariates includes firm age, number of employees, and fixed assets. We regress the treatment dummy d_{ict} on the set of covariates to generate the predicted treatment values $\hat{d}_{ict}$. We obtain the inverse probabilities by calculating the $\frac{1}{\hat{d}_{ict}}$ for treated firms and $\frac{1}{1-\hat{d}_{ict}}$ for non-treated firms. We use these weights afterward in the inverse probability-weighted OLS regressions (Equation 3 on the firm level for each cluster separately).

C Generalized Propensity Score Matching

For the methodology on Generalized Propensity Score Matching, we follow Fong et al. (2018). We start by averaging the firm-level variables across each cluster and defining the treatment variable as the proportion of treated firms within the cluster. This proportion is the average of the treatment dummy on the firm level. The distribution of the treatment variable is skewed to the left; many clusters do not receive any funding or only a few firms receive funding. Therefore, we use the Box-Cox transformation in equation 11 to transform the distribution of the treatment variable closer to normal. We find the most suitable transformation by computing the distribution correlation

between the Box-Cox transformed treatment and the normal distribution. We find the correlation maximizing λ by searching on a grid from 150 to -150, where the best λ is at -49.

$$\frac{(p_r + 1)^\lambda - 1}{\lambda} \quad (11)$$

We then fit four different models: a Maximum Likelihood Estimator (MLE), Generalized Boosted Regression Modelling (GBM), the regular Covariate Balancing Generalized Propensity Score (CBPS), and the non-parametric version of the Covariate Balancing Generalized Propensity Score (npCBPS). Figure 3 shows the absolute Pearson correlation between each covariate and the transformed treatment variable. The Maximum Likelihood Estimator improves covariate balancing, while GBM, CBPS, and the non-parametric CBPS perform better. The CBPS estimates have the smallest absolute correlation of the covariates. GBM and npCBPS perform slightly worse and come with higher computational effort. Therefore, we use CBPS to estimate Generalized Propensity Scores on the cluster-level. CBPS iteratively optimizes covariate balancing and the treatment prediction, resulting in a good model fit and covariate balance while retaining computational feasibility.

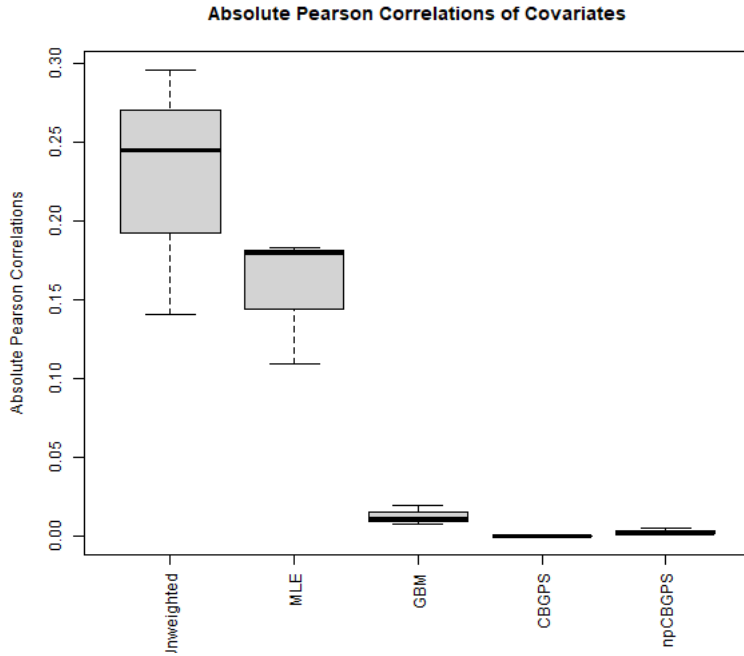


Fig. 3 Covariate balancing propensity score estimation

Additionally, we perform the generalized matching procedure on the cluster level with different sets of covariates. To reflect the covariates for the estimations with fixed assets and number of employees as outcomes, we exclude the fixed assets or number of employees variables, respectively, from the generalized propensity score estimation and calculate covariate balancing statistics for the different estimators. Figure 4 shows that for all sets of covariates, the CBPS estimator minimizes covariate correlation. Therefore, we use CBPS throughout our analysis for all cluster-level generalized propensity score estimations.

D Bootstrapped Standard Errors

As our analysis includes calculating potential outcomes and involves a multi-step methodology, we bootstrap the standard errors for the confidence intervals shown throughout the paper to assess the variability or uncertainty in our treatment effect estimates. We randomly select samples of firms from our dataset and calculate treatment effects for each sample. We do this process 180 times, creating 180 bootstrap replications. For each bootstrap replication, we calculate different types of treatment effects, such as the direct effect $\tilde{\gamma}_{pp}^{10}$, the indirect effect $\tilde{\gamma}_{p0}^{00}$,

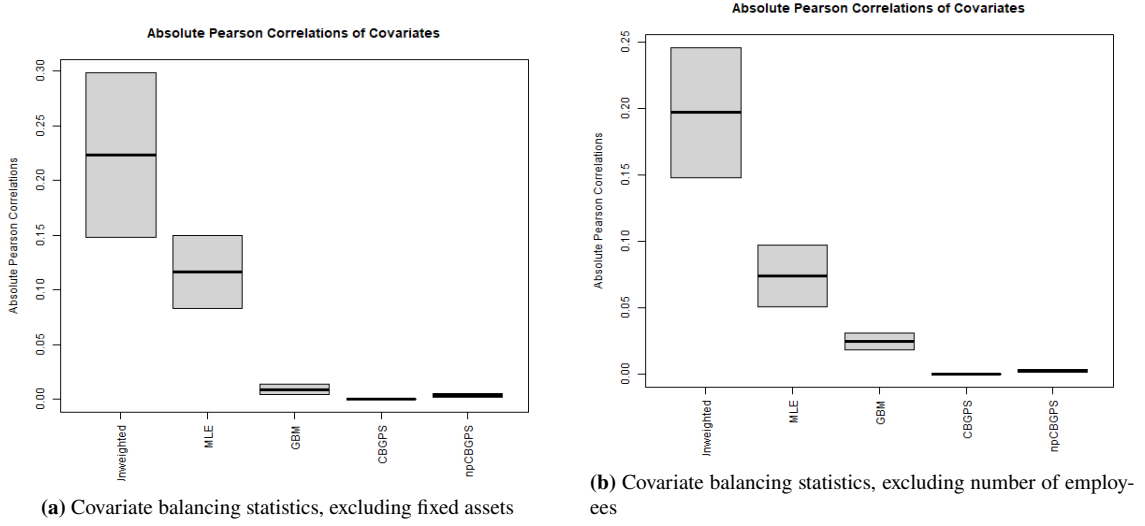


Fig. 4 Covariate balancing statistics: Pearson correlation of covariates

and the overall effect $\bar{\gamma}_{p0}^{10}$. These effects are estimated for various levels of the proportion of treated firms. We follow Girma et al. (2015) for calculating the bootstrap standard errors according to equation (12). We simplify the notation by using $\bar{\gamma}$ as a placeholder for the different types of treatment effects $\bar{\gamma}_{pp}^{10}$, $\bar{\gamma}_{p0}^{00}$ and $\bar{\gamma}_{p0}^{10}$. $\bar{\bar{\gamma}}_B$ is the mean of the obtained treatment effects across the bootstrap replications, while $\bar{\gamma}_B$ is the treatment effect obtained from bootstrap replication B .

$$se(\bar{\gamma}) = \sqrt{\frac{1}{180} \sum_{B=1}^{180} (\bar{\gamma}_B - \bar{\bar{\gamma}}_B)^2} \quad (12)$$