

Cluster and Local Science-Industry Collaborations: Evidence from a Place-based Innovation Policy

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Abstract

Cluster policies seek to enhance collaboration among co-located actors as proximity improves interactions and the recombination of existing ideas. However, there is little evidence that place-based policies foster science-industry collaborations. Using data from a national cluster program in France and a novel control group—other industrial clusters—I examine the policy effects on local science-industry co-patent applications. The results show that R&D clusters increase science-industry collaboration. This effect occurs gradually over time, and patents tend to be of higher quality. These results suggest that place-based innovation policies affect the organization of science-industry research within clusters.

Keywords: Science-Industry Collaborations, Cluster policy, Organizational change, Regional Innovation.

JEL Codes: J24, O31, O34.

1 Introduction

There is widespread evidence that the creation and diffusion of new ideas are significantly influenced by agglomeration externalities, which enhance interactions among co-located actors (Jacobs, 1969; Jaffe, 1986; Marshall, 1890). Among these interactions, science-industry collaborations have emerged as a critical factor for fostering regional innovation systems and promoting economic growth (Graf and Broekel, 2020; Roncancio-Marin et al., 2022). Despite the increasing emphasis policymakers have placed on place-based innovation policies to promote effective collaborations among universities, public research institutions, and industry, evidence remains limited to the additionality effect of cluster policies on individual firms' performance (Bellégo and Dortet-Bernadet, 2014; Falck et al., 2010; Nishimura and Okamuro, 2011). However, little is known about the effectiveness of such policies on the structure of local collaborations by aligning the divergent objectives of these organizations, ranging from fundamental research to commercialization (Guzman et al., 2023; Neumark and Simpson, 2015).

In this paper, I address this gap by providing novel empirical evidence on the long-term effects of place-based cluster policies on local science-industry collaborations. Specifically, I analyze the impact of one of the largest place-based innovation policies in France, the Competitive Cluster program (Pôles de Compétitivité), launched in 2005. This policy aimed to strengthen manufacturing competitiveness and innovation by fostering collabora-

tion between co-located firms, universities, and public research institutions. Unlike conventional R&D grants that mainly address market failures, this policy is designed to tackle coordination failures among different actors by promoting direct and indirect interactions and knowledge spillovers (Juhász et al., 2023; Nishimura and Okamuro, 2011). Notably, the program targeted both leading and lagging industrial clusters, providing a unique setting to study the overlapping effects of industrial and place-based innovation policies (N’Ghauran and Autant-Bernard, 2022).¹

To assess the causal impact of the cluster policy, I use a difference-in-differences approach using newly collected local data on science-industry co-patent applications from 2000 to 2018. The control group consists of clusters from the Local Productive Systems (LPS) policy, an earlier industrial cluster-oriented initiative in France. LPS shares similarities with the place-based innovation policy (Fontagné et al., 2013; Lafféter, 2013). Among them are the top-down approach and the spatial dimension, which aim to encourage collaboration between firms in the same sectors. Furthermore, according to the archival data, several selected and rejected R&D clusters participated in the LPSs, which makes them a natural control group. Therefore, LPSs are a suitable control group if the number of science-industry collaborations in commuting zones with clusters had followed parallel trends in the absence of the place-based cluster policy.

The findings can be summarized as follows: Patenting between scientists from public research institutes (including universities) and firms increases in CZs affected by the place-based policy. I find that R&D clusters produce around 18% more science-industry patents on average than other industrial clusters. In the first phase of the policy (i.e., 2005–2008), science-industry collaborations remain comparable across R&D and other industrial clusters. The positive effects grow over several years and remain permanently greater during the third phase of the program (i.e., 2013–2018). These additional science-industry collaborations tend to be of higher quality, suggesting that the policy increases the productivity of researchers and inventors involved in collaborative R&D projects. Finally, this effect is more pronounced in chemical/pharmaceuticals, electronic/optics, and transport technological dimensions. Importantly, pretrends in the number of collaborations are comparable for commuting zones with and without clusters, supporting the empirical strategy. I also show that the results are robust across several alternative specifications, including matching procedures.

Next, I investigate two potential mechanisms that could drive the positive relationship between place-based cluster policy and science-industry collaborations. First, I examine whether the policy induces more collaboration between new inventors or teams previously engaged in patenting activities based on the structure of inventors (Wernsdorf et al., 2022). I find that the number of patents from new teams increases significantly. In contrast, the effect on teams that worked together previously is close to zero and insignificant. These findings suggest that inventors located in R&D clusters are more likely to form new ties to develop innovations. Second, I explore whether innovative searches and science-based patents increased after the implementation of the policy. I estimate the effect on the number of citations to prior knowledge and non-patent literature, which is related to both an increase in the degree of novelty and proximity to basic research. The number of citations for prior knowledge increases, suggesting that science-industry inventors build more on existing knowledge than inventors outside R&D clusters. Finally, science-industry collaborations rely more on inventions from public research facilities. These

¹For instance, the European Union (EU) has established various European Structural and Investment Funds. The European Regional Development Fund (ERDF), established in 1975, is the primary tool for reducing regional imbalances in the EU.

findings are consistent with the idea that a place-based policy facilitates technology transfers from basic science to commercialization.

This paper contributes to two strands of the literature. First, the impact of public policies on collaborations has attracted much attention in the literature. This strand of the literature, however, examines the effect of public incentives solely on firm performance, such as R&D spending and patents, providing mixed evidence (Bellégo and Dortet-Bernadet, 2014; Falck et al., 2010; Fontagné et al., 2013; Hassine and Mathieu, 2020). Although these studies are instructive, they overlook the significant effects of place-based policies on collaborations between universities and firms with a local and regional dimension. Aggregated effects of such place-based policies are important because of the rationale behind their implementation. A notable exception is N’Ghaoran and Autant-Bernard (2022), who examined the effect of the French cluster policy on firm collaborations. They found that regionally tailored interventions enhance firm collaboration in the short term but have an insignificant effect on the embeddedness of firms participating in collaboration networks. This paper contributes to the literature by providing causal estimates of the effects of establishing R&D clusters on long-term science-industry collaborations within geographically targeted areas. Furthermore, the paper highlights the mechanism at work by demonstrating the development of new R&D teams, including inventors from firms and scientists from public institutions, which support previous findings (Graf and Broekel, 2020; Töpfer et al., 2017).

This paper also relates to the literature that theoretically and empirically examines the relationship between the Marshallian agglomeration related to local knowledge spillovers and innovation (Jaffe et al., 1993; Moretti, 2021; Singh and Marx, 2013). For instance, Balsmeier et al. (2023) estimated the differences in local citations between deceased and still-living coinventors, highlighting that those citations (i.e., knowledge spillovers) for deceased inventors dropped by 25.8% within a 20-mile radius relative to coinventors. In another context, Helmers and Overman (2017) found that the establishment of a scientific research facility in the United Kingdom increased the number of related publications. This paper confirms the effects of geographic proximity by showing the behavioral additionally within CZs that facilitate access to each other’s knowledge, resources, and expertise.

The remainder of the paper is organized as follows: Section 2 outlines the institutional background of the cluster policy; Section 3 presents the data and descriptive statistics; Section 4 describes the empirical strategy; Section 5 discusses the results and robustness checks; Section 6 explores potential mechanisms driving the effects; and Section 7 concludes.

2 Institutional background

The empirical analysis focuses on the Competitive Cluster program, which was initiated in 2005 with the aim of promoting innovation through R&D collaborations between universities and industry. The cluster policy is part of a broader industrial ambition than in the past, aiming to foster manufacturing competitiveness through firm collaboration within local targeted areas.

Cluster Policy— Several cluster policies have been introduced in many countries based on the rationale of Marshallian agglomeration economies: labor market pooling, input sharing, and knowledge spillovers. However,

empirical evidence regarding the effectiveness is mixed (Kline and Moretti, 2014; Neumark and Simpson, 2015).² On September 14, 2004, the French government and local authorities launched the French Competitive Cluster program. The public policy is based on the study by Blanc (2004), which supports the creation of industrial clusters with a scientific base. It is characterized by an agglomeration dynamic that adds to the overall structure that supports and accompanies innovative firms. Thus, clusters were defined as follows: "*gathering, on a well-identified area and on a targeted theme, of small, medium, or large firms, research laboratories, and training establishments*" (Interministerial Committee for Territorial Planning and Development, CIADT 2005). The aim was to promote R&D and innovation by stimulating collaboration among firms, universities, and public research facilities within the same geographical area and in common technological fields. The policy also sought to strengthen the competitiveness of firms worldwide (Fontagné et al., 2013).

The first call for proposals was initiated on December 2, 2004, in a competitive scheme to select technological clusters at the national level. In the first phase of the program, 105 applications were submitted and reviewed by external reviewers. On July 5, 2005, the public authorities (CIADT) selected 66 clusters from various research and manufacturing fields, such as aerospace, microelectronics, health, mechanics, electronics, and optics.³ Clusters were selected based on their innovative potential with geographical locations specialized in distinct technological research activities (e.g., R&D agglomeration). Furthermore, proposals must include firms, incumbents, SMEs, universities, and research facilities, as well as three critical factors: (i) a network approach, (ii) a knowledge base, and (iii) worldwide recognition within the same geographical area.

Clusters were established in organizations labeled by public authorities. Thus, each cluster has its governance, which brings all its members, from firms to public institutions. The clusters are supported by funding structures from local authorities and members. Collaborative R&D projects emerging from cluster participants receive R&D subsidies awarded by two French agencies, the Fonds Unique Interministériel (FUI) and Agence Nationale de la Recherche (ANR), founded in 2005. These subsidies for collaborative R&D projects were awarded in response to calls issued regularly, following the selection of R&D clusters. Therefore, this industrial policy follows a "top-down" approach, which contrasts with the first cluster policy, Systèmes Productifs Locaux (LPS), launched in 1998. However, this cluster policy was not intended to reinforce innovation exclusively but to focus on firm performance. The LPS aims to reduce inequalities across areas by assisting struggling manufacturing sectors (Hassine and Mathieu, 2020). Furthermore, the budget grew significantly from approximately €4 million in 1999–2007 to approximately €1.5 billion in the first phase (Guillaume, 2008). According to Fontagné et al. (2013), the €500 million per year represents around 5.5% of the French national budget allocated to universities and public research institutes. Between 2005 and 2021, 2,000 R&D collaborative projects were financed and supported by clusters, receiving approximately €7.5 billion. The government's efforts to encourage innovation investment within clusters constitute one of the largest place-based innovation policy in France.⁴

Structure of the Cluster Policy— The cluster policy was structured in three distinct phases from 2005 to 2018, each with specific aims for each phase. The first phase of the policy was issued over three years (2005–2008).

²A fundamental concern raised in the literature is that spatially targeted policies may simply shift economic activity from one area to another, resulting in a zero-sum game.

³67 clusters were initially selected by the French authorities, but two merged following recommendations.

⁴Beyond direct public support for innovation, France has implemented extensive indirect support through R&D tax credits (i.e., "Credit Impôt Recherche"), which represent over €6 billion per year.

Based on the proposals submitted to public authorities, the first phase was intended to initiate R&D collaboration between firms, universities, and public institutions. Based on the criteria, these collaborations aim to align actors on technological dimensions. Finally, the public authorities defined three cluster categories reflecting differences in the expected potential. This ranking was defined as follows: "worldwide clusters" (i.e., 6 clusters); "potentially worldwide clusters" (i.e., 9 clusters); and "national clusters" (i.e., 51 clusters). The second phase of the policy was conducted between 2009 and 2012. Compared to the first phase, there have been two changes in science-industry collaboration and cluster ranking. First, the local dimension was slightly relaxed to establish synergies with other national and municipal policies and actors that promote innovation. According to N’Ghauran and Autant-Bernard (2022), this change aimed to improve the national coherence of France’s innovation policy, suggesting that clusters would be more open to long-distance collaborations than merely those with local firms, universities, or public research facilities. In addition, cluster ranking into three categories was removed. Finally, the third phase, which occurred between 2013 and 2018, followed the initial objective of encouraging and increasing local innovation through R&D collaborations. However, public authorities incentivized clusters to increase innovation output, such as patents, the introduction of new products and services, firm and employment growth, rather than R&D expenditures.

3 Data and descriptive statistics

Clusters— To identify areas hosting R&D clusters selected in 2005, I take advantage of archival data from multiple sources: the French Interministerial Committee for Territorial Planning and Development archives (CIADT), the Délégation à l’Aménagement du Territoire et à l’Action Régionale (DATAR), and several application files.⁵ To create a cluster-year panel, I gather data for each cluster on the name (including name changes and mergers between clusters) and location. Location information is supplemented with hand-collected data on the exact geographical boundaries at the city level of clusters approved by the Constitutional Council and published in the official gazette of the French Republic (Journal Officiel). Boundaries were formed as a result of the place-based policy, which included R&D tax incentives for firms involved in joint projects inside the zones’ boundaries. This indirect funding, which supplemented the main grant scheme through project calls, was discontinued in 2009. Therefore, I assign R&D clusters to commuting zones (CZs) using cities’ identifiers and define CZs with R&D clusters selected in 2005 as the treatment group. Finally, access to several cluster proposals confirms the concentration of firms, universities, and public research institutions within CZs.⁶ Of the 105 applicants, 66 R&D clusters were chosen and located throughout the country.

In the empirical analysis, I use other industrial clusters to create a novel set of counterfactual areas. I hand-collect information on the industrial clusters that participated in the former French cluster policy, *Systèmes Productifs Locaux (LPS)*.⁷ From surveys conducted by the Institut National de la Statistique et des Etudes Economiques (INSEE) and archival records from DATAR, I track industrial clusters backward in time, gathering information on their names, locations, and creation dates.

⁵This information is retrieved from official documents and websites using the Wayback machine.

⁶To participate in the call for projects, clusters had to provide an inventory of the organizations engaged, including their sector of activity and collaborative projects, and delineate a geographical area that brought all of these groups together.

⁷Note that some of the accepted and rejected applicants participated in the former policy or were ultimately selected a few years later in the *Grappes d’entreprises* program that took place in 2011

Science-Industry Collaborations— To estimate the effect of the place-based policy on collaborations, I rely on patent data from the OECD REGPAT. For each patent applied to the European Patent Office (EPO), I have a unique patent identifier number, filing date, International Patent Classification (IPC) codes, and the names of assignees and inventors along with their residential addresses. To assign local patents to areas hosting clusters, I use the address to link the inventor-patent pair with at least one inventor who has a residential address in France to a unique city identifier (ZIP code).⁸ When there are several inventors per patent application, I proportionately distribute patents to CZs by allocating part of the patent to each CZ equal to the inverse of the number of inventors (Andrews, 2023; Moretti, 2021).

The main dependent variable of interest is science-industry collaborations. However, collaborations between scientists and inventors are not directly observed. Instead, connections are defined through inventors' patent lists, as in the network literature. Science-industry collaborations are based on patents co-assigned to scientists from universities or public institutions and inventors from firms in geographical and time dimensions. For instance, public institutions include French universities and other public research facilities such as the Centre National de la Recherche Scientifique (CNRS) and the Commissariat à l'Énergie Atomique (CEA). Since 2000, the number of patent applications from public research facilities has risen significantly (see Fig. A.1), as a result of the Allègre Law (Law 99-587) of July 12, 1999, which changed the intellectual property regime for public institutions, incentivizing the production, licensing and the commercialization of innovations (Art. 19-1).⁹ Using the standardized assignee name associated with each patent application, I classify each assignee as either a firm, a public institution, a university, or none of the above (Akcigit et al., 2021).¹⁰

Finally, I use other measures related to assessing the quality and type of science-industry patents. To control for the skewed patent value distribution, I use a weighted patent count measure with, the total number of forward citations received by those patents within a five-year window. I count the number of backward citations of collaborative patents (Balsmeier et al., 2017). This measure captures, to some extent, innovative searches in well-known and mature technology dimensions. Lastly, I count the number of backward citations to non-patent literature (NPL), including mostly scientific articles. A large number of citations that a patent makes to NPLs reflect patent reliance on scientific and academic knowledge.

Control Variables— I assemble a set of control variables that account for structural differences across areas. I merge several CZ-level datasets into R&D and industrial clusters from the 1990 and 1999 French harmonized censuses. Census data are provided at the city level and are aggregated at the CZ level using boundaries. This set of control variables includes the number of cities, population, manufacturing employment, number of students, number of firms, number of R&D facilities, and number of universities and engineering schools with their corre-

⁸I use the inventor's residential address instead of the assignee address because it may indicate the location where research was conducted, since it is often the address of the R&D facility rather than the headquarters (Moretti, 2021). Furthermore, Baccaïni et al. (2007) show that since 2004, 50% of French employees have lived within 8 km of their workplace. This distance is more important for workers in rural areas, with a median commute of 10.6 km, as opposed to 5.3 km for workers in urban areas (Chaumeron and Lécroart, 2023).

⁹The Allègre Law is similar to the Bayh-Dole Act that was effective in July 1981 in the U.S. This law incentivizes patent production from universities and faculty and the commercialization of new knowledge, changing science-industry relationships (Hausman, 2022)

¹⁰I do so by manually identifying private firms with word acronyms SA, SAS, INC, LLC, LC, CO, CORP, BV, COMPANY, LP, or LTD in the assignee name. Public sector, college, and university patents are identified based on the following words: CNRS, CEA, CHU, UNIVERSITE, UNIVERSITY, COLLEGE, or INSTITUTE. The remaining unclassified patents capture individual inventors.

sponding research units.¹¹

Sample Restrictions and Summary Statistics— I make several restrictions on the CZs hosting clusters included in the baseline sample. First, I exclude 15 clusters defined as the most innovative by public authorities to ensure a comparison across clusters with similar observable characteristics.¹² Indeed, R&D clusters placed in the regions surrounding Paris, Lyon, and Toulouse have the highest population density and innovation. I also excluded clusters selected for participating in the program during the first call issued in 2004, of which access to grants was suspended at the end of the first phase of the program in 2008.¹³ Finally, I exclude a sample of 5 R&D clusters selected in 2007 for political reasons. The resulting sample consists of a balanced panel of 68 clusters in 157 CZs from the years 2000 to 2018, 40 R&D clusters in 127 CZs are defined into the treatment group, and the 28 other clusters in 30 CZs are included in the comparison group. In particular cases, a cluster involves several geographical areas close to each other. The overall number of CZ-year observations is equal to 2,983.

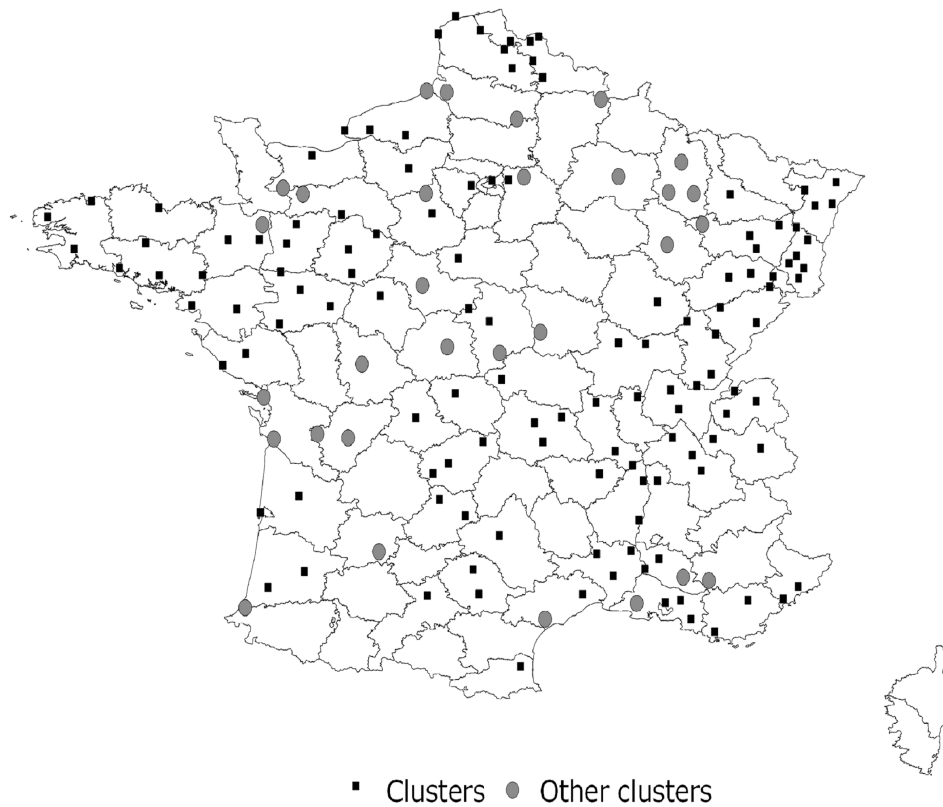


Figure 1. Commuting Zones by Treatment Status

Notes: This figure shows the location of clusters. Markers indicate the capital city of each CZ. R&D clusters are indicated by squares, and other clusters by circles.

Fig. 1 shows a map of targeted areas of selected R&D and other industrial clusters in continental France. This

¹¹Universities and engineering schools' localization and their corresponding research units are from the annual Regional Atlas of student population of the Ministry of Higher Education, Research, and Innovation.

¹²As discussed in Section 2, R&D clusters have been classified into three categories, with the caveat that I do not observe similar classifications around the innovative potential for other clusters.

¹³I ensure that the results are robust to the inclusion of these 6 clusters that experience negative events by including negative events in the baseline specification and assuming symmetric effects than positive events.

map shows that clusters targeted both leading and lagging areas. However, certain R&D clusters are concentrated in the Northwest and Northeast. The map also indicates that the targeted and untargeted areas are far apart.

Table 1 presents summary statistics for CZs hosting R&D and other clusters. Column 1 reports the mean of characteristics for the full sample of cluster-hosting CZs. Panel A reports innovation outcomes in the year before the policy implementation, Panel B reports the characteristics measured in levels from the 1999 census, and Panel C reports the changes between 1990 and 1999.¹⁴ Columns (2) and (3) show the characteristics of CZs hosting R&D and other clusters, respectively. Column (4) reports the mean difference, and the last column reports the p-value of the t-test of mean equality.

CZs hosting R&D clusters have more science-industry collaborations than other clusters, but the difference is not statistically significant. CZs with R&D clusters also had higher population, manufacturing employment, students in higher education, and stocks of firms and private R&D facilities. If the public authorities selected clusters that were more productive with respect to those characteristics, the baseline estimates might not be representative of the average effects of cluster policy on science-industry patents. Reassuringly, the differences in trends in manufacturing employment, research units, and science-industry collaborations are statistically insignificant.

Table 1. Summary Statistics

	Full Sample (1)	Accepted Clusters (2)	Industrial Clusters (3)	p-value (4)
Panel A. Innovation in the year before policy				
Collab. Public-Private	0.66	0.78	0.14	0.24
Cite-Weighted Collab.	2.20	2.71	0.03	0.31
New Collaborations	2.81	3.35	0.53	0.21
Old Collaborations	0.03	0.03	0.00	0.54
Panel B. CZ Characteristics (levels)				
Population (1999)	215,566.3	238,962.1	116,524.1	0.01***
Agricultural Emp. (1999)	2,602.09	2,645.1	2,420.03	0.55
Manufacturing Emp. (1999)	13,678.83	15,176.2	7,340	0.00***
Share of Emp. in Manufacturing	0.07	0.07	0.07	0.64
Universities (1999)	0.46	0.55	0.10	0.11
Other Schools (1999)	0.28	0.31	0.13	0.30
Research Units (1999)	912.80	1,065.08	268.17	0.17
N. Students (2004)	9,339.96	11,031.79	2,177.87	0.02**
N. Firms (1999)	25,975.57	28,469.46	15,418.10	0.02**
N. R&D Facilities (1999)	33.98	39.97	8.67	0.02**
N. Cities	113.72	111.76	122.03	0.52
Panel C. CZ Characteristics (changes)				
Population (1999-1990)	9,274.91	10,833.72	2,675.93	0.02**
Agricultural Emp. (1999-1990)	-351.99	-346.43	-375.57	0.75
Manufacturing Emp. (1999-1990)	-1,032.38	-1,198.19	-330.47	0.13
Universities (1999-1990)	0.04	0.05	0.03	0.74
Other Schools (1999-1990)	0.04	0.04	0.03	0.88
Research Units (1999-1990)	267.57	299.09	134.17	0.31
N. Students (2004-2001)	417.34	487.39	120.83	0.09*
N. Firms (1999-1990)	14,321.61	15,829.44	7,938.47	0.02**
N. R&D Facilities (1999 -1990)	19.29	22.67	5.00	0.02**

Notes: Columns 1 to 3 show mean values for the full sample, R&D, and other industrial clusters at the CZ level. The last column shows the p-value for the t-test of equality with the associated significance levels. Panel A shows the innovation outcomes in the year before policy implementation. Panel B shows the pretreatment characteristics in levels, and Panel C shows the change between 1990 and 1999 for CZs in which R&D and other industrial clusters were localized.

¹⁴For the students enrolled in universities or engineering schools, I report the mean and changes for the last censuses in 2001 and 2004.

4 Empirical strategy

LPS clusters as counterfactual— The main empirical challenge in estimating the causal effect of cluster policy on local science-industry collaborations is that the selection is not random. As discussed previously, R&D clusters differ from the rest of the country. Therefore, including the full sample of CZs could result in an overestimated effect of the policy (Andrews, 2023). To overcome this challenge, I identified a novel control group of untargeted areas benefiting from the previous LPS policy, which are the most similar to R&D clusters. LPSs are attractive as a control group for at least two reasons. First, the LPS policy was considered the first cluster policy implemented in France (Martin et al., 2011). It intends to fund collaborative projects between firms on the same technological and geographical dimensions, intending to strengthen cluster dynamics. As a result, the LPS policy followed the common and well-established definition of clusters of Porter (1998) :

"firms grouped together in a local area around an activity or, even a technology, maintaining more or less intense relations with each other, the surrounding environment, and, in particular, institutions that support the productive system. These relationships are not only commercial; they can be informal and, produce additional value, and they benefit from coordination and industry-research or training interfaces that should stimulate the system and place it on the path to innovation." (Lafféter, 2013; Pommier, 2004).

Second, there were parallels between the two initiatives since the local selection process was handled by the same institution (i.e., DATAR), and followed a similar format. There were two project calls, one in September 1998 and the other in September 1999.¹⁵ Starting from a preselection at the local level, the final cluster was selected by external reviewers at the national level (Le Duc and Reverdy, 2001).¹⁶ Furthermore, the call was opened to firms willing to cooperate within the same geographical and technological dimensions. Thus, LPSs satisfy the formal requirement for applying to the place-based innovation policy. They have a concentration of firms within the same manufacturing sector, intending to promote R&D spending based on knowledge transfers and know-how likely to lead to tangible results reinforced by public research institutions (including universities). Among the 93 LPSs, 21 clusters applied to the call for projects in 2004.

Baseline Specification— The empirical framework implements two-way fixed effects regression (Roth et al., 2023), as follows:

$$y_{it} = \beta \text{Cluster}_i \times \text{Post}_t + \gamma_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where y_{it} is either the number of science-industry patents or a binary indicator of positive outcomes in CZ i in year t . Cluster_i is a dummy that takes a value of one if the CZ host an R&D cluster and zero otherwise. Post_t is a dummy equal to one from 2005 onward. The cluster fixed effect γ_i controls for time-invariant differences across clusters. The year fixed effect γ_t controls for yearly factors common to clusters, such as macro-level shocks. I also replace γ_t with $\text{Region}_r \times \gamma_t$ fixed effects to flexibly control for the heterogeneous effects of shocks and spatial correlation. For instance, the policy focused on certain technological dimensions that might be related to different

¹⁵From these two calls, 202 proposals were received and 93 projects have been accepted for granted.

¹⁶The list of cities and CZs to be included in the R&D cluster was first drafted by members (i.e., firms and research institutions) of the cluster on the criteria included in the program specifications and later approved by the Council of State.

impacts across regions if some innovation affects sectors more than others, leading to biased estimates. To address potential heteroskedasticity and within-commuting zone correlation over time, I cluster standard errors at the CZ level, following (Bertrand et al., 2004), though I also present alternative standard errors that more flexibly account for spatial correlation.¹⁷

The analysis is conducted at the commuting zone-year level, taking into account the direct and indirect support provided by R&D clusters. Each proposal focuses on a specific technological field, which may encompass several two-digit industry sectors. In addition, CZs can host several R&D clusters. By employing this approach, I can estimate the overall impact of the policy on collaborations between universities and firms.

The coefficient of interest is β . I expect to be positive as clusters that were selected in 2005 shifted science-industry collaborations over the long run. This coefficient estimates the causal effect of the program under the assumption that—without the establishment of R&D clusters—changes in science-industry collaborations after 2005 would be comparable to those in selected and other clusters.¹⁸

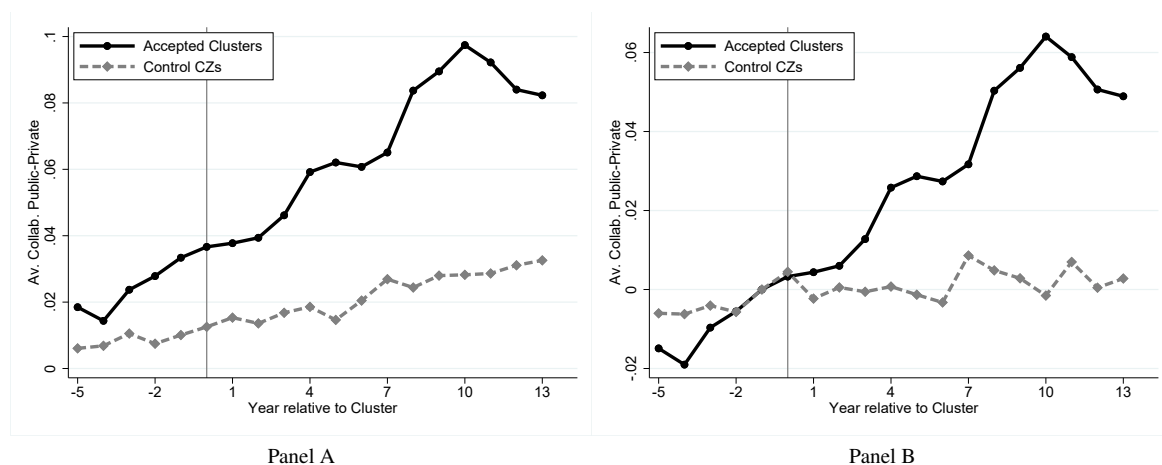


Figure 2. Average Number of Science-Industry Collaborations

Notes: This figure plots the average number of science-industry collaborations for R&D and other clusters in the 5 years before and 14 years after the policy. Panel A shows the raw average, and Panel B normalizes the average relative to its value in the year before the policy implementation.

Tests of the Identification Strategy— To assess the plausibility of the identification assumption, I perform several tests. First, I compare the time series of science-industry collaborations for CZs hosting R&D and other clusters. The raw comparisons in Panel A of Fig. 2 show that clusters benefiting or not from the policy had followed the same trends until 2005, except for a small divergence four years earlier. This pattern is confirmed in Panel B of Fig. 2 in which the number of science-industry collaborations is normalized to zero the year before the policy occurs. After policy implementation, science-industry collaborations diverge between the treated and control groups.

Second, as is standard in difference-in-differences regressions, I test whether treated and control clusters were

¹⁷In Appendix Table A.8, I provide estimates using alternative clustering approaches: commuting zone-year, and commuting zone \times year levels. I also report estimates by clustering at the region; region-year and region \times year levels. The results are robust to these alternative inference procedures. Here, the one exception is that standard errors at the region level are smaller than those in the baseline specification (column 2 of Table 2). Clustering at a level that is too aggregate may be harmful (Abadie et al., 2022). Because the sample includes only 21 regions, I prefer a more conservative approach.

¹⁸The empirical framework follows the standard difference-in-differences literature with treatment group, one control group, and a treatment year in 2005. In contrast to the staggered adoption setting (de Chaisemartin and D’Haultfoeuille, 2020), the standard difference-in-differences estimates the average treatment effect on the treated even with treatment heterogeneity (Abadie, 2006).

on parallel trends if the policy had not occurred using the following dynamic specification:

$$y_{it} = \sum_{\tau=2000, \tau \neq 2004}^{\tau=2018} \beta_{\tau} (\text{Cluster}_i \times \text{Year} = \tau) + \gamma_i + \gamma_t + \varepsilon_{it} \quad (2)$$

where the variable *Years after Cluster* represents an indicator for each year between 2005 and 2018. Each β_{τ} coefficient captures the dynamic effect of the program τ years after its implementation. The omitted coefficient is $\beta_{\tau=2004}$, which corresponds to the year before the policy was implemented. Fig. 3 reports the results. The estimated coefficients indicate that S-I collaborations in R&D clusters before 2005 are not statistically different from those in other clusters. Point estimates between 2000 and 2004 are all close to zero and not jointly statistically significant with and without region-year fixed effects (p-values = 0.19 and 0.23).¹⁹ These results are consistent with the parallel trend assumption and provides some confidence that the estimates represent a causal effect.

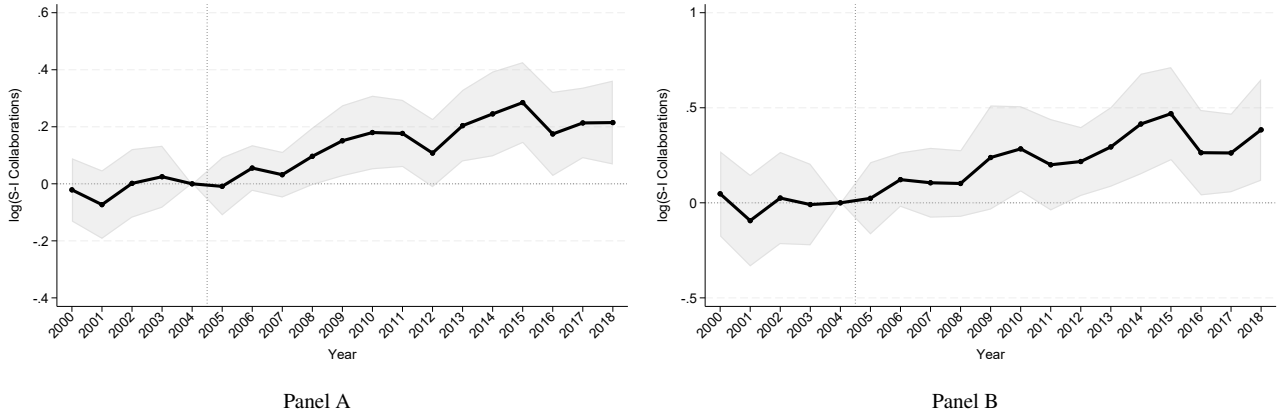


Figure 3. Yearly Effects of R&D Cluster on Science-Industry Collaborations

Notes: This figure shows estimated coefficients for the effects of the establishment of R&D clusters on science-industry collaborations. Year 2004 is normalized to zero. The regression includes CZ fixed effects and region-year fixed effects. 95% confidence intervals are included.

Even in the absence of pretrends, cluster location decisions may reflect a selection bias from public authorities (i.e., conditional independence assumption). Specifically, targeted areas hosting R&D clusters have similar observable characteristics to other areas. To assess this assumption, I test whether CZs that hosted clusters were statistically indistinguishable in terms of characteristics before 2005. As discussed previously, comparisons of the observable pretreatment characteristics suggest that the two sets of clusters are indistinguishable for several CZ characteristics but exhibit some differences in population, manufacturing employment, a higher number of students, a higher firm stock, and private R&D facilities. The parallel trend assumption addresses this issue of imbalance if the bias is the same for the pretreatment period and after policy implementation.²⁰ As a result, the absence of pretrends removes this form of selection (Heckman et al., 1998). However, I account for differences between selected and other clusters throughout the analysis using several approaches. First, the baseline

¹⁹In Fig. A.2, I test the sensitivity of the last post-reform estimate to violations of parallel trends following Rambachan and Roth (2023). This formal method compares the confidence intervals that permit departures from the parallel trend assumption up to limits M with the confidence intervals derived from the baseline specification. Assuming linear trends ($M=0$), the 95% confidence intervals exclude zero and increase with larger deviations from linearity by excluding zero for values of M up to 0.02 (15% of the standard errors). This indicates that the results are robust to some level of nonlinear violations of parallel trends.

²⁰Appendix Table A.1 shows that differences between CZs hosting R&D clusters and other CZs not covered by LPSs are more pronounced. As a result, other CZs with statistically significant differences in observable characteristics were not considered in the baseline specification, strengthening the credibility of the identification strategy.

specification is augmented with control measured in the pretreatment period and interacted with year dummies. Specifically, once I control for employment in the manufacturing sector, none of the characteristics are related to the treatment. I also address concerns about potential biases from unobserved differences between R&D and other clusters; I re-estimate all specifications based on a matched sample obtained through Coarsened Exact Matching (Iacus et al., 2012), where treated and control clusters are comparable in terms of observable characteristics before 2005 (see Section 5.3). In addition, I use a doubly robust estimator proposed by Sant’Anna and Zhao (2020). This estimator allows us to condition the parallel trend assumption for some pretreatment characteristics. The aim of this estimator is to make the treated and control groups more similar, thereby increasing the credibility of the identification. This estimator combines an inverse probability weighting estimator and a regression adjustment procedure (Heckman et al., 1998; Sant’Anna and Zhao, 2020).

5 Effects of R&D Cluster

5.1 Baseline Results

Table 2 reports the estimated effect of the place-based policy on science-industry collaborations. The dependent variable is $\log(\text{S-I Collab.} + 1)$ in columns (1-3), the inverse hyperbolic sine of science-industry collaborations in column (4)²¹, and an indicator of having at least one co-patent per year in column (5). I gradually include region fixed effects and a control variable for the number of pre-2005 patents using Equation (1). The specification in column (2) is the preferred specification since it controls for within-region variation. Consistent with the visual evidence, there is a large and significant effect on the number of S-I collaborations within CZs hosting R&D clusters. OLS estimates suggest that clusters selected by public authorities for benefiting from R&D public investments produced 17.9% more additional science-industry collaborations after 2005, compared with other clusters (with an estimate of 0.165, $e^{(0.165)} - 1 = 0.179$. Table 2, column 1; significant at 5%). The estimated coefficient controlling for region-year fixed effects is slightly larger but shows a similar pattern, with an increase of 28% (column 2).

As previously discussed, one potential explanation for the positive effect on science-industry collaborations is that clusters differ relative to their research potential, which may explain the selection of R&D clusters. Following Kantor and Whalley (2022), I control for the number of pre-2005 patents.²² Column (3) shows that the estimates remain similar. In the remaining columns, the dependent variables are replaced with the inverse hyperbolic sine transformation and a binary indicator for positive values. Result is robust when using this alternative transformation (column 4). In contrast, when estimating the effects of the cluster policy on the probability of having at least one co-patent per year, I find that the effect is not statistically significant at conventional levels (column 5). These findings suggest that the effect is confined to the intensive margin.

Overall, a place-based innovation policy that stimulates collaboration between basic and applied research significantly increases the number of collaborations within R&D clusters. This is consistent with findings in the

²¹The inverse hyperbolic sine transformation $\text{arcsinh}(x) = \ln(1 + \sqrt{x^2 + 1})$ allows the inclusion of observations with zero patents. The coefficient estimate yields a similar interpretation to that of a standard logarithmic specification (Bellemare and Wichman, 2020).

²²Note that I used the number of pre-2005 patents to account for different trends in research potential regardless of the program instead of the number of pre-existing science-industry collaborations because of the small number. However, the results are robust in specifications where I add pre-2005 collaborations $\times \frac{1}{N}$ as control. In Appendix Table A.8, I also control for manufacturing employment and the number of R&D facilities to capture differences in cluster research potential.

literature that policies fostering the development of research clusters result in new interactions between firms and universities in China (Hsu et al., 2023) and researchers in France (Carayol et al., 2023).

Table 2. Effects of R&D Clusters on Science-Industry Collaborations

Dependent Variable	log(S-I Collab.)			arcsinh(S-I Collab.)	S-I Collab.
	(1)	(2)	(3)	(4)	(5)
Cluster×Post	0.165*** (0.041)	0.247*** (0.065)	0.174*** (0.056)	0.317*** (0.082)	0.065 (0.066)
Mean Dependent Variable	0.349	0.349	0.349	0.436	0.432
Obs.	2,983	2,983	2,983	2,983	2,983
Adj. R ²	0.810	0.773	0.829	0.760	0.473
Cluster FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	No	No
Region x Year FEs	No	Yes	Yes	Yes	Yes
Patent×Year FEs	No	No	Yes	No	No

Notes: This table reports the effect of cluster policy on local science-industry collaborations. Cluster is an indicator variable for CZs that host an R&D cluster. Post-Cluster is an indicator equal to one for 2005 and afterward. The dependent variable in columns 1-3 is log(S-I Collab. + 1). Column 4 presents results for the inverse hyperbolic sine of science-industry collaborations. Column 5 presents results for the extensive margin specification. The unit of observation is CZ×year. Standard errors are clustered at the CZ level.

5.2 Further Analysis

Effects by Phases— The yearly effects in Fig. 2 indicate a long-lasting effect over time for clusters that were selected. The increasing effects on local collaborative innovation could reflect lags in the responses of universities and firms to develop follow-on innovation from basic research. This suggests that it takes time for the results of public R&D to translate into new collaborations. Scientists and inventors may have varying incentives to create new knowledge, which may hinder their ability to collaborate effectively. Furthermore, firms may lack the absorptive capacity to build on academic research. To shed light on whether collaborations have evolved over time, the coefficient of interest was estimated separately for each phase of the program (Table 3). Overall, the effects grew slightly until 2012, namely during the first two phases (2005–2008 and 2009–2012) of the program after the selection of clusters. Time-varying estimates increase to 9.9% more additional science-industry patents for the first phase (2005–2008) and remain positive throughout the second phase (2009–2012). After the second phase of the program, which ended in 2012, the effects are more precisely estimated, with an increase of 42.5% in 2013–2018. However, the estimated effect on the probability of having at least one co-patent between science and industry is statistically insignificant for the three phases. The 8-year lag estimates seem to compare well with those found in Hassine and Mathieu (2020) which find that private investments in R&D increased by 24.6% four years after the policy was implemented in 2005.²³ The growing effect of the policy is also consistent with the different phases—from the embryonic to the established phase—enabling successful science-industry collaborations proposed by O’Dwyer et al. (2022).

Effects by Industry— So far, I have examined the aggregate effect of the cluster policy. Next, I estimate whether the R&D incentives affect the technological dimension of CZs that host clusters. The policy targeted clusters specializing in technological areas may not affect all science-industry collaborations across the entire technolog-

²³This finding is also consistent with previous findings in the U.S. For instance, de Rassenfosse et al. (2019) found an average lag of 33 months between an R&D procurement contract and patent filing, or the average two-year lag between a negative federal funding shock and patenting in Babina et al. (2023).

Table 3. Dynamic Effects across Phases

Dependent Variable	log(S-I Collab.)		arsinh(S-I Collab.)	S-I Collab.
	(1)	(2)	(3)	(4)
Cluster×Phase 1	0.057 (0.035)	0.094 (0.062)	0.121 (0.079)	0.015 (0.087)
Cluster×Phase 2	0.167*** (0.046)	0.241*** (0.071)	0.310*** (0.091)	0.077 (0.090)
Cluster×Phase 3	0.236*** (0.052)	0.354*** (0.080)	0.453*** (0.101)	0.089 (0.078)
Mean of the Dep. Var.	0.349	0.349	0.436	0.433
Obs.	2,983	2,983	2,983	2,983
Cluster FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	No
Region x Year FEs	No	Yes	Yes	Yes

Notes: This table reports the effect of cluster policy on local science-industry collaborations. Cluster is an indicator variable for CZs that host an R&D cluster. Phase 1-3 are indicators of years spanning the first through the third phase of the policy. The dependent variable in columns 1-3 is $\log(\text{S-I Collab.} + 1)$. Column 4 presents results for the inverse hyperbolic sine of science-industry collaborations. Column 5 presents results for the extensive margin specification. The unit of observation is CZ×year. Standard errors are clustered at the CZ level.

ical domain. Knowledge transfers from basic research to applied invention through formal joint R&D projects may vary according to the technological opportunities faced by firms to improve products and processes and the intensity of the knowledge flows required. For instance, [Cohen et al. \(2020\)](#) find that in fields where the degree of technological proximity is higher, such as engineering and applied sciences (e.g., chemistry, electrical, and mechanical engineering), patenting activities are more important for scientists than physical sciences. Finally, collaborations may also differ in the intensity of research among manufacturing sectors. Knowledge-intensive fields may rely more on science as an input to produce radical innovation than others ([Schartinger et al., 2002](#)). Therefore, if both technological proximity and intensity foster collaborations, I would expect an increase in innovation for those sectors.

To examine the heterogeneous effects of the development of R&D clusters across technological dimensions, I estimate Equation (1) on $\log(\text{S-I Collab.} + 1)$ for nine industries. Industries are based on the IPC merged to the European industry classification at the two-digit level (NACE Rev. 2).²⁴ I find the largest effects for the chemistry and pharmaceuticals, electronics, optic equipment, and the transport sector.²⁵ For instance, the chemistry and pharmaceutical manufacturing sectors produced 9% more additional patents after 2005.²⁶ In contrast, I find small and statistically insignificant effects for less knowledge-intensive fields, such as food (0.004, s.e. = 0.005), or metal (-0.003, s.e. = 0.005). These results are consistent with previous evidence by [Schartinger et al. \(2002\)](#), suggesting that the effect of the policy is restricted to industries with a scientific orientation.

Effects by Patent Quality— I now turn to exploring the effect of policy on the quality of new science-industry patents. The quality of patents varies widely and represents only a minor scientific advance. On the one hand,

²⁴I recoded the highly detailed IPC classification into a slightly modified version of the technology area classification established by [Van Looy et al. \(2015\)](#) to produce a unique technology classification from the set of accessible IPC classes at the 4-digit level, which is listed on a patent application form. The reclassified technology information is used to determine the dominant technology area for each patent based on the modal value.

²⁵Note that positive effects on science-industry collaborations occurred after the policy was implemented in 2005. Furthermore, the time-varying effects are consistent with the parallel trends assumption and provide some confidence that the estimates represent a causal effect ([Appendix Fig. A.3](#)).

²⁶Note that the results are also driven by the technological field of Chemistry when I use an alternative classification that aggregates IPC classes to 5 subfields ([Schmoch, 2008](#)).

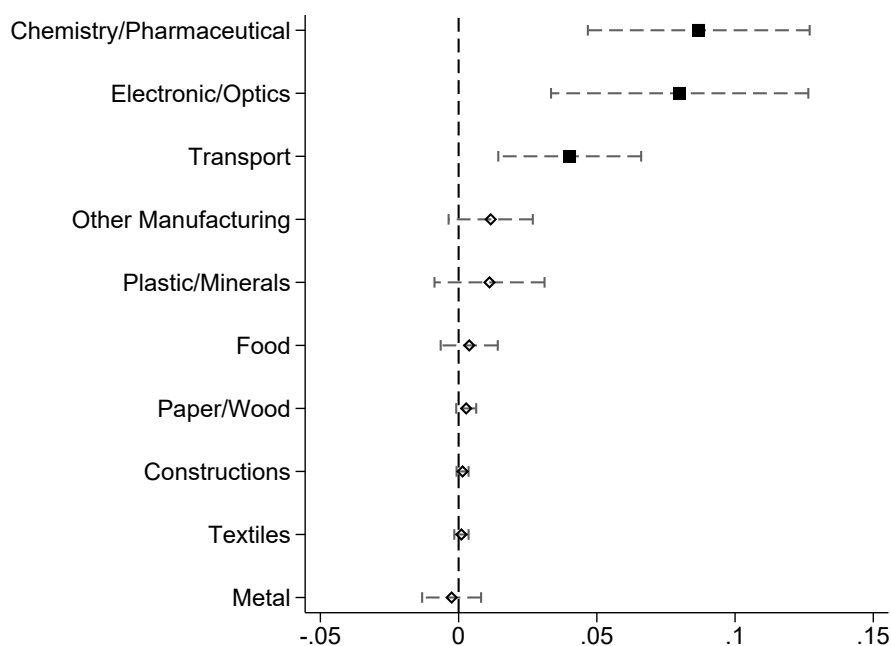


Figure 4. Heterogeneous Effects of R&D Cluster by Sectors

Notes: This figure shows estimates of Equation (2) of the effects of the establishment of R&D clusters on science-industry collaborations by manufacturing sectors. The dependent variable is $\log(\text{S-I Collab.} + 1)$. Each point is from a separate regression. 95% confidence intervals are included.

incorporating basic research into public-private R&D projects can spur the technological value of patents, enhancing the impact of new inventions. For example, cite-weighted patent numbers are shown to have a relationship with financial value (Kogan et al., 2017). On the other hand, firms can encounter difficulties in internalizing basic research (i.e., absorptive capacity) from scientific research, which could decrease the quality of newly produced innovation.

To shed light on the effect of the policy on the value of science-industry collaborations, I estimate Equation (1) with cite-weighted collaborative patents as the dependent variable. Table 4 reports the results. The estimated coefficient is positive and statistically significant, suggesting a rise in quality for patents resulting from public-private teamwork of about 11-17%.²⁷ In terms of magnitude, the median number of forward citations is three, implying 0.7 more future citations. Taken together, these findings show that a rise in new science-industry collaborations is related to an improvement in patent quality.

5.3 Robustness Checks

Placebo Checks— One concern is that R&D clusters were selected based on unobserved factors, such as political motivations, which may subsequently shape collaborations. I test whether the results are robust to falsification

²⁷Appendix Fig. A.9 confirms the positive effect in the short term and then decreases sharply after 2013. The effect decreases significantly because I use the five-year cumulative number of citations received, which poses several challenges in the difference-in-differences framework. For instance, some patents were filed before the policy implementation, whereas some citations were received after. Similarly, patents filed at the end of the sample period are less likely to receive citations, resulting in yearly effects that are less precisely estimated.

Table 4. Effects of R&D Clusters on Cite-weighted Patents

	log(Cits)		arcsinh(Cits)	
	(1)	(2)	(3)	(4)
Cluster×Post	0.106*** (0.037)	0.161*** (0.054)	0.135*** (0.047)	0.204*** (0.069)
Mean of the Dep. Var.	0.192	0.192	0.244	0.244
Obs.	2,983	2,983	2,983	2,983
Cluster FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No
Region x Year FEs	No	Yes	No	Yes

Notes: This table reports the effect of cluster policy on cite-weighted science-industry collaborations. Cluster is an indicator variable for CZs that host an R&D cluster. Post-Cluster is an indicator equal to one for 2005 and afterward. The dependent variable in columns 1-2 is $\log(\text{Cites} + 1)$. Columns 3-4 present results for the inverse hyperbolic sine of science-industry collaborations weighed by forward citations. The unit of observation is CZ×year. Standard errors are clustered at the CZ level.

test by assigning a placebo treatment (i) in 1985, 30 years before the cluster policy; (ii) to CZs that did not experience cluster policies (including LPSs started in 1997) and using selected R&D clusters as a control group; and (iii) to the original control group and using other CZs as the control group (excluding CZs hosting selected R&D clusters). Estimates of the placebo treatments are close to zero and statistically insignificant. These results are supported by the dynamic effects (Appendix Fig. A.6). Differences in pretrends and post-treatment effects are small and statistically insignificant. These falsification tests provide evidence that the main results do not capture factors underlying the rise of S-I collaborations produced.

Matching procedure— The identifying strategy relies on the assumption that R&D clusters and other clusters differ only as a result of the policy. However, differences in observable characteristics between clusters may bias baseline estimates. To minimize concerns about selection bias, I re-estimate the baseline specification on a sample of clusters for which the observable characteristics are balanced. Specifically, I use a coarsened exact matching (CEM) procedure to balance the sample. CEM has several advantages over other matching procedures (e.g., propensity score matching) by balancing observable characteristics across their entire distribution, improving causal inference (Iacus et al., 2012). The matching procedure uses the following characteristics: total employment in the manufacturing sector and the number of S-I collaborations in 2004. An exact match was found for 71 CZs (56%) in the treatment group and 25 comparable CZs in the control group. Appendix Table A.5 shows that the matching procedure eliminated the average differences for all observable characteristics, with no statistically significant differences. The results in Appendix Table A.6 and Fig. A.7 are quantitatively similar to baseline estimates throughout. The point estimates range from 0.056 to 0.075, resulting in an increase of 5.7-7.8%. I also provide evidence using a doubly robust estimator to condition the parallel trend assumption on observed characteristics (Sant’Anna and Zhao, 2020). This estimator combines two estimation procedures: the inverse probability weighting estimator and regression adjustment procedure to increase comparison between both groups. Results are reported in Fig. A.8. The results remain positive and statistically significant, with an effect ranging from 11-12% and pretrends verified conditionally on the pre-treatment observed characteristics.

Further Robustness Checks— An additional threat to the identification strategy is that the policy could be driven

by specific clusters categorized as more innovative or specialized in high-technological sectors (e.g., aeronautics, chemistry, and pharmaceuticals). Results are robust to excluding clusters specialized in space/aeronautics (row 2 of Table A.8) and clusters specialized in chemicals (row 3). In row 4, I control for manufacturing employment and find similar conclusions. In row 5-6, I control for the number of public and private research facilities. I found similar positive effects but only statistically significant at the 10% level when controlling for private research facilities. In the remaining rows, I report estimates using alternative inference procedures: (i) clustered at the commuting zone-year level; (ii) clustered at the commuting zone \times year level; (iii) clustered at the region level; (iv) clustered at the region-year level; and (v) clustered at the region \times year level. The standard errors are similar across these approaches. As a further specification, I test whether the main effect is not driven by the response of any cluster. In Appendix Fig. A.9, I re-estimate the main specification, dropping R&D clusters one by one.²⁸ I find that the estimated coefficients are very comparable. Finally, I use alternative transformations of the dependent variable, using a smaller number (0.001) for the natural logarithm transformation, the count of collaborative patents per year, winsorizing the number of patents at the 5th percentile, and using the Poisson Quasi-Maximum Likelihood estimator. Appendix Table A.9 reports the results. I find results similar to those obtained from the baseline specification.

6 Potential Mechanisms

So far, the analysis documents that science-industry collaborations increased within clusters, suggesting that direct and indirect support addresses coordination failures. For instance, this positive effect might be the result of improved matching between close inventors within clusters. Instead, inventors involved in firms can change their invention strategy and rely on scientific content by learning from their peers in public research institutes. Understanding the potential mechanisms that drive this positive effect can inform policymakers aiming to foster local innovation through place-based interventions. This section is dedicated to exploring these potential explanations.

6.1 Has the policy changed local ties?

Does the program increase collaboration through new or existing ties? The place-based policy aims to strengthen local innovation between universities and firms. Thus, the policy can also change the formation of ties within clusters through new or existing teams (Graf and Broekel, 2020; Töpfer et al., 2017). To examine whether the positive effect on science-industry collaborations is due to the formation of a new R&D team or team previously involved in patenting activities, I measure whether individual inventors were previously involved in co-patented inventions before the policy implementation. Columns (1) and (2) of Table 5 show that there is an increase in collaborative patents for selected clusters from newly assembled R&D teams, whereas the estimated effect for teams previously patented together is especially small in magnitude. However, estimated coefficients are statistically insignificant at conventional levels.²⁹ Despite insignificant effects on both new and old collaborations,

²⁸To assess the possible effect of any individual R&D cluster on the baseline estimates, I conduct a jackknife-like exercise and report the estimated coefficients from 40 regressions. For each regression, I drop all CZs where an R&D cluster operated.

²⁹Re-estimating this specification at the commuting-zone-industry level, I find that the policy increases average science-industry collaborative patents from new R&D teams by about 5.4%, while the estimated effect is close to zero for R&D teams with previous collaboration

the sign and magnitude of the estimated effects appear to be more consistent with the mechanism implying that the policy strengthens innovation by stimulating the creation of new teams.

Table 5. Effects of R&D Clusters on Collaborations and Science

	New Team (1)	Old Team (2)	Backward Cits. (3)	NPL Cits. (4)
Cluster × Post	0.102 (0.064)	-0.002 (0.011)	0.114* (0.063)	0.148* (0.031)
Mean Dependent Variable	0.736	0.019	0.722	0.792
Obs.	2,983	2,983	2,983	2,983
Adj. R ²	0.72	0.06	0.66	0.64
Cluster FEs	Yes	Yes	Yes	Yes
Region x Year FEs	Yes	Yes	Yes	Yes

Notes: This table reports the effect of cluster policy on collaborations and science. Cluster is an indicator variable for CZs that host an R&D cluster. Post-Cluster is an indicator equal to one for 2005 and afterward. The dependent variable in column 1 is log(New Team) and log(Old Team) in column 2. Column 3 presents results for the log(Backward Cits) and column 4 for the log(NPL Cits). The unit of observation is CZ×year. Standard errors are clustered at the CZ level.

6.2 Innovative Search Strategy and Science

Finally, I examine whether the policy changed teams' search strategy and whether they relied more on scientific knowledge. For instance, new inventions patented by science-industry pairs can be dissociated from basic research without changing firms' commercialization objectives. Alternatively, the matching process induced by the policy may generate technology transfers from scientists to applied inventors, increasing reliance on basic research.

First, I focus on the number of citations each patent makes to other patents. Backward citations to prior art provide information about the degree of novelty of the invention. Therefore, an increase in the number of citations made to prior knowledge may reflect an increase in innovative search strategy but, toward technologies more familiar to inventors' teams (Balsmeier et al., 2017). Column (3) of Table 5 reports the estimated coefficient, suggesting that collaborative patents induced by the R&D public policy rely more on prior art.

Then, I focus on the number of citations to non-patent literature (NPL). NPL refers to prior knowledge, such as scientific articles, conference proceedings, and databases (e.g., DNA structures, gene sequences, and chemical compounds). An increase in the number of NPL citations reflects how innovation relies on scientific research to develop ideas. Furthermore, they return to the proximity between science and technological inventions (Callaert et al., 2006). Column (4) shows that science-industry collaborations within R&D clusters had higher citations for NPL than those in other clusters. Citations on NPL increased by 19% compared to the average of 0.792 after the policy implementation.

Overall, this evidence about the potential mechanisms that drive the main effects on local science-industry patents suggests that incentivizing R&D partnerships leads to a shift in innovation toward a higher innovative search strategy and higher reliance on basic science from universities and public research facilities, and to some extent changes the structure of teams within R&D clusters.

experience. Moreover, the point estimates are more precise with this specification.

7 Conclusion

Place-based innovation policies, which aim to enhance local innovation by reshaping interactions among co-located institutions, have become a popular industrial policy instrument. While substantial research has been conducted to evaluate the additionality of place-based innovation policies in stimulating R&D spending and patenting at the firm-level (Schweiger et al., 2022), the impact on collaboration between public research scientists and inventors from firms is still missing. Furthermore, evidence at the aggregate level is underexplored. To shed light on this question, this paper focused on the effects of the French cluster policy on local science-industry collaborations. I identify causal effects by relying on the establishment of R&D clusters for access to funding for innovations, as well as the existence of other industrial clusters, which partially address the endogeneity of cluster nonrandom locations. I find that the emergence of R&D clusters had long-lasting positive effects on local science-industry co-patenting. This collaboration has increased since 2012 when the policy entered its third phase. These new patents, which result from collaborations between public scientists and private sector inventors, have not experienced decline in quality. Furthermore, these patents are primarily focused on technological areas where the degree of proximity between basic and applied research is particularly high. Several robustness checks confirmed the baseline effects, including different estimation approaches and measurements.

Next, I examine potential mechanisms. The cluster policy that incentivized new projects led to an increase in local collaborations and, innovative search strategies for new inventions. Specifically, I find that the number of citations to prior knowledge of new patented inventions significantly increases after implementation of the program. I also find that these collaborations lead to patents that rely more on fundamental scientific research conducted at public research institutions. Lastly, the findings are also in line with the policy of gathering scientists and inventors for new technological projects, which leads to the formation of new R&D teams. These findings highlight the potential gains from stimulating collaborations between scientists and inventors within geographical areas to diffuse knowledge and generate innovation. While the agglomeration of innovative actors matters for generating new ideas, place-based innovation policies can overcome coordination failures and facilitate the formation of new interactions.

The present study provides interesting insights into how the establishment of R&D clusters changes the organization of research. However, it is important to acknowledge the limitations that present opportunities for further research. First, I highlight certain data limitations that may lead to further research. I investigated the science-industry collaboration process through patent publications. However, not all collaborations translate into patents, meaning that peer-reviewed publications or the commercialization of corporate firms are not observed. As a result, the estimated effects on patent outcomes are likely to represent lower estimates of the true effects. Furthermore, this paper focuses on fundamental research as a potential mechanism. Because of data restrictions, I am unable to follow the paper trail between science and how the resulting collaborations depend on it, which may limit the capacity to accurately match every publication involving both public and private. A second limitation is the inability to explore the attributes of universities, public institutions, and firms participating in the program. Efforts to collect information on R&D grants for collaborations may help explain differences between clusters and participants, allowing further exploration of mechanisms at a fine-grained level. Furthermore, it would be interesting to disentangle the effect of public authorities' traditional support for R&D spending and indirect networking support

that arises from each cluster. However, this paper provides aggregate evidence that has significant implications for policymakers who must decide whether to support local innovative communities. It also complements the existing literature on the effectiveness of cluster policies.

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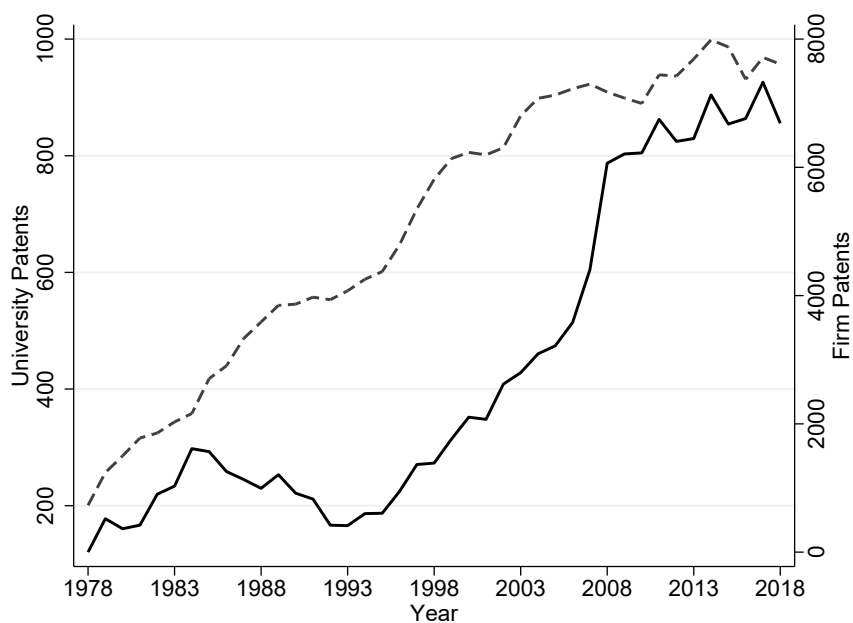


Figure A.1. University and Firm Patenting in France

Source: OECD-STI Micro Lab.

Table A.1. Summary Statistics for the Full Sample

	Full Sample (1)	Accepted Clusters (2)	Rest of CZs (3)	p-value (4)
Panel A. Innovation in the year before policy				
Collab. Public-Private	0.45	0.78	0.23	0.02**
Cite Weighted	1.49	2.71	0.64	0.07*
New Collaboarations	1.99	3.35	1.05	0.03**
Old Collaborations	0.01	0.03	0.00	0.13
Panel B. CZ Characteristics (Levels)				
Population (1999)	175904.77	238962.11	132381.49	0.00***
Agricultural Emp. (1999)	2183.36	2645.10	1864.66	0.00***
Manufacturing Emp. (1999)	10763.08	15176.20	7717.07	0.00***
Share Emp. Manufacturing (1999)	0.07	0.07	0.06	0.00***
Universities (1999)	0.37	0.55	0.24	0.11
Other Schools (1999)	0.24	0.31	0.18	0.29
Research Units (1999)	576.03	1065.08	238.48	0.00***
N. Students (2004)	6955.63	11031.79	4142.20	0.01***
N. Firms (1999)	22173.04	28469.46	17827.14	0.04**
N. R&D Facilities (1999)	31.35	39.97	25.40	0.36
N. Cities (1999)	104.66	111.76	99.76	0.17

Notes: *p<0.1, **p<0.05, ***p<0.01

Table A.2. Dynamic Effects of R&D Clusters on Science-Industry Collaborations

	log(S-I Collab.)		arcsinh(S-I Collab.)	
	(1)	(2)	(3)	(4)
Cluster×2000	-0.021 (0.056)	0.047 (0.114)	-0.024 (0.072)	0.057 (0.147)
Cluster×2001	-0.073 (0.061)	-0.094 (0.122)	-0.088 (0.077)	-0.123 (0.158)
Cluster×2002	0.001 (0.061)	0.025 (0.123)	0.004 (0.078)	0.031 (0.159)
Cluster×2003	0.025 (0.055)	-0.009 (0.109)	0.034 (0.071)	-0.009 (0.141)
Cluster×2005	-0.009 (0.052)	0.023 (0.096)	-0.013 (0.068)	0.029 (0.125)
Cluster×2006	0.055 (0.041)	0.122* (0.073)	0.073 (0.051)	0.154 (0.093)
Cluster×2007	0.032 (0.041)	0.106 (0.093)	0.041 (0.051)	0.140 (0.119)
Cluster×2008	0.096* (0.051)	0.102 (0.089)	0.119* (0.067)	0.126 (0.117)
Cluster×2009	0.151** (0.063)	0.238* (0.139)	0.188** (0.083)	0.300 (0.183)
Cluster×2010	0.180*** (0.065)	0.284** (0.114)	0.231*** (0.084)	0.372** (0.147)
Cluster×2011	0.177*** (0.060)	0.200 (0.122)	0.225*** (0.077)	0.261 (0.158)
Cluster×2012	0.108* (0.061)	0.217** (0.092)	0.133* (0.079)	0.272** (0.119)
Cluster×2013	0.204*** (0.064)	0.294*** (0.106)	0.254*** (0.082)	0.375*** (0.137)
Cluster×2014	0.245*** (0.075)	0.415*** (0.134)	0.303*** (0.098)	0.521*** (0.173)
Cluster×2015	0.285*** (0.072)	0.469*** (0.124)	0.361*** (0.091)	0.601*** (0.161)
Cluster×2016	0.175** (0.075)	0.264** (0.114)	0.223** (0.097)	0.337** (0.148)
Cluster×2017	0.213*** (0.063)	0.262** (0.105)	0.273*** (0.081)	0.344** (0.137)
Cluster×2018	0.215*** (0.075)	0.384*** (0.136)	0.273*** (0.096)	0.488*** (0.176)
Mean of the Dep. Var.	0.349	0.349	0.436	0.436
Obs.	2,983	2,983	2,983	2,983
Cluster FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No
Region x Year FEs	No	Yes	No	Yes

Notes: *p<0.1, **p<0.05, ***p<0.01

Table A.3. Effects by Industry

Industry	Cluster×Post	Std. error
Food	0.004	(0.005)
Textiles	0.001	(0.001)
Paper/Wood	0.003	(0.002)
Chemistry/Pharmaceutical	0.087***	(0.020)
Plastic/Minerals	0.011	(0.010)
Metal	-0.003	(0.005)
Electronic/Optics	0.080***	(0.024)
Transport	0.040***	(0.013)
Constructions	0.001	(0.001)
Others Manufacturing	0.012	(0.008)

Notes: *p<0.1, **p<0.05, ***p<0.01

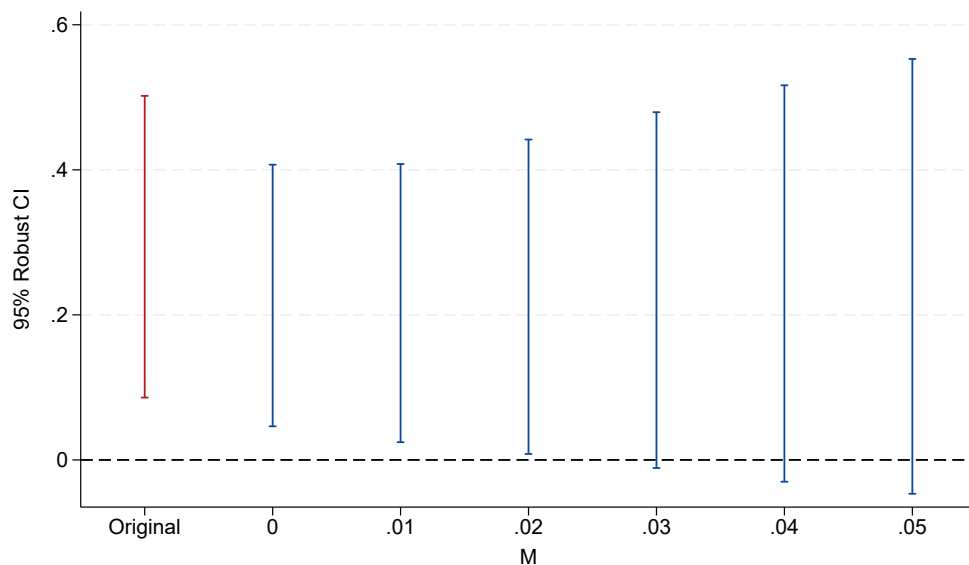


Figure A.2. Sensitivity Analysis for Non-linear pre-trends

Table A.4. Falsification Tests

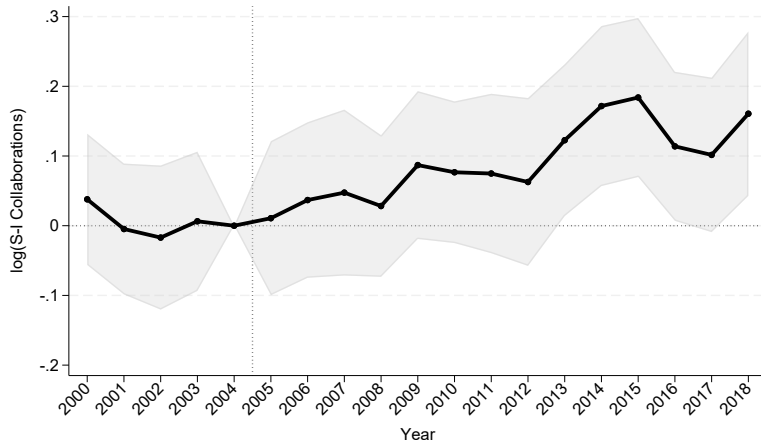
	log(S-I Collab.)		
	(1)	(2)	(3)
Cluster×Post (Placebo)	0.011 (0.020)	-0.030 (0.028)	-0.032 (0.025)
Mean Dependent Variable	0.064	0.089	0.089
Obs.	2,983	3,287	3,287
Adj. R ²	0.249	0.77	0.77
Cluster FEs	Yes	Yes	Yes
Region x Year FEs	Yes	Yes	Yes

Notes: *p<0.1, **p<0.05, ***p<0.01

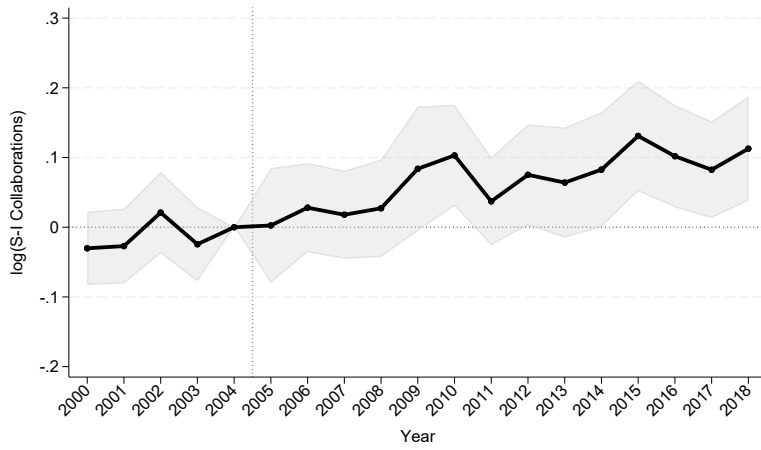
Table A.5. Summary Statistics Matched Sample

	Accepted Clusters (1)	Industrial Clusters (2)	Diff (3)	Std. Diff (4)	p-value (5)
Collab. Public-Private	0.00	0.01	0.00	0.19	0.33
Population (1999)	110,538.32	103,365.72	-7,172.60	-0.14	0.55
Manufacturing Emp. (1999)	8,222.24	6,952.52	-1,269.72	-0.36	0.13
Share of Emp. in Manufacturing	0.08	0.07	-0.01	-0.08	0.28
Universities (1999)	0.06	0.04	-0.02	-0.08	0.75
Other Schools (1999)	0.03	0.12	0.09	0.28	0.14
Research Units (1999)	176.07	187.80	11.73	0.04	0.86
N. Students (2004)	1500.07	1224.64	-275.43	-0.13	0.56
N. Firms (1999)	13288.38	12818.12	-470.26	-0.07	0.76
N. R&D Facilities (1999)	6.25	6.40	0.15	0.02	0.91
N. Cities	92.97	122.84	29.87	0.49	0.03

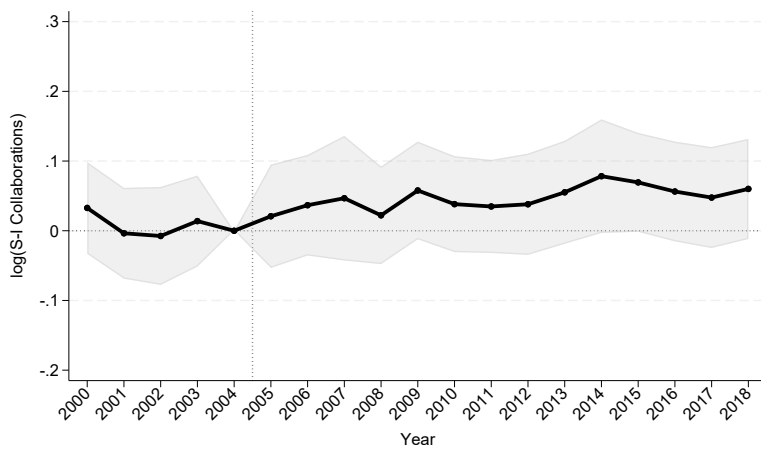
Notes: *p<0.1, **p<0.05, ***p<0.01.



Panel A



Panel B



Panel C

Figure A.3. Yearly Effects of R&D Cluster on Science-Industry Collaborations by Industry

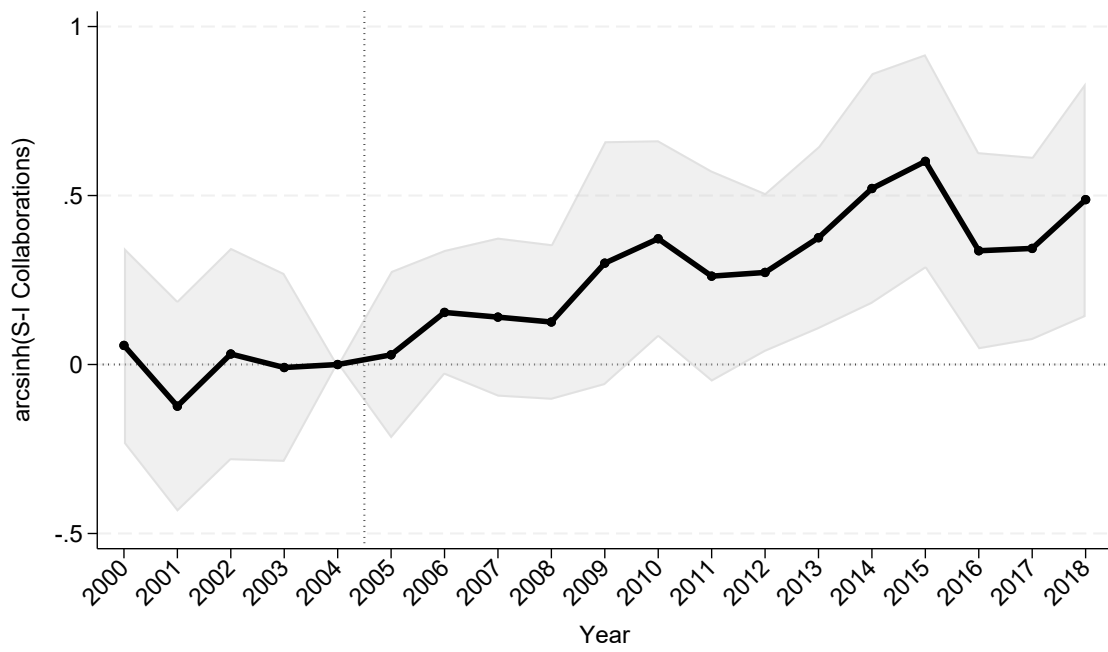


Figure A.4. Yearly Effects of R&D Cluster on Science-Industry Collaborations at the CZ-industry level

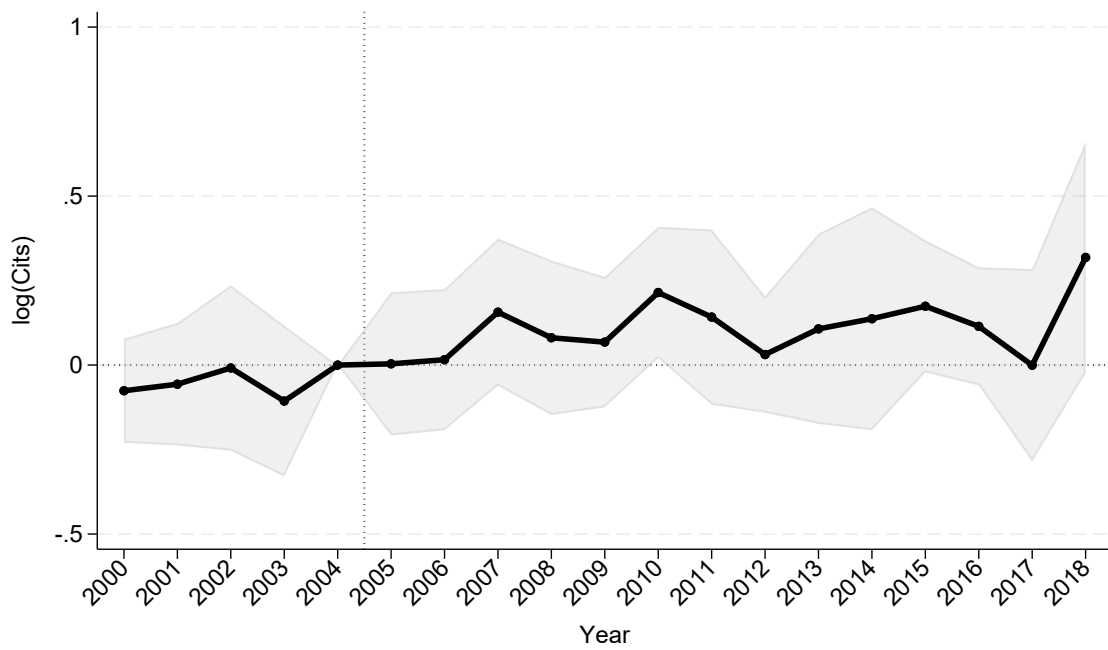
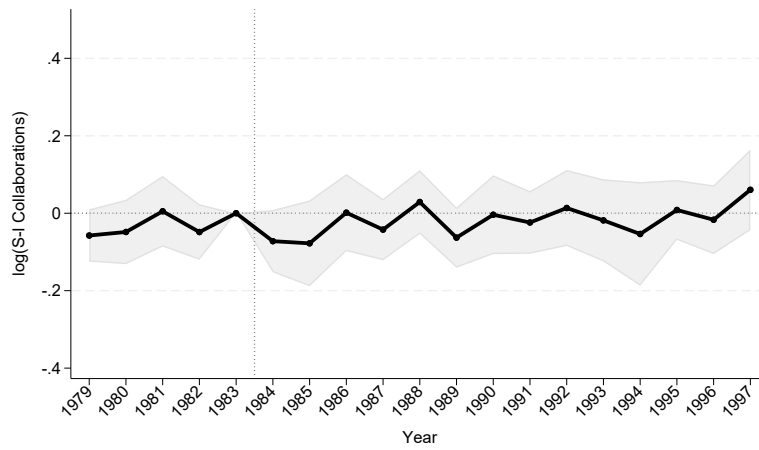
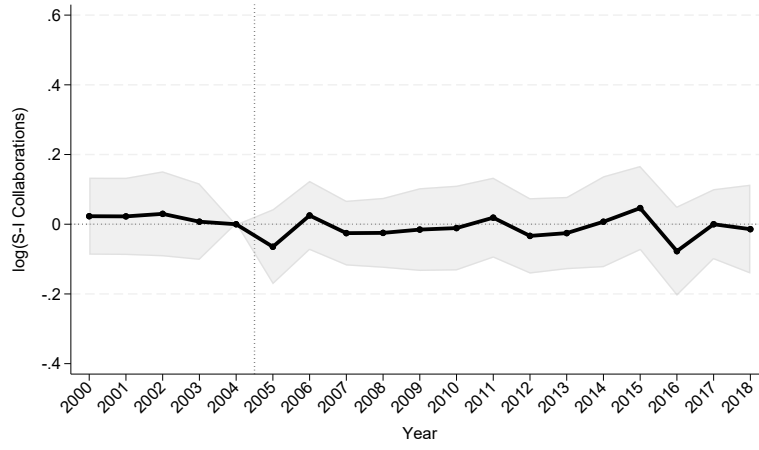


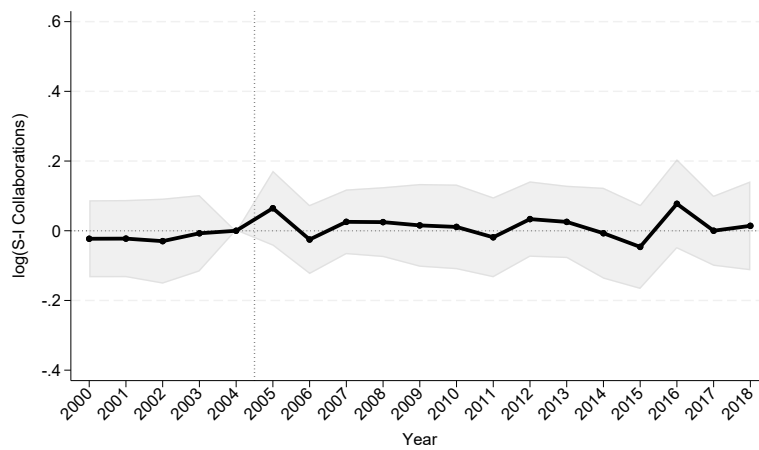
Figure A.5. Yearly Effects of R&D Cluster on Cite-weighted Patents



Panel A



Panel B



Panel C

Figure A.6. Yearly Effects of R&D Cluster on Science-Industry Collaborations: Placebo

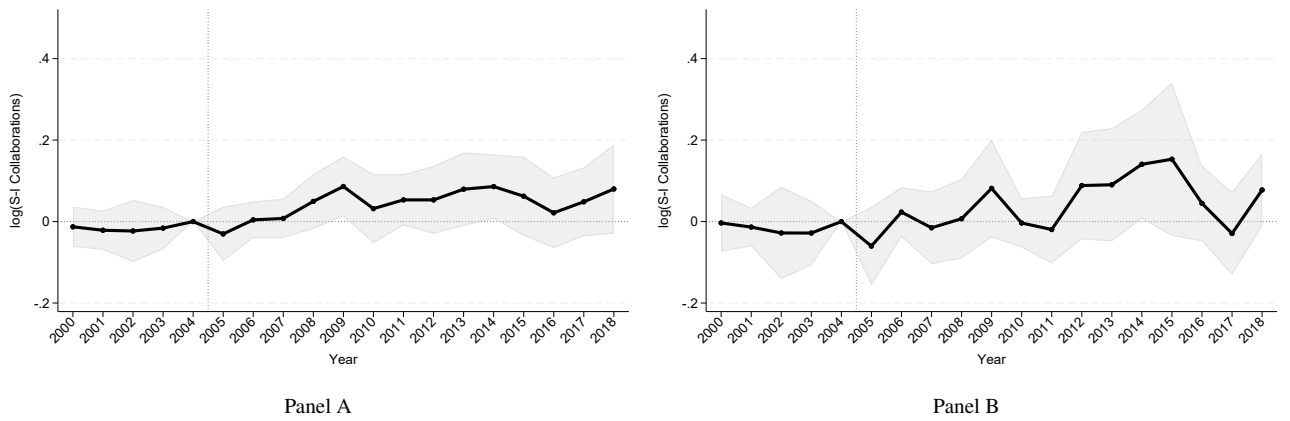


Figure A.7. Yearly Effects of R&D Cluster on Science-Industry Collaborations: CEM

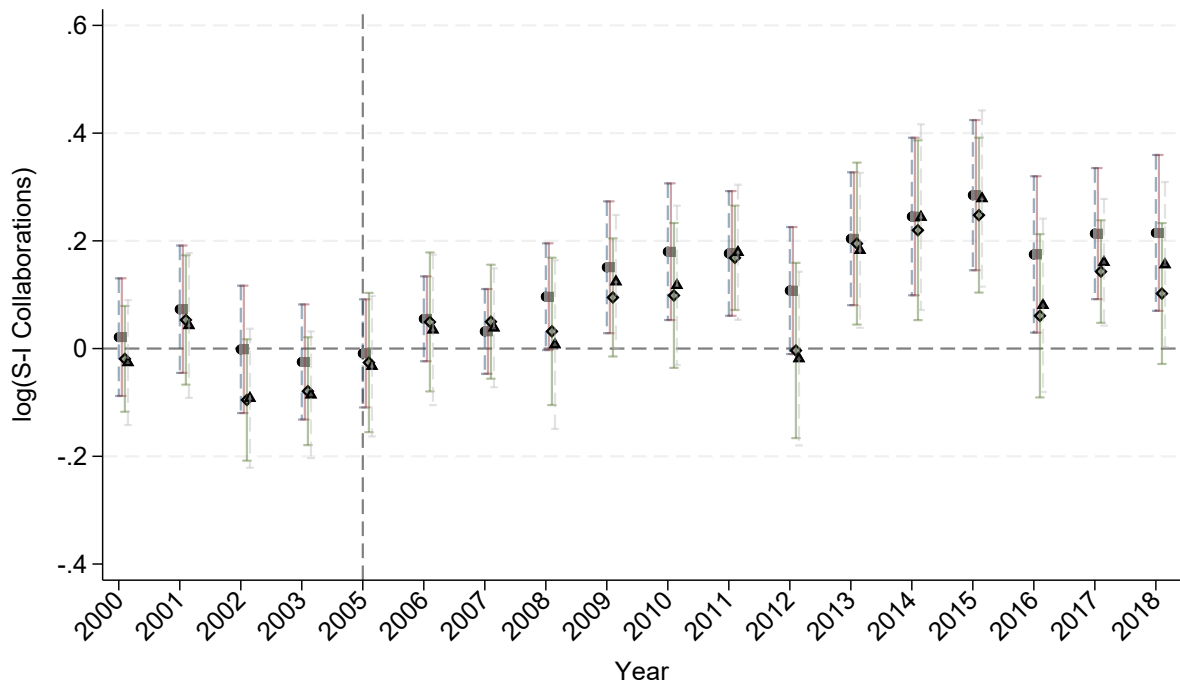


Figure A.8. Yearly Effects of R&D Cluster on Science-Industry Collaborations: Doubly Robust Estimator

Table A.6

Table A.7. Effects of R&D Clusters on Science-Industry Collaborations (Matched Sample)

	log(S-I Collab.)		arcsinh(S-I Collab.)	
Cluster×Post	0.060**	0.056*	0.075**	0.071**
	(0.024)	(0.029)	(0.030)	(0.035)
Mean of the Dep. Var.	0.080	0.079	0.095	0.095
Obs.	1,824	1,805	1,824	1,805
Cluster FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No
Region x Year FEs	No	Yes	No	Yes

Notes: *p<0.1, **p<0.05, ***p<0.01

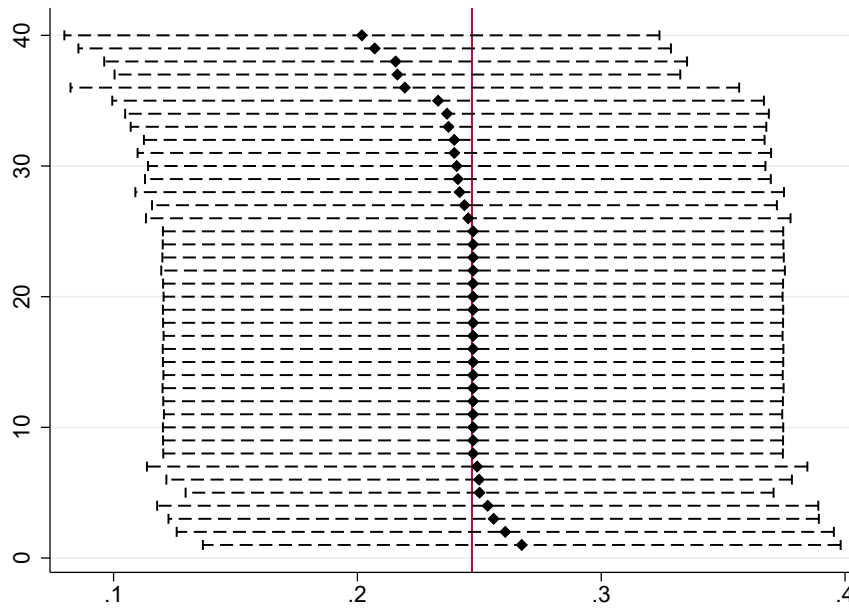


Figure A.9. Leave-out estimates of R&D Cluster on Science-Industry Collaborations

Table A.8. Alternative Specifications

	Cluster \times Post	Std. error	Obs.
Baseline	0.247***	(0.065)	2,983
Panel A: Alternative Specifications			
Exc. Aeronautic/Space Cluster	0.247***	(0.065)	2,964
Exc. Chemical Cluster	0.247**	(0.065)	2,964
Manufacturing Emp. \times Year FEs	0.119**	(0.057)	2,983
N. R&D Units \times Year FEs	0.197***	(0.061)	2,983
N. R&D Facilities \times Year FEs	0.094*	(0.050)	2,983
Panel B: Alternative Clustering			
CZ-Year	0.247***	(0.064)	2,983
CZ \times Year	0.247***	(0.039)	2,983
Region	0.247***	(0.045)	2,983
Region-Year	0.247***	(0.046)	2,983
Region \times Year	0.247***	(0.039)	2,983

Notes: *p<0.1, **p<0.05, ***p<0.01

Table A.9. Alternative Dependent Variable

	Cluster \times Post (1)	Std. error (2)	Obs. (3)
Baseline	0.247***	(0.064)	2,983
log(S-I Collab. + 0.001)	0.632**	(0.279)	2,983
log(S-I Collab. + 1)-Winsorized	0.246***	(0.064)	2,983
log(S-I Collab.)	0.337***	(0.117)	2,983
S-I Collab.	0.924***	(0.292)	2,983
S-I Collab. (Poisson)	0.836**	(0.369)	2,528

Notes: *p<0.1, **p<0.05, ***p<0.01