



2181

Discussion Papers

Deutsches Institut für Wirtschaftsforschung

2026

Firm-level Evidence on Direct and Indirect Effects of Cluster Policy

Knarik Poghosyan, Martin Kalthaus, Nadine Riedel, Michael Rothgang, Anne-Marie Scholz

Opinions expressed in this paper are those of the author(s) and do not necessarily reflect views of the institute.

IMPRESSUM

© DIW Berlin, 2026

DIW Berlin
German Institute for Economic Research
Anton-Wilhelm-Amo-Str. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
<http://www.diw.de>

ISSN electronic edition 1619-4535

Papers can be downloaded free of charge from the DIW Berlin website:
<http://www.diw.de/discussionpapers>

Discussion Papers of DIW Berlin are indexed in RePEc and Econstor:
<http://ideas.repec.org/s/diw/diwwpp.html>
<https://www.econstor.eu/handle/10419/10>

Firm-level evidence on direct and indirect effects of cluster policy

Knarik Poghosyan^{1,2}, Martin Kalthaus³, Nadine Riedel⁴, Michael Rothgang⁵, and Anne-Marie Scholz⁶

¹DIW Berlin – German Institute for Economic Research, Entrepreneurship Research Group,
Anton-Wilhelm-Amo-Straße 58, 10117 Berlin, Germany

²TU Dortmund, Department of Economics, Vogelpothsweg 87, 44227 Dortmund, Germany

³University of Southern Denmark, Business School, Centre for Integrative Innovation Management, Campusvej
55, 5230 Odense M, Denmark

⁴WWU Münster, Institute for Public and Regional Economics, Am Stadtgraben 9, 48143 Münster, Germany

⁵RWI – Leibniz Institute for Economic Research, Hohenzollernstr. 1–3, 45128 Essen, Germany

⁶ISG – Institut für Sozialforschung und Gesellschaftspolitik, Weinsbergstr. 190, 50825 Cologne, Germany

September 21, 2026

Abstract

We estimate the direct and indirect causal effects of Germany’s Leading-Edge Cluster Competition on firm size, inventive activity, and joint patenting. With €600 million allocated to 15 clusters, this program is one of the largest cluster policy programs in Europe. Using a staggered event-study design, we estimate the direct effect of the cluster policy on firms within the funded clusters. Additionally, we differentiate between funded and non-funded cluster members to assess the effects of the financial and the systemic components of the policy. Furthermore, we estimate the indirect spillover effect of this program on firms in close proximity to the funded clusters that are not associated with them. Our results show that the cluster policy has a direct overall positive effect on firm size and inventive activity, but a negative effect on collaboration in inventive activity. Differentiating between funded and non-funded cluster members reveals that the latter benefit strongly from the systemic component of the cluster policy, increasing their inventive activity while having no significant effect on collaboration. In contrast, we do not observe any indirect effects on geographically proximate non-cluster firms. Our results provide causal evidence of the direct benefits of cluster policy at the firm level but call into question the anticipated indirect effects of cluster policy on neighboring non-cluster firms.

Keywords: Cluster Policy, Spillover Effects, Policy Evaluation, Patent Data, Event Study

JEL Classification: O33, O38.

Acknowledgments: This research was conducted as part of the DFG RTG 2484 “Regional Disparities & Economic Policy” program. We are deeply grateful to our colleagues from the RTG and the participating universities TU Dortmund, University of Duisburg-Essen, and Ruhr University Bochum for their continuous feedback and support. Previous versions of this paper were presented at the RTG Retreats in Essen (2021) and Hattingen (2022), ASPEC (2022), the EU-SPRI Conference (2022), the 19th International Joseph A. Schumpeter Society conference (2022), the 10th Annual International Conference on Sustainable Development (2022), the first meeting

1 Introduction

Cluster policy has become a widely used policy tool for stimulating innovation and regional growth in the 21st century (Uyarra & Ramlogan, 2016). Its central objective is to support a typically geographically concentrated group of related firms and other actors in their collaborative and innovative activities (OECD, 2007; Porter, 1998; Smits & Kuhlmann, 2004). Cluster policy uses different instruments to achieve these goals. Its main focus is on innovation-oriented approaches that combine financial support for R&D projects with measures that foster cluster development, management, and other supporting activities. In doing so, cluster policy complements traditional R&D subsidies with systemic components that promote interaction, coordination, and knowledge exchange among actors (Smits & Kuhlmann, 2004). Beyond directly supporting cluster members, this innovation-oriented cluster policy has a strong regional focus with the aim of generating agglomeration economies and knowledge spillovers within the regional innovation system, thereby indirectly benefiting geographically proximate actors alongside their collaborative and innovative activities (Boschma, 2005; Breschi & Lissoni, 2005; Peri, 2005). Specifically, these indirect regional spillovers are frequently cited as key rationale for cluster policy. However, despite their growing popularity and substantial public investment, the direct and indirect effectiveness of cluster policy remains an open question (e.g., Graf & Broekel, 2020; Rothgang et al., 2021).

Empirical research predominantly examine the regional effects of cluster policy (Uyarra & Ramlogan, 2016). The evidence is mixed. While many studies report positive correlations of cluster policy with innovation activity and regional outcomes (e.g., Baptista & Swann, 1998; Breschi & Lissoni, 2009; Crass et al., 2019; Engel et al., 2019; Hinzmann et al., 2019; Lehmann & Menter, 2018), others argue that cluster policy is costly and generates only short-term or limited benefits (e.g., Duranton, 2011; Engel et al., 2013; Graf & Broekel, 2020; Martin et al., 2011). By contrast, causal evidence at the firm level remains scarce. Falck et al. (2010) find that the Bavarian High-Tech Offensive increased firms' likelihood of becoming innovators and improved their access to external knowledge, academic collaboration, and skilled human capital. For Uruguay, Aboal et al. (2020) report positive effects of a cluster program on firms' exports but only weak effects on sales. Similarly, Angelino et al. (2026) show that firms belonging to clusters supported by the Flemish Spearhead Cluster policy increased their total factor productivity by approximately 4%. In contrast, Nishimura and Okamuro (2011) find only weak effects of direct R&D funding on innovative output in Japan's Industrial Cluster Project. At the same time, their findings show that support measures aimed at expanding firms' innovation networks generated substantially stronger effects.

Existing studies predominantly estimate average treatment effects at the regional or aggregate level and rarely disentangle the mechanisms through which cluster policies operate. Consequently, we have only limited understanding of whether the observed effects of cluster policy arise directly from (i) financial support to subsidized firms, (ii) the increasing systemic embeddedness within the cluster network, or indirectly via (iii) increasing knowledge spillovers to geographically proximate

of the DFG Network "The Dynamics of Innovation Systems" (2022), DRUID Academy (2023), PhDays (2023), DIW Research Seminar (2024), the 14th European Meeting of the Urban Economics Association (2025), the workshop "Kausale Auswirkungen und Mechanismen der Forschungs-, Technologie- und Innovationspolitik" (2025), and the 16th Annual Meeting of the Armenian Economic Association (2026). We thank the participants for their valuable comments and discussions. We are especially grateful to Avtandil Abashishvili, Stefano Basilico, Pablo D'Este, Nina Furbach, Johannes Gallé, Philip Jung, Alexander Kritikos, Philipp Markus, Alexander Schiersch, Theodor Vladasel, and Galina Zudenkova for valuable discussions and comments.

firms outside the cluster. Distinguishing between these mechanisms is crucial for understanding whether cluster policy primarily functions as a funding instrument, as a systemic intervention that strengthens firm interactions and localized knowledge diffusion within the regional innovation network, or as a catalyst of knowledge transfer and regional development beyond the cluster.

We address this gap by exploiting the German Leading-Edge Cluster Competition (LECC), one of Europe’s largest cluster policy programs. The overall policy aim was to use cluster development as an instrument to develop Germany into a leading nation in research and technology. To this end, the LECC supported 15 German high-tech clusters with up to €40 million each in the period 2008–2017. The funding was used mainly for collaborative R&D projects as well as building up strong cluster management, fostering collaboration and interaction between firms, universities, research institutes, and other organizations. The design of the LECC allows us to distinguish between three groups of firms: cluster firms receiving R&D subsidies, cluster firms without direct financial support, and geographically proximate non-cluster firms within 5 and 10km distance bands. This setting provides a unique opportunity to disentangle not just direct financial and systemic effects but also indirect spillover effects of cluster policy within a single empirical framework. Using geo-referenced firm-level data from Orbis matched with patent data from PATSTAT for the period 2004–2016 and a novel dataset on the cluster firms, we employ a dynamic event-study approach following Sun and Abraham (2021) combined with matched difference-in-differences estimation (Iacus et al., 2011, 2012). This empirical strategy enables us to estimate the causal effect of the LECC on inventive activity (proxied by quality adjusted patent applications), joint patenting as a result of R&D collaboration (proxied by patent co-application), and firm size (proxied by employment cost) across the different groups of firms. This allows us to provide the first firm-level causal evidence that disentangles the direct financial and systemic component of cluster policy as well as the indirect spillover effects simultaneously.

Our results show an overall direct positive causal effect of the LECC on inventive activity and firm size, but a negative effect on joint patenting. While the increase in firm size occurs immediately after cluster selection, inventive activity increases only later during the funding period. Distinguishing between cluster firms that receive R&D funding and those that do not receive funding reveals that the positive effect on inventive activity is statistically significant only for non-funded cluster firms. By contrast, funded cluster firms experience substantially stronger growth in firm size, but no overall increase in inventive activity. Joint patenting declines only among funded cluster firms, whereas the effect for non-funded cluster firms is not statistically significant. Regarding the indirect effects of the LECC on neighboring non-cluster firms, we find little evidence of localized spillovers. Regardless of whether firms are located within 0–5 km or 5–10 km distance bands of cluster firms, no average increase in inventive activity, joint patenting, or firm size is observable.

The findings have several implications for economic theory and policymakers. By disentangling the direct financial and systemic and indirect spillover effects of the LECC, we demonstrate that cluster policy influences firms through multiple mechanisms rather than a single treatment effect. In particular, the positive effects observed for non-funded cluster firms indicate that the systemic components of cluster policy that strengthen networking, intermediary organizations, and the connectivity of regional innovation systems can stimulate inventive activity in addition to the direct effect of R&D funding, indicating the relevance of systemic instruments. One channel through

which this can occur is that cluster organizations foster the transfer of newly created knowledge. At the same time, the stronger effects of direct funding on firm growth suggest that financial and systemic support address different constraints to innovation rather than simply reinforcing one another. Furthermore, the absence of measurable spillovers to neighboring non-cluster firms indicates that the benefits of cluster policy is largely confined to participating firms and do not automatically spill over. Together, these findings suggest that the effectiveness of cluster policy depends not only on the provision of financial resources but also on the systemic conditions that facilitate knowledge exchange and collaboration. They also highlight the importance of evaluating cluster policy as integrated policy package by considering its different transmission mechanisms rather than relying solely on average treatment effects or individual policy instruments.

The remainder of the paper is organized as follows. Section 2 reviews the related literature and develops the hypotheses on the direct and indirect effects of cluster policy. Section 3 introduces the LECC and discusses its policy objectives and application procedure. Section 4 describes the data and presents summary statistics, while Section 5 outlines the empirical strategy. Section 6 presents the empirical results, and Section 7 concludes.

2 Theoretical background and hypotheses

2.1 Theoretical rationale for cluster policy

Cluster policy is a policy instrument designed to stimulate knowledge creation, exchange, innovation, and the formation of innovation networks (Grashof, 2021; Smits & Kuhlmann, 2004; Woolthuis et al., 2005). It is a core policy tool developed to address multiple market and systemic failures under the umbrella of research and innovation policy (e.g., Edler & Fagerberg, 2017; Kuhlmann & Edler, 2003). The rationale for cluster policy is twofold. First, it directly supports actors within the cluster by providing financial resources, particularly R&D subsidies, while simultaneously improving the environment in which firms operate through the provision of shared infrastructure, establishing intermediary organizations, changing the institutional environment, and other collaboration-supporting activities (Liu et al., 2023; Woolthuis et al., 2005). Usually, these measures are accompanied by the establishment or strengthening of a cluster organization that coordinates activities and provides services to the cluster members. Through these mechanisms, cluster policy can mitigate market failures, including incomplete appropriability of R&D, underinvestment arising from uncertainty and information asymmetries, and network externalities. At the same time, it can address systemic failures, such as insufficient coordination, weak complementarities, limited intermediation, and barriers to collective learning, by strengthening interactions among the cluster members and embeddedness in the regional innovation system to improve knowledge exchange (OECD, 1997; Uyarra & Ramlogan, 2016). Thereby, cluster policy allows regional actors to develop a common strategy apart from the entrenched funding structure of technical programs and expand existing cooperation networks. Thus, cluster policy combines financial and systemic interventions to jointly address these failures that coexist within regional innovation systems.

Second, cluster policy has a strong regional dimension. With its objective to foster regional embeddedness by nurturing innovation networks, stimulating entrepreneurial opportunities, and establishing relevant institutions, spillovers to actors who are not part of the supported cluster

can be generated. Such indirect effects arise through agglomeration economies and localized knowledge spillovers, thus providing an additional rationale for cluster policy. Ultimately, these have the potential to strengthen not only the supported cluster structure but also the regional innovation system more broadly (Autant-Bernard et al., 2013; Chatterji et al., 2014; Delgado et al., 2016). Against this background, cluster policy can be used to stimulate economic activity in structurally weaker regions, to support the emergence of promising regional innovation hubs, and/or to provide innovation impulses in already leading cluster regions (Autio & Rannikko, 2016; Müller & Korsgaard, 2018).

Overall, cluster policy represents a strategic innovation policy instrument that directly enhances individual members of a supported cluster but also indirectly strengthens the surrounding regional innovation system. It seeks to facilitate interaction, improve knowledge exchange, enhance access to skills and finance, attract investments, and generate other positive externalities. Consequently, cluster policy has become a widely used innovation policy instrument and has attracted considerable attention in the empirical literature (see Uyarra & Ramlogan, 2016, for a review). In the following, we develop a hypothesis on the overall direct effect of cluster policy. Furthermore, we develop hypotheses that distinguish between cluster firms that receive R&D subsidies and those that benefit only from the systemic components of the policy. We then derive a hypothesis on the indirect effects of cluster policy for geographically proximate non-cluster firms to test for localized knowledge spillovers.

2.2 Direct effects on cluster firms

A large body of empirical evidence suggests that cluster policy can stimulate innovative activity and collaboration among participating firms, although the magnitude and persistence of these effects remain contested. Comprehensive reviews conclude that cluster policy often increases firms' propensity to innovate and foster new inter-firm linkages, particularly during the funding period (Uyarra & Ramlogan, 2016). Positive effects on innovation and productivity have been documented in Norway, the United Kingdom, Sweden, Spain, and Japan, where cluster policy is associated with higher engagement in innovative activities and collaboration (Aranguren et al., 2013; Martin et al., 2011; Nishimura & Okamuro, 2011; Uyarra & Ramlogan, 2016). However, these effects are heterogeneous across firms and regions and often diminish once policy support ends (Graf & Broekel, 2020; Martin et al., 2011; Uyarra & Ramlogan, 2016).

At the same time, a critical strand of the literature questions whether cluster policy generates the intended effects (Brakman & van Marrewijk, 2013). Concerns include the risk of "picking winners," crowding out private investment, and exacerbating regional inequalities rather than creating net welfare gains (Brown et al., 2017; Cantner & Kösters, 2011; Duranton, 2011). In some cases, observed productivity effects are small or transitory, raising doubts about the long-term effectiveness of cluster-based interventions (Graf & Broekel, 2020; Martin et al., 2011).

For Germany, several studies evaluate the effects of cluster policies on R&D expenditure and innovation performance. Existing evidence from the LECC indicates that funded firms increased their R&D expenditures during the funding period (Engel et al., 2019; Rothgang et al., 2017a) and expanded cooperation networks within funded clusters (Cantner, 2013; Hinzmann et al., 2019; Rothgang et al., 2017a; Töpfer et al., 2019). One other study observed that the LECC strengthened regional productivity (Lehmann & Menter, 2018). Research on other German cluster poli-

cies also reports short-term increases in innovative activity and collaboration in both quantitative (Engel et al., 2013; Falck et al., 2010; Graf & Broekel, 2020) and qualitative studies (Fromhold-Eisebith & Eisebith, 2008; Kiese & Hundt, 2014). However, most existing studies either focus on funded firms or estimate aggregate regional effects.

In light of the theoretical rationale for cluster policy and the existing empirical evidence, we expect cluster policy to increase inventive activity, strengthen collaborative R&D activity, and provide resources for firm growth. Accordingly, we hypothesize

Hypothesis 1: *Cluster policy increases cluster firms' inventive activity, R&D collaboration, and firm size relative to comparable non-cluster firms.*

From a theoretical perspective, cluster policy combines two types of support. First, it provides targeted financial resources, particularly (joint) R&D subsidies, which relax budget constraints and can directly stimulate inventive activity, collaborative R&D, and firm growth. Second, it establishes or strengthens cluster organizations that facilitate coordination, networking, and knowledge exchange among cluster members, thereby enhancing the regional innovation system. This distinction implies that policy effects may be heterogeneous across cluster firms. While the systemic component affects all cluster firms, the funding component is firm-specific. Such funded cluster firms receive both types of support: financial support to conduct R&D and systemic support that increases collaborative activity and services by program-funded cluster organizations. In an optional case, the two types of support are complementary. Contrary to this, non-funded cluster firms benefit only from the systemic component that supports collaboration and provides cluster-wide resources and services. Additionally, from a dynamic perspective, these firms can also receive benefits from the additional knowledge created and exchanged from funded cluster firms once their R&D generates results. Cluster intermediaries can be relevant to facilitate the exchange and integration of such knowledge. Consequently, companies that receive R&D subsidies benefit from both the systemic and the financial components of the policy, while companies that do not receive subsidies benefit only from the systemic component.

Empirical evidence on the influence of general systemic and targeted financial R&D support within funded clusters is scarce. While some studies suggest that certain aspects of systemic support, such as networking and coordination, may be more effective than direct monetary subsidies (Nishimura & Okamuro, 2011), the broader literature on R&D subsidies generally finds limited crowding-out but also modest additionality (Dimos & Pugh, 2016). Building on this literature, we argue that cluster firms receiving R&D subsidies should benefit from both dimensions of the policy. The R&D support enables additional investments in R&D and innovation, while the systemic support facilitates collaboration and access to firm-external knowledge, especially from within the cluster. Together, these mechanisms are expected to increase inventive activity, collaborative R&D activity, and firm size. Accordingly, we hypothesize

Hypothesis 2a: *Cluster firms that receive R&D subsidies exhibit higher inventive activity, greater R&D collaboration, and larger firm size than comparable non-cluster firms.*

Similar to directly funded cluster firms, those cluster firms that do not receive R&D subsidies may nevertheless benefit from participation in the cluster in several ways. Such systemic effects can arise from the provision of shared R&D infrastructure and the activities of intermediaries

that support collaboration and knowledge exchange (Smits & Kuhlmann, 2004). Nishimura and Okamuro (2011) argue that these systemic support mechanisms can be more important than R&D subsidies. Furthermore, the increased resources available to funded cluster members may enhance their capacity and willingness to collaborate and exchange knowledge with non-funded members, thereby generating additional benefits for non-funded members. Unlike funded firms, however, non-funded cluster members do not receive direct financial support for R&D. Consequently, the policy is not expected to have an effect on firm size, but increased inventive activity and more R&D collaboration due to the systemic component are plausible. We therefore argue that cluster members whose R&D activities are not subsidized can still benefit from the cluster policy through systemic mechanisms that stimulate inventive activity and R&D collaboration:

Hypothesis 2b: *Cluster firms that do not receive R&D subsidies exhibit higher inventive activity and greater R&D collaboration than comparable non-cluster firms.*

2.3 Indirect effect on non-cluster firms in the cluster region

Beyond their direct effects on cluster firms, cluster policy may also generate indirect effects on geographically proximate firms that are not members of the cluster. Policymakers frequently justify funding of cluster initiatives by arguing that geographically concentrated innovation activities generate localized knowledge spillovers that benefit not only cluster members but also surrounding firms. This argument builds on the literature on localized knowledge spillovers, which shows that innovative activity is spatially bounded and that firms benefit disproportionately from nearby sources of knowledge (Almeida, 1996; Jaffe et al., 1993).

This argument builds on the Marshall–Arrow–Romer (MAR) framework that argues that industry concentration facilitates localized learning and cumulative knowledge creation through knowledge spillovers among firms operating in the same industry (Glaeser et al., 1992; Grossman & Helpman, 1991; Lucas, 1988; Romer, 1986). By strengthening interactions among geographically proximate firms, cluster policy may reinforce these mechanisms. At the same time, cluster organizations often connect firms with universities, research institutes, and firms from related industries. Such interactions may also give rise to Jacobs externalities, which emphasize the role of knowledge exchange across diverse industries in stimulating innovation (Jacobs, 1969). Cluster policy may therefore foster both specialization-based and diversity-based knowledge spillovers, potentially generating innovation benefits that extend beyond participating firms.

Empirical evidence shows that knowledge spillovers decline with distance and are often concentrated within relatively narrow spatial radii (Fritsch & Slavtchev, 2005; Funke et al., 2000). Firm-level studies demonstrate that geographic and technological proximity to innovative firms enhances firms’ innovation performance by facilitating access to external knowledge (Almeida, 1996; Jaffe et al., 1993; Lychagin et al., 2016). Extending this argument to cluster policy, geographic proximity to a supported cluster may improve the innovative performance not only for the funded cluster firms but also neighboring non-cluster firms through localized knowledge spillovers.

However, the extent to which cluster policy strengthens or generates such spillovers remains unclear. For example, Crass et al. (2019) find no evidence that geographical clustering increases input or output additionality of firms participating in a German R&D funding scheme. While Figal Garone et al. (2015) document positive medium- to long-term effects of Brazil’s cluster

development policy on SMEs’ performance and export outcomes, they also identify short-term negative effects, particularly on employment during the first year after program implementation. Similarly, Gilbert et al. (2008) and Shaver and Flyer (2000) argue that industry clustering enhances the innovative performance of weaker firms, such as startups, through localized externalities. Case studies of established clusters suggest that local interactions can facilitate knowledge exchange and learning among cluster firms (Dahl & Pedersen, 2004, 2005), although the relative importance of local versus global knowledge networks may vary (Moodysson, 2008).

At the same time, agglomeration may also generate adverse effects. Critics argue that dominant clusters can create “agglomeration shadows” by attracting resources, talent, and investment away from surrounding regions, thereby weakening neighboring firms and locations (Dobkins & Ioannides, 2001; Fujita et al., 1999; Partridge et al., 2009). Consistent with this argument, evidence from Germany suggests that positive regional productivity effects of cluster policy are largely confined to regions with sufficient absorptive capacity, while Audretsch et al. (2018) identify negative spillover effects for some non-cluster firms, suggesting intensified competition.

In summary, from a conceptual perspective, cluster policy can indirectly affect geographically proximate firms that do not participate in the cluster. First, funded R&D projects can increase the regional stock of knowledge, thereby raising the potential for knowledge spillovers. Second, expanded collaboration networks and the mobility of skilled workers may facilitate transmission of knowledge across organizational boundaries. Third, improved regional visibility and investments in innovation-related infrastructure may enhance the region’s attractiveness and indirectly benefit nearby firms. At the same time, such spillovers are not guaranteed. If the knowledge generated within the cluster remains largely confined to participating firms or if cluster policy primarily re-allocates resources toward selected actors, indirect benefits for non-cluster firms may be limited or even negative. Nevertheless, building on theories of agglomeration, localized knowledge spillovers, and regional innovation systems, we expect positive indirect effects of cluster policy on nearby non-cluster firms on innovative activity and R&D collaboration. Accordingly, we propose:

Hypothesis 3: *Geographically proximate non-cluster firms exhibit higher inventive activity and greater R&D collaboration than comparable geographically distant non-cluster firms as a result of cluster policy.*

3 Institutional setting: The Leading-Edge Cluster Competition

The empirical case of this study is the German Leading-Edge Cluster Competition (LECC), a large-scale cluster policy program launched by the German Federal Ministry of Education and Research (BMBF) in 2007. The LECC was a core element of Germany’s Hightech Strategy from 2006 (BMBF, 2006). The Hightech Strategy sought to develop Germany into a leading nation in research and technology. The LECC was a central element of this goal. At the national level, the program was one of the best funded in Europe, comparable to the pôles de compétitivité in France. The political aim of the LECC was to strengthen Germany’s technological competitiveness by supporting regionally concentrated networks of firms, universities, and research organizations in strategically important industries. According to the program targets, Leading-Edge Clusters should evolve into the top group of globally leading clusters in their respective technology fields. The program also aimed to stimulate better performance and increased R&D cooperation not only among funded members but also to expand the policy benefits to members of cluster initiatives

that did not receive public funding, as well as to neighboring regions and the economy as a whole.

Open to cluster initiatives from all high-tech fields, the LECC was implemented in three competitive rounds, starting in 2008, 2010, and 2012, respectively. In each round, clusters submitted proposals outlining the collaborative R&D projects of their members and internal governance structures. In total, 87 applications from a broad range of industries were submitted in the three subsequent rounds. Several clusters that failed in the 1st or 2nd contest rounds applied again in the consecutive round(s). When considering the individual clusters only, 67 clusters have applied for the LECC.¹ In each round, five clusters were selected for funding based on an assessment of an expert jury (see Appendix A for a brief description of the selected clusters). Each winning cluster received up to €40 million of government funding over a five-year period. The LECC required that individual funding recipients match the received funding with internal R&D expenses. Overall, the LECC mobilized about €1.2 billion of funding (about 90% of which was R&D investment) between 2008 and 2017 (BMBF, 2009). The received funding was not granted to the overall cluster, but was allocated to individual organizations within the cluster. Members of a winning cluster received funding for collaborative R&D projects selected in a competitive process. Since not all project proposals were chosen for funding and not all cluster actors were part of such proposals, cluster membership did not automatically imply receipt of public funding. Therefore, within clusters, both funded and non-funded cluster members exist.

From a geographical perspective, the funded clusters are well distributed across Germany: seven clusters in the South of Germany, three in the Eastern part, and the remaining five in the Northern and Western part of Germany. Within the clusters, the geographical spread of the cluster members was quite different, depending on the traits of the technology, the individual distribution of firms in the network, and administrative factors (Rothgang et al., 2014). In some clusters, such as Hamburg Aviation, the administrative component and the supply chain were very dominant, leading to a large and coherent region. Other cluster regions consist of dispersed firms (e.g., Solarvalley or CI3), or a smaller region characterized by a homogeneous economic structure (Effizienzcluster Logistik in the Ruhr area).

4 Data and variables

4.1 Data

We construct a comprehensive firm-level panel dataset for the 2004–2016 period to analyze the effects of the German LECC. The unit of analysis is the firm-year. The final dataset combines firm-level information, patent data, and detailed information on LECC participation.

First, we extract business records for approximately two million German firms from Bureau van Dijk’s Orbis database (extracted in September 2020). Orbis provides information on firms’ balance sheets, including total assets and employment costs, as well as the year of incorporation, sector classification, and intellectual property records. We use firms’ headquarters addresses for geo-referencing.

Second, we link Orbis firms to patent information from the European Patent Office’s PATSTAT

¹A comparison of the applicants and winner clusters with around 350 technology-oriented cluster initiatives that are classified as “federal state” or “federal clusters” in Germany shows that the industry structure of the winning clusters is quite similar to the industry structures of all innovation clusters in high-tech and medium high-tech sectors in Germany (Rothgang et al., 2014).

(Spring Edition 2020). In total, 69,898 firms are successfully matched to patent applications. Based on these data, we construct a quality-adjusted patent measure and identify joint patents through patent co-applications.

Third, we use detailed information on LECC participation collected as part of the accompanying LECC evaluation (Rothgang et al., 2014), including program monitoring data and membership information collected from cluster management organizations.

The data includes a complete list of members of the 15 funded cluster organizations and their location information. In total, the funded clusters comprise 2,349 members, of which 1,685 are firms, 399 universities and research organizations, and 265 other organizations. Among all cluster members, 821 received direct LECC funding (573 of them are firms), while 1,528 members participated without direct financial support. This information allows us to distinguish between funded cluster firms and non-funded cluster firms. This distinction is important and allows us to assess the effect of the systemic part of the cluster policy that goes beyond the R&D funding.

We matched the list of cluster firms to the Orbis data. Out of the initial 1685 LECC firms, 1301 were successfully matched to Orbis records based on firm names and addresses. After data cleaning and restricting the sample to firms with at least five observations and available pre-treatment information in 2007 relevant for matching, the final sample consists of 751 treated firms, which is our sample of cluster firms for the analysis.

For the control group, we use information on all other German firms from Orbis. The same cleaning procedure was applied to these non-cluster firms as well. This yields a pool of 588,730 non-cluster firms. Together with the 751 cluster firms, the cleaned dataset therefore contains 589,481 firms before matching. We use this pool of non-cluster firms to construct the matched comparison group for the direct-effect analysis.

For the indirect spillover analysis, where we do not apply matching, we start with the same pool of 588,730 non-cluster firms and further restrict it to cluster-targeted industries and firms with available longitude and latitude information. The industry restriction is intended to focus the analysis on firms for which the knowledge generated within the supported clusters is technologically relevant, and that may possess the capabilities needed to absorb it. The latter is also supported by the study of Audretsch et al. (2018), who documents the absence of positive spillover effects for firms outside targeted industries. The resulting spillover sample comprises 384,265 non-cluster firms, including both geographically proximate firms and more distant comparison firms.

We calculate the straight-line air distance between each non-cluster firm and every LECC cluster firm using their longitude and latitude coordinates. For each non-cluster firm, we retain the distance to the nearest LECC cluster firm. This distance does not account for travel distance, road network, geographical obstacles such as rivers or mountains, or other local frictions. Following studies that use similar distance bands to trace the spatial effects of place-based policies (Gallé et al., 2024; Görg & Mulyukova, 2024), we classify firms located within 10 km of a cluster firm as potentially exposed to localized spillovers. Firms located more than 10 km from the nearest cluster firm constitute the comparison group. This approach builds on evidence that agglomeration and knowledge externalities attenuate rapidly with geographic distance (Barbieri et al., 2022; Ruffner & Spescha, 2018). To examine whether potential spillover effects attenuate with distance, we distinguish two mutually exclusive exposure bands. The first comprises non-cluster firms located within 0–5 km of the nearest LECC cluster firm, while the second comprises firms

located more than 5 km and up to 10 km away. The 0–5 km band captures the immediate local environment, where informal interaction, face-to-face contact, and localized knowledge transfer are most plausible. The 5–10 km band represents a broader local environment and allows us to examine whether potential spillover effects weaken at greater distances.²

4.2 Variables

To identify the effects of the cluster policy, we construct treatment indicators based on firms’ participation in LECC-funded clusters. The indicator is conditional to the funding cohort and starts in 2008, 2010, or 2012, respectively.

Furthermore, based on the merged dataset, we construct three outcome variables capturing firms’ inventive activity, joint patenting as a result of R&D collaboration, and firm size. Following standard practice, all variables are transformed using $\log(1 + x)$.

Inventive activity is measured using the quality-adjusted number of patents, *Patents (adjusted)*, which reflects not only the quantity but also the technological relevance of firms’ inventive activities. Using simple patent counts as an indicator for inventive and innovative activity poses challenges as they vary in economic value and technological impact (Griliches, 1990; Harhoff et al., 2003). While most patents have limited value, a select few represent significant technological breakthroughs (Gambardella et al., 2008). In the absence of explicit value data, citation-based measures provide one of the best approximation of patent quality (Gambardella et al., 2008; Harhoff et al., 2003). Patents frequently cited by subsequent patents are generally considered higher quality, provided that differences in citation propensity are controlled for (Harhoff et al., 1999; Jaffe & de Rassenfosse, 2017; Trajtenberg, 1990). However, citation frequencies are heterogeneous across countries due to differences in national patent office procedures, examination practices, and other factors (Harhoff et al., 2003; Michel & 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. This measure accounts for 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. The resulting measure is particularly suitable in our context because cluster policy explicitly aims to stimulate internationally competitive high-quality innovation rather than merely increasing patent counts. Furthermore, given the technological breadth of the funded clusters, technology specific citation frequencies are accounted for, allowing for comparison across clusters.

Joint patents as a result of R&D collaboration are patents that are filed by two or more applicants (Hagedoorn, 2003). Joint patenting provides a well-established and observable indicator of R&D cooperation and knowledge-sharing relationships between organizations (Breschi & Lissoni, 2009; Breschi & Lissoni, 2004). In this way, they capture a central mechanism through which cluster policy is expected to generate knowledge spillovers and strengthen inter-firm linkages.

Firm size is measured by *Employment costs* obtained from Orbis. *Employment costs* provide

²Besides the theoretical argument for these distance bands, the geographic distribution of the cluster firms limits the distance consideration. Since LECC cluster firms are geographically dispersed across Germany, extending the exposure radius substantially beyond 10 km would markedly reduce the pool of available comparison firms and increasingly concentrate the remaining comparison group in rural and peripheral locations. This would weaken common support and risk confounding geographic exposure with systematic urban–rural differences. Thus, the two distance bands should be interpreted as empirical exposure categories rather than as natural boundaries of knowledge diffusion.

a good account of the workforce in the firm, especially accounting for employment intensity. Even though changes in employment costs can not only stem from changes in headcount, but also changes in work hours, salary, or other components, which are tightly regulated by German law and not conditional on the LECC. Employment costs therefore provide a good measure for labor input and reflects medium-term adjustments in firm size that cluster policy may trigger.

5 Estimation Strategy

5.1 Coarsened exact matching for cluster firms

The LECC policy targeted a specific group of firms, implying that selection into cluster support was not random. Cluster firms differ systematically from non-cluster firms in observable characteristics such as size, age, and industry composition. A direct comparison would therefore risk conflating treatment effects with pre-existing firm differences. Ideally, identification would rely on comparisons between accepted and rejected applicants within the same cluster cohort. However, such information is unavailable, as firm-level data on runner-up firms in the rejected clusters is not available.

To address potential selection concerns, we implement Coarsened Exact Matching (CEM) (Iacus et al., 2011, 2012) to match each cluster firm with a suitable non-cluster firm. Matching is performed using pre-treatment characteristics measured in 2007, prior to the first LECC entry wave. Firms are matched exactly on coarsened values of: firm age (calculated as $Year_{2007} - Year_{Incorporation}$), logarithm of total assets, and 2-digit NACE industry classification. Industry matching is particularly important, as LECC cohorts differ substantially in sectoral composition (high concentration in knowledge-intensive industries), which strongly influences selection into the LECC program. Matching on firm age and total assets ensures comparability in organizational maturity and resource endowment. To obtain one-to-one matches, we apply nearest-neighbor matching within CEM (specifying $k2k = TRUE$) using the Mahalanobis distance metric. This procedure yields a balanced sample, in which all 751 treated firms are successfully matched to 751 control firms, resulting in a matching rate of 100%.

Table 1: Descriptive statistics for cluster and non-cluster firms before and after matching, 2007

Variable	Before matching			After matching		
	LECC (N= 751)	Non-LECC (N= 588,730)		LECC (N= 751)	Non-LECC (N= 751)	
Variable	mean (SD)	mean (SD)	<i>p</i> -value	mean (SD)	mean (SD)	<i>p</i> -value
Firm age	19.6 (27.3)	17.1 (20.8)	0.013	19.6 (27.3)	19.4 (26.3)	0.873
Log Total assets	15.6 (2.84)	13.1 (2.11)	0.001	15.6 (2.84)	15.5 (2.64)	0.479
Log Employment costs	16.7 (1.93)	14.4 (1.92)	0.001	16.7 (1.93)	16.3 (1.90)	0.013
Log Adjusted patents	0.68 (1.51)	0.01 (0.19)	0.001	0.68 (1.51)	0.31 (1.03)	0.001
Log Joint patents	0.32 (0.98)	0.004 (0.09)	0.001	0.32 (0.98)	0.13 (0.61)	0.001

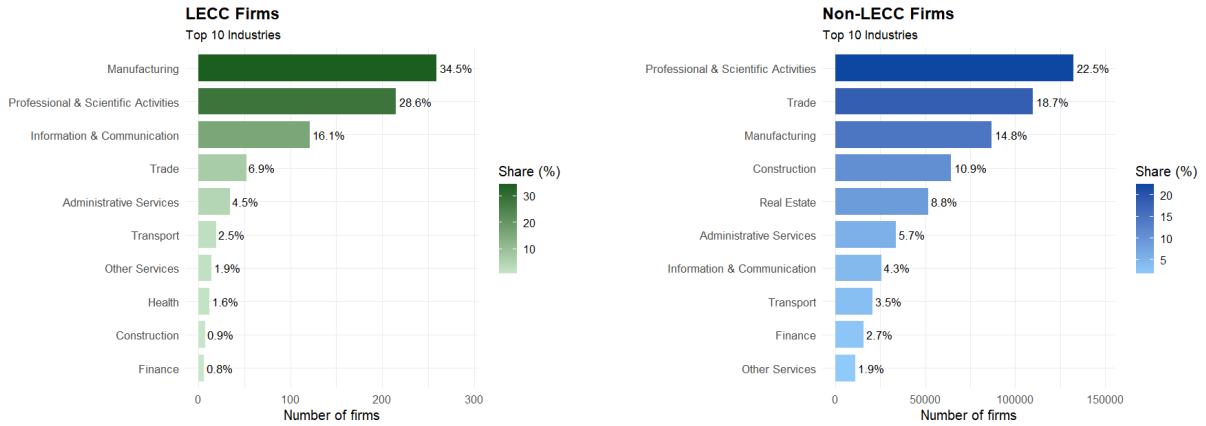
Note: The table reports means and standard deviations (in parentheses) for LECC and non-LECC firms before and after coarsened exact matching (CEM) for the year 2007. *p*-values are based on two-sample t-tests of mean differences between LECC and non-LECC firms. Matching is performed on firm age, total assets, and 2-digit NACE industry classification.

Table 1 presents descriptive statistics for cluster and non-cluster firms before and after match-

ing. Prior to matching, cluster firms are statistically significantly older, substantially larger, and considerably more innovation-intensive than non-cluster firms. Specifically, cluster firms have an average age of 19.6 years, compared to 17.1 years for non-cluster firms, and total assets amount to 15.6 for LECC firms, compared to 13.1 for non-LECC firms. Innovation-related indicators reveal similar differences: The average log number of adjusted patents is 0.68 among LECC firms, compared to 0.01 for non-LECC firms. Likewise, LECC-funded firms display greater engagement in joint patenting activities, suggesting stronger participation in collaborative R&D activity and knowledge-sharing arrangements. Differences in firm size are similarly pronounced. The average log employment costs are 16.7 and 14.4, respectively.

With respect to industry differences, Figure C1 illustrates the distribution of cluster and non-cluster firms across aggregated NACE-based industry groups. The sectoral composition differs substantially between the two groups. Cluster firms are concentrated in manufacturing and knowledge-intensive activities, with Manufacturing accounting for the largest share (34.5%), followed by Professional & Scientific Activities (28.6%) and Information & Communication (16.1%). By contrast, non-cluster firms are more broadly distributed across sectors, with Professional & Scientific Activities (22.5%), Trade (18.7%), and Manufacturing (14.8%) representing the largest shares. Traditional sectors such as Construction (10.9%) and Real Estate (8.8%) are considerably more prevalent among non-cluster firms, while Information & Communication accounts for only 4.3% of the untreated group.

Figure 1: Industry composition of cluster and non-cluster firms before matching, 2007



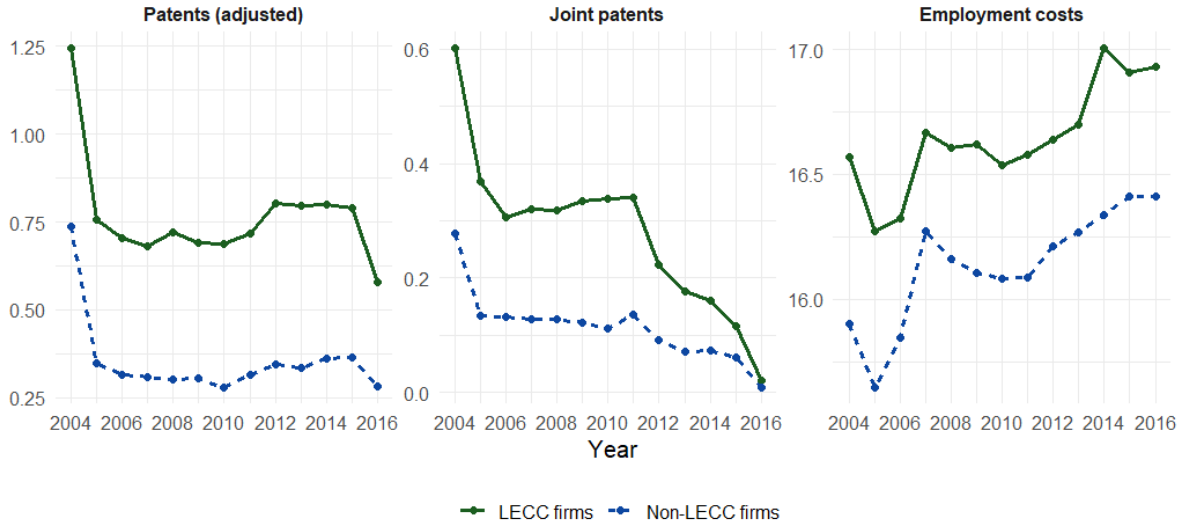
Note: The figure shows the industry distribution of LECC cluster firms and non-cluster comparison firms in 2007. Industry groups are constructed by aggregating two-digit NACE classifications into broader sectors. Shares are calculated separately for each group among firms with available industry information.

After matching, firm age and log total assets are closely balanced between LECC and non-LECC firms, with mean differences no longer statistically significant ($p = 0.873$ and $p = 0.479$, respectively). Differences in pre-treatment non-matched outcomes also narrow but remain statistically significant. LECC firms have higher mean log employment costs (16.7 versus 16.3), log adjusted patents (0.68 versus 0.31), and log joint patents (0.32 versus 0.13). The difference in employment costs is significant at the 5% level, while both patent measures differ at the 1% level. With respect to industry differences, after matching, the sectoral distribution between LECC and non-LECC firms becomes identical by construction. Overall, the results indicate that matching successfully improves comparability between treated and untreated firms.

Figure 2 illustrates the evolution of quality-adjusted patents, joint patents, and employment costs for cluster firms and their matched controls from 2004 to 2016. Overall, the pre-treatment trends are highly similar across treated and control firms, supporting the validity of the matching procedure and the comparability of the two groups prior to the cluster policy.³ Following the introduction of LECC, treated firms exhibit slightly stronger growth in quality-adjusted patents and employment costs relative to their matched controls. Joint patenting activity follows a different pattern, declining gradually for both treated and control firms after 2011. Despite this decline, LECC firms maintain consistently higher levels of joint patenting throughout most of the observation period.

Finally, CEM is also applied to sub-samples of funded and non-funded cluster members to assess heterogeneity in the direct effects of the LECC policy. In this step, we use the already matched control group of 751 non-LECC firms as the donor pool and reapply CEM. Specifically, funded and non-funded cluster firms are matched on the same pre-treatment characteristics as in the main specification, such as firm age, log total assets, and 2-digit NACE industry classification, to ensure comparability within the cluster population (see Appendix C for details).

Figure 2: Outcome trends for cluster and matched non-cluster firms, 2004–2016



Notes: The figure reports mean log-transformed outcomes at the firm-year level for LECC and matched non-LECC firms over 2004–2016. Variables include quality-adjusted patents, joint patents, and employment costs. Means are computed separately by treatment status and year. The LECC firms are funded in three rounds in 2008, 2010, and 2012, respectively.

5.2 Event study design for direct effects

To analyze the dynamic effects of the LECC on cluster firms, we apply the interaction-weighted event-study estimator proposed by Sun and Abraham (2021). This approach is designed for staggered treatment adoption and allows for heterogeneous treatment effects across cohorts while allowing not-yet-treated and never-treated units to serve as counterfactual comparison groups. Our identification strategy relies on the standard assumptions underlying this framework, namely

³The substantial decline from 2004 to 2005 in both groups for all variables stems from a reduced sample in 2004 due to missing observations, especially for small firms. Since the missingness affects treatment and control groups equally, it does not challenge the parallel trend assumption.

that in the absence of treatment, outcome trends would have evolved in parallel across cohorts (parallel trends) and never-treated units, conditional on firm and time fixed effects.

Treatment is defined as participation in a LECC cluster. We define a binary treatment indicator $D_{i,t}$ that equals one once firm i has been exposed to the program. The timing of initial exposure is denoted by E_i , which varies across firms. Since the LECC policy was implemented in three rounds, we observe three treated cohorts, $e \in \{2008, 2010, 2012\}$, where each cohort consists of all firms first treated in year e , that is, $\{i : E_i = e\}$. Firms that never participate in the program are defined as never-treated units and are assigned $E_i = \infty$. Their untreated potential outcome, denoted by $Y_{i,t}^\infty$, serves as the baseline outcome, that is, the potential outcome in the absence of treatment.

We estimate two types of effects: the firm-level treatment effect and the cohort-specific average treatment effect on the treated. The firm-level treatment effect is estimated as the difference between the observed outcome and the never-treated counterfactual outcome: $Y_{i,t} - Y_{i,t}^\infty$. The cohort-specific average treatment effect on the treated (CATT) is defined as:

$$CATT_{e,\ell} = E[Y_{i,e+\ell} - Y_{i,e+\ell}^\infty \mid E_i = e]. \quad (1)$$

where ℓ denotes event time relative to the initial treatment period e . Thus, $\ell < 0$ corresponds to pre-treatment periods and $\ell \geq 0$ to post-treatment periods.

The general binned specification is

$$Y_{i,t} = \alpha_i + \lambda_t + \beta \cdot \sum_{\ell < -K} D_{i,t}^\ell + \sum_{\ell = -2}^{-2} \mu_\ell D_{i,t}^\ell + \sum_{\ell = 0}^L \mu_\ell D_{i,t}^\ell + \gamma \cdot \sum_{\ell > L} D_{i,t}^\ell + \varepsilon_{i,t}, \quad (2)$$

where $Y_{i,t}$ is the outcome of interest (quality-adjusted number of patents, joint patents, employment costs) for firm i at time t , α_i denotes firm fixed effects, λ_t denotes the time fixed effects, μ_ℓ captures the average treatment effect at relative time ℓ (i.e., ℓ periods before or after treatment for cohort e), $D_{i,t}^\ell$ is the relative period indicator (lags/leads of treatment), and $\varepsilon_{i,t}$ denotes the error term (heteroscedasticity robust standard errors are clustered at the firm level).

Following Sun and Abraham (2021), we implement two modifications to ensure sufficient support in event time and reduce sparsity in the tails. First, we omit the period immediately preceding treatment ($\ell = -1$) as the reference category. Second, we collapse extreme event-time observations into boundary bins: all leads with $\ell \leq -4$ are grouped into a single pre-treatment bin, and all lags with $\ell \geq 4$ are grouped into a single post-treatment bin. This yields a finite set of event-time indicators that ensures stable estimation across cohorts while preserving dynamic variation in the central event window.

The resulting specification aggregates cohort-specific effects into a unified dynamic treatment path using the interaction-weighted estimator. In a second step, we further distinguish between funded and non-funded cluster members to assess heterogeneity in treatment effects relative to non-cluster firms.

In addition to the main specification, we perform robustness checks using alternative fixed-effects structures, such as industry-year and state-year fixed effects. Further details are provided in the Appendix D.

5.3 Event study design for indirect spillover effects

In the second empirical setup, we examine whether the LECC generates local spillovers to nearby non-cluster firms. We use the TWFE model for staggered treatment by Sun and Abraham (2021), restricting our sample to firms that are not selected by the policy by dropping the cluster firms. In contrast to direct effect analysis, where the treatment group comprises cluster firms and the control group comprises non-cluster firms, here our treatment group represents the non-cluster neighbors that are within a 10 km distance of cluster firms, and the control group consists of all other non-cluster firms located beyond a 10 km distance. We estimate the TWFE model for both subgroups of neighbors (within 5km and 5-10 km distance) separately by applying Equation 2.

Contrary to the direct-effect analysis, we do not match the spillover sample because the distance groups are broadly comparable in terms of their pre-treatment firm characteristics and outcomes (Table B1 in the Appendix). However, differences in their industry composition remain (Figure B1 in the Appendix), and firms across locations may face heterogeneous regional shocks. We therefore include additional year-by-two-digit-industry and year-by-NUTS-3-region fixed effects. With these interacted fixed effects, we account for time-varying industry-specific and regional shocks.

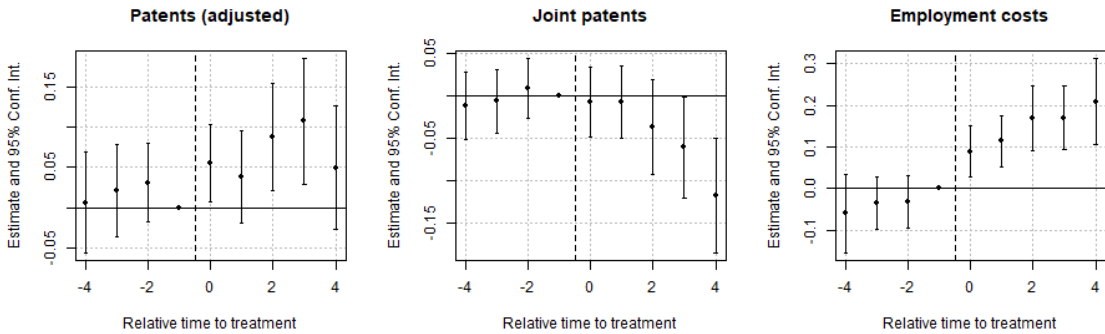
6 Results

6.1 The direct effect of the LECC

6.1.1 The overall effect of the LECC on all cluster firms

Our first results focus on the overall direct effect of the LECC policy on all firms in a cluster, corresponding to Hypothesis 1. The results of the Sun and Abraham (2021) TWFE models are depicted in Figure 3 and Table 2. Across the three different outcomes, adjusted patents, joint patenting, and employment costs, the event study coefficients for the pre-treatment periods are small and statistically insignificant, providing no evidence of systematic differential pre-trends between treated and untreated firms prior to the LECC. This supports the parallel trends assumption required for causal interpretation.

Figure 3: Event-study estimates for all cluster firms



Notes: The figure presents event-study estimates following Sun and Abraham (2021) for all LECC cluster firms relative to non-cluster comparison firms. Treatment timing is defined by the year in which the respective cluster received LECC funding. Points denote coefficient estimates and vertical bars indicate 95% confidence intervals. Event time $t = -1$ is the omitted reference period. The endpoints at $t = -4$ and $t = 4$ pool all event times $t \leq -4$ and $t \geq 4$, respectively. All dependent variables are transformed as $\log(1 + x)$. All specifications include firm and year fixed effects, and standard errors are clustered at the firm level.

At the time of treatment (Year 0), we observe a statistically significant increase in adjusted patents (0.0550) and employment costs (0.0892), indicating an immediate response of firms to the LECC. While the immediate response in employment costs is consistent with adjustments in labor demand, the contemporaneous increase in patents should be interpreted more cautiously, as it may partly reflect pre-existing innovation trajectories or anticipation effects in the clusters.

Table 2: Event-study estimates, average and cohort-specific treatment effects for all cluster firms

Dependent Variables: Model:	Patent (adjusted) (1)	Joint patents (2)	Employment costs (3)
<i>Variables</i>			
Year = -4	0.0068 (0.0315)	-0.0117 (0.0203)	-0.0589 (0.0479)
Year = -3	0.0217 (0.0290)	-0.0059 (0.0190)	-0.0346 (0.0316)
Year = -2	0.0314 (0.0246)	0.0092 (0.0177)	-0.0311 (0.0321)
Year = 0	0.0550** (0.0243)	-0.0078 (0.0209)	0.0892*** (0.0310)
Year = 1	0.0381 (0.0288)	-0.0069 (0.0219)	0.1140*** (0.0316)
Year = 2	0.0877*** (0.0337)	-0.0364 (0.0283)	0.1697*** (0.0392)
Year = 3	0.1071*** (0.0394)	-0.0606** (0.0304)	0.1706*** (0.0390)
Year = 4	0.0499 (0.0388)	-0.1170*** (0.0341)	0.2088*** (0.0528)
ATT	0.0625** (0.0288)	-0.0629*** (0.0241)	0.1640*** (0.0371)
CATT (cohort = 2008)	0.0360 (0.0743)	-0.0648 (0.0499)	0.2116*** (0.0627)
CATT (cohort = 2010)	0.0592* (0.0318)	-0.0362 (0.0275)	0.1314*** (0.0434)
CATT (cohort = 2012)	0.1246** (0.0607)	-0.1830*** (0.0669)	0.1829** (0.0886)
<i>Fixed-effects</i>			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
<i>Fit statistics</i>			
Observations	16,109	16,109	7,071
Number of firms	1502	1502	1502
R ²	0.89070	0.79082	0.95806
Within R ²	0.00344	0.01183	0.01751

Notes: The table reports event-study estimates following Sun and Abraham (2021) for all LECC cluster firms relative to non-cluster comparison firms. Treatment timing is defined by the year in which each respective cluster received LECC funding. All dependent variables are transformed as $\log(1 + x)$. Event time $t = -1$ is the omitted reference period. The endpoints at $t = -4$ and $t = 4$ pool all event times $t \leq -4$ and $t \geq 4$, respectively. The ATT is the weighted average of the post-treatment effects across cohorts and event periods. The CATTs report the average post-treatment effect separately for the 2008, 2010, and 2012 treatment cohorts. All specifications include firm and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

With respect to patenting activity over time, the event study estimates indicate a gradual increase, with statistically significant effects emerging from Year 2 and 3 (0.0877 in Year 2 and 0.1071 in Year 3). This pattern is consistent with the lag structure typically associated with innovation processes. Correspondingly, the aggregated Average Treatment Effect on the Treated (ATT)⁴ for adjusted patents is positive and statistically significant (0.0625, $p < 0.05$), indicating a moderate increase in patenting following the LECC. There is, however, heterogeneity across cohorts. While the first cohort (2008) shows no statistically significant effect, the second (2010)

⁴The ATT summarizes the average effect of LECC participation across all treated cohorts and event-time periods, relative to the never-treated counterfactual.

and third (2012) cohorts exhibit positive and statistically significant effects (0.0592 and 0.1246, respectively), suggesting that innovation responses may have shown themselves more clearly in patenting activities in later funding waves.

In contrast, for the number of joint patents, the results point to a decline over time. While early post-treatment effects are small and insignificant, the coefficients become negative and statistically significant in later periods (-0.0606 in Year 3 and -0.1170 in binned Year 4). The overall ATT is negative and statistically significant (-0.0629, $p < 0.01$), indicating a reduction in joint patenting following the LECC funding relative to the control group. This effect is primarily driven by the 2012 cohort, which shows a large and significant decline (-0.1830), whereas the earlier cohorts do not exhibit statistically significant changes.

With respect to firm size, measured by employment costs, we observe strong and persistent positive effects. The coefficients are positive and highly significant from Year 0 onward and increase in effect size. The significant ATT is 0.1640 ($p < 0.01$). Unlike patenting, the effect is relatively consistent across cohorts, with only small differences in magnitude.

Overall, in line with our hypothesis, we find that the LECC has a positive effect on firm size and, to a lesser extent, inventive activity. However, we do not find support for a positive effect on collaborative R&D activity; instead, joint patenting declines following the policy. The results further point to heterogeneity across cohorts, indicating that the impact of the LECC varies across funding waves and possibly across clusters.

We further conduct a series of robustness checks by augmenting the baseline specification with additional high-dimensional fixed effects, including industry-year and state-year interactions. The results, reported in the Appendix D, confirm that the main findings are robust to these alternative specifications except for the negative ATT of joint patenting, which turns insignificant.

6.1.2 The direct effect on funded and not funded cluster members

With respect to our second hypothesis, we differentiate cluster firms into firms that receive R&D subsidies through the LECC and firms that did not receive R&D subsidies, but were nevertheless part of the cluster and could potentially benefit from the systemic effect of the LECC. Figure 4 and Table 3 report the estimation results.

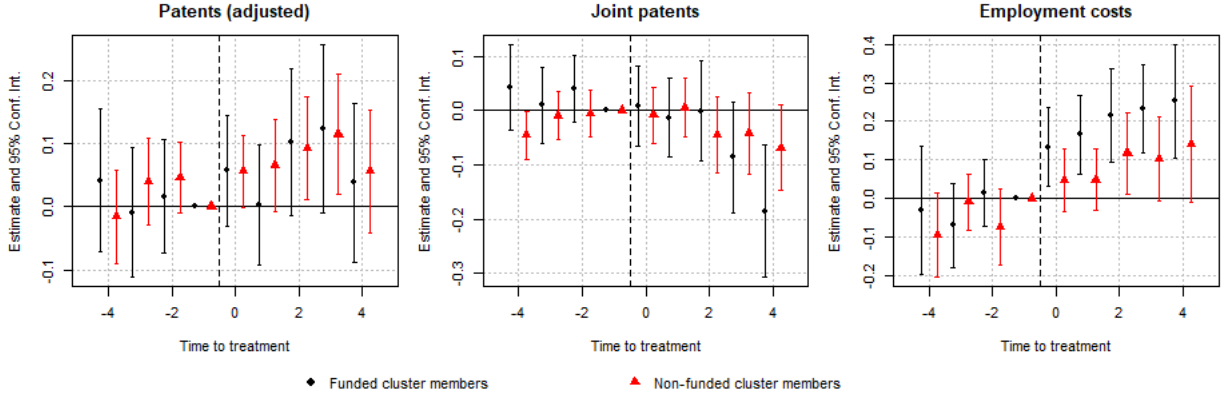
For funded cluster members, the estimates indicate positive effects on patenting activity in Years 2 and 3 after treatment (0.1020 and 0.1236), although the overall ATT for adjusted patents is not statistically significant. The cohort-specific effects reveal that this pattern is primarily driven by the 2010 cohort, for which the CATT is positive and highly significant (0.1391). In contrast, there is no statistically significant effect for the 2008 and 2012 cohorts.

Regarding joint patenting, the results point to a decline in collaborative R&D among funded firms. While the coefficients are mostly insignificant in the early post-treatment years, they become negative and statistically significant in Year 3 and binned Year 4. Correspondingly, the aggregated ATT is negative and significant (-0.0902, $p < 0.05$). This effect is largely driven by the 2012 cohort, which exhibits a sizeable negative CATT (-0.2634). Hence, we do not find evidence that direct LECC support increases joint patenting among funded firms.

For employment costs, the estimates indicate strong and persistent positive effects. Employment costs show an overall increase with a positive and significant aggregated ATT of 0.2142. Cohort-specific estimates suggest that the effect on employment costs increases more consistently

across cohorts, although the effect is not statistically significant for the last cohort ($p=0.113$).

Figure 4: Event-study estimates for funded and non-funded cluster members



Notes: The figure presents event-study estimates following Sun and Abraham (2021), reported separately for funded and non-funded cluster members. Each subgroup is compared with non-cluster firms selected through a separate matching procedure from the pool of 751 comparison firms used in the baseline analysis. Treatment timing is defined by the year in which the respective cluster received LECC funding. Points denote coefficient estimates and vertical bars indicate 95% confidence intervals. All dependent variables are transformed as $\log(1+x)$. Event time $t = -1$ is the omitted reference period, while the endpoints at $t = -4$ and $t = 4$ pool event times $t \leq -4$ and $t \geq 4$, respectively. All specifications include firm and year fixed effects, and standard errors are clustered at the firm level.

Overall, these findings provide support for Hypothesis 2a with respect to firm size. In contrast, the evidence for inventive activity is mixed. While some increases in patenting activity emerge for specific cohorts, there is no robust overall increase in patenting among funded firms. Contrary to our hypothesis, collaborative R&D activities decline over time.

For the cluster firms that did not receive any R&D subsidies, the estimation results indicate several differences. For adjusted patents, the coefficients become positive and statistically significant from Year 2 onward, and the ATT is positive and significant (0.0714, $p < 0.05$), suggesting moderate increases in patenting activity among non-funded cluster members. The cohort-specific estimates indicate that this effect is mainly driven by the 2012 cohort, which exhibits a large and highly significant CATT (0.1757).

For joint patenting, the results are considerably weaker than for funded firms. Most coefficients remain statistically insignificant, although a small negative effect emerges in binned Year 4 (-0.0694). The ATT itself is not statistically significant, indicating no systematic decline in collaborative patenting among non-funded firms.

The results for employment costs display a positive and significant effect from year 2 onward. The ATT is positive and weakly significant (0.1015, $p < 0.1$), while the cohort-specific estimates indicate that this effect is primarily driven by the 2008 cohort.

Table 3: Event-study estimates for funded and non-funded cluster members

Dependent Variables: Model:	Funded Cluster Members			Non-Funded Cluster Members		
	Patent (adjusted) (1)	Joint patents (2)	Employment costs (3)	Patent (adjusted) (4)	Joint patents (5)	Employment costs (6)
<i>Variables</i>						
Year = -4	0.0416 (0.0579)	0.0430 (0.0403)	-0.0304 (0.0842)	-0.0165 (0.0377)	-0.0460** (0.0230)	-0.0940* (0.0559)
Year = -3	-0.0095 (0.0522)	0.0096 (0.0360)	-0.0689 (0.0555)	0.0399 (0.0351)	-0.0098 (0.0223)	-0.0093 (0.0372)
Year = -2	0.0158 (0.0460)	0.0392 (0.0314)	0.0145 (0.0438)	0.0455 (0.0288)	-0.0053 (0.0220)	-0.0727 (0.0497)
Year = 0	0.0574 (0.0447)	0.0070 (0.0376)	0.1341*** (0.0511)	0.0561* (0.0292)	-0.0094 (0.0260)	0.0467 (0.0411)
Year = 1	0.0026 (0.0485)	-0.0133 (0.0370)	0.1667*** (0.0518)	0.0658* (0.0370)	0.0050 (0.0274)	0.0486 (0.0408)
Year = 2	0.1020* (0.0591)	-0.0018 (0.0470)	0.2158*** (0.0610)	0.0930** (0.0415)	-0.0455 (0.0357)	0.1178** (0.0535)
Year = 3	0.1236* (0.0683)	-0.0863* (0.0518)	0.2333*** (0.0586)	0.1144** (0.0483)	-0.0420 (0.0381)	0.1021* (0.0552)
Year = 4	0.0382 (0.0643)	-0.1855*** (0.0621)	0.2528*** (0.0751)	0.0562 (0.0496)	-0.0694* (0.0402)	0.1405* (0.0765)
ATT	0.0569 (0.0491)	-0.0902** (0.0417)	0.2142*** (0.0560)	0.0714** (0.0362)	-0.0405 (0.0300)	0.1015* (0.0521)
CATT (cohort = 2008)	-0.0803 (0.1098)	-0.1236 (0.0763)	0.1997** (0.0858)	0.1591 (0.1018)	0.0233 (0.0635)	0.2184** (0.0958)
CATT (cohort = 2010)	0.1391*** (0.0483)	-0.0201 (0.0493)	0.2061*** (0.0586)	0.0286 (0.0415)	-0.0434 (0.0340)	0.0501 (0.0659)
CATT (cohort = 2012)	0.0753 (0.1141)	-0.2634** (0.1110)	0.2687 (0.1692)	0.1757*** (0.0671)	-0.1157 (0.0840)	0.1154 (0.0736)
<i>Fixed-effects</i>						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Observations	5,902	5,902	3,189	9,782	9,782	3,636
Number of firms	532	532	532	932	932	932
R ²	0.90999	0.82590	0.95475	0.86144	0.73100	0.95869
Within R ²	0.00765	0.02598	0.02594	0.00649	0.00578	0.01454

Notes: The table reports event-study estimates following Sun and Abraham (2021), separately for funded and non-funded cluster members. Each subgroup is compared with non-cluster firms selected through a separate matching procedure from the pool of 751 comparison firms used in the baseline analysis. Of the initial 275 funded and 476 non-funded cluster members, 266 and 466, respectively, are retained after matching. Together with their matched comparison firms, the two estimation samples contain 532 and 932 firms. Treatment timing is defined by the year in which the respective cluster received LECC funding. All dependent variables are transformed as $\log(1 + x)$. Event time $t = -1$ is the omitted reference period, while the endpoints at $t = -4$ and $t = 4$ pool event times $t \leq -4$ and $t \geq 4$, respectively. The ATT is the weighted average of the post-treatment effects across cohorts and event periods. The CATTs report the average post-treatment effect separately for the 2008, 2010, and 2012 treatment cohorts. All specifications include firm and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Overall, the findings provide partial support for Hypothesis 2b, suggesting that non-funded cluster firms may benefit indirectly from the LECC through systemic effects. While patenting activity increases among non-funded firms, there is little evidence of stronger collaborative R&D effects. At the same time, unlike funded firms, non-funded firms do not experience a pronounced decline in joint patenting activity.

For both subsamples, we also perform robustness checks by adding Industry-Year and State-Year fixed effects. The results, reported in the Appendix D, remain qualitatively unchanged, confirming the robustness of the baseline estimates.

6.2 Indirect spillover effects on neighbor firms

In the second part of the analysis, we investigate potential geographic spillover effects of the LECC on non-cluster firms. Applying the distance-band construction described in Section 5.3, we estimate the effects separately for firms located within 0–5 km and within 5–10 km of the nearest funded cluster firm. Firms located more than 10 km away constitute the comparison group. This distinction allows us to compare effects in the immediate and broader local environments and to examine whether potential spillovers attenuate with distance.

The first group comprises 159,999 non-cluster firms located within 0–5 km of the nearest funded cluster firm, while the second consists of 68,711 non-cluster firms located within 5–10 km. Each group is analyzed separately and compared with the same control group of 155,555 non-cluster firms located more than 10 km from the nearest funded cluster firm. These figures refer to the number of firms observed in 2007. Descriptive statistics for the three groups before the introduction of the cluster policy are reported in Appendix Table B. Overall, the three groups are relatively similar in terms of their observable characteristics. Firms located within 0–5 km are slightly younger, with an average age of 17.3 years, than firms located within 5–10 km (18.8) and control firms (18.6). Average log total assets are very similar across the three groups. Similarly, there is hardly any difference between the groups in average log employment costs. Differences in patenting activity are small. Average log adjusted patents amount to 0.0214 among firms within 0–5 km, 0.0244 among firms within 5–10 km, and 0.0201 among control firms. Average log joint patents are slightly higher among firms located within 10 km of a funded cluster firm than among control firms, although the corresponding averages are low in all three groups. Regarding the industry composition, Figure B1 in the Appendix shows the share over the three distance groups. Structural differences are rather small, except for Professional and scientific activities which are the largest in both treated groups (25% and 21%) but only the third largest in the control group (18%). Correspondingly, Manufacturing is on third position in the two treated groups (11% and 17%) but first in the control group (21%). Overall, firms located closest to cluster firms are more concentrated in knowledge-intensive and service-oriented industries, while manufacturing and related industries are more prevalent at greater distances.

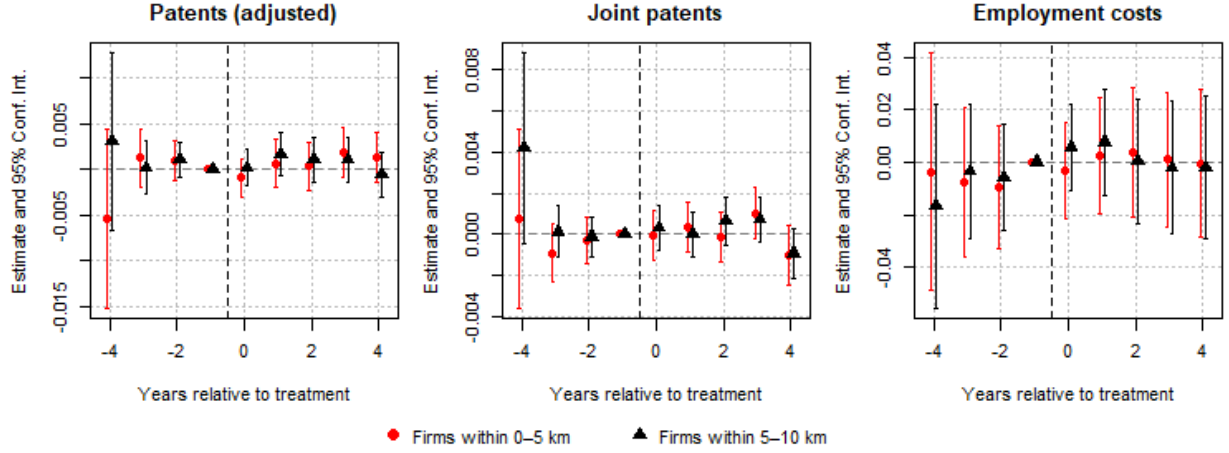
We estimate dynamic treatment effects using the interaction-weighted event-study estimator developed by Sun and Abraham (2021). Our preferred specification includes firm fixed effects as well as year-by-two-digit-industry and year-by-NUTS-3-region fixed effects. Standard errors are clustered at the firm level. The year immediately preceding treatment serves as the reference period. Event times four or more years before and after treatment are pooled into the endpoints of the event-study window.

Table 4 and Figure 5 present the results for non-cluster firms located within 0–5 km (Models 1–3) and 5–10 km (Models 4–6) of a funded cluster firm. First, for the non-cluster firms within 0–5 km distance, we find no statistically significant effects on adjusted patents (1) or joint patents (2) in any of the post-treatment periods. We also find no statistically significant effects on employment costs (3). Moreover, none of the pre-treatment coefficients are statistically significant across all outcomes.

For non-cluster firms located within 5–10 km of a funded cluster firm, none of the post-treatment coefficients are statistically significant for adjusted patents (4), joint patents (5), or employment costs (6). The overall ATT is statistically insignificant for all three outcomes in both

distance groups.

Figure 5: Event-study estimates for non-funded neighbor firms within 0–5km and 5–10 km



Notes: The figure presents event-study estimates for non-cluster firms located within 0–5 km and 5–10 km of the nearest LECC cluster firm relative to non-cluster firms located more than 10 km away. Points indicate coefficient estimates and vertical bars denote 95% confidence intervals. Event time $t = -1$ is the omitted reference period. The endpoints at $t = -4$ and $t = 4$ pool event times $t \leq -4$ and $t \geq 4$, respectively. All specifications include firm, year-by-two-digit-industry, and year-by-NUTS-3-region fixed effects. Standard errors are clustered at the firm level.

Overall, we find no evidence that the LECC generated measurable spillover effects on non-cluster firms located within 0–5 km and 5–10 km of funded cluster firms. Taken together, the estimates do not provide support for Hypothesis 3 among non-cluster firms located within both 0–5 km and 5–10 km of a funded cluster firm.

Table 4: Event-study estimates for non-funded neighbor firms within 0–5 km and 5–10 km

Dependent Variables: Model:	Distance: 0–5 km			Distance: 5–10 km		
	Patents (adjusted) (1)	Joint patents (2)	Employment costs (3)	Patents (adjusted) (4)	Joint patents (5)	Employment costs (6)
<i>Variables</i>						
Year = -4	-0.0055 (0.0050)	0.0008 (0.0022)	-0.0035 (0.0232)	0.0031 (0.0050)	0.0042* (0.0024)	-0.0167 (0.0199)
Year = -3	0.0012 (0.0016)	-0.0009 (0.0007)	-0.0074 (0.0145)	0.0002 (0.0015)	0.0001 (0.0006)	-0.0035 (0.0132)
Year = -2	0.0009 (0.0011)	-0.0003 (0.0006)	-0.0095 (0.0118)	0.0011 (0.0010)	-0.0001 (0.0005)	-0.0057 (0.0102)
Year = 0	-0.0009 (0.0011)	-4.37×10^{-5} (0.0006)	-0.0032 (0.0094)	0.0001 (0.0010)	0.0003 (0.0005)	0.0058 (0.0083)
Year = 1	0.0006 (0.0013)	0.0003 (0.0006)	0.0027 (0.0112)	0.0016 (0.0012)	3.49×10^{-5} (0.0006)	0.0077 (0.0103)
Year = 2	0.0003 (0.0013)	-0.0001 (0.0006)	0.0037 (0.0126)	0.0010 (0.0013)	0.0007 (0.0006)	0.0004 (0.0121)
Year = 3	0.0018 (0.0014)	0.0010 (0.0006)	0.0010 (0.0130)	0.0010 (0.0013)	0.0007 (0.0006)	-0.0020 (0.0129)
Year = 4	0.0012 (0.0014)	-0.0010 (0.0007)	-0.0003 (0.0144)	-0.0006 (0.0013)	-0.0009 (0.0006)	-0.0019 (0.0138)
<i>Fixed-effects</i>						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year-Region	Yes	Yes	Yes	Yes	Yes	Yes
ATT	0.0008 (0.0011)	-0.0003 (0.0006)	0.0004 (0.0115)	0.0002 (0.0010)	-0.0002 (0.0005)	0.0005 (0.0110)
<i>Fit statistics</i>						
Observations	3,273,362	3,273,362	468,915	2,349,254	2,349,254	338,813
R ²	0.68400	0.55317	0.94563	0.66587	0.51481	0.95242
Within R ²	4.79×10^{-6}	6.99×10^{-6}	3.12×10^{-6}	4.62×10^{-6}	2.32×10^{-5}	1.82×10^{-5}

Notes: This table reports event-study estimates of the spillover effects of the LECC on non-cluster firms located both within 0–5 km and 5–10 km of the nearest cluster firm. The treatment group consists of two samples: non-cluster firms located within 0–5 km and 5–10 km of the nearest cluster firm, while the control group consists of non-cluster firms located more than 10 km away. All dependent variables are transformed using $\log(1 + x)$. The omitted event period is $t = -1$. The coefficients at $t = -4$ and $t = 4$ pool event times $t \leq -4$ and $t \geq 4$, respectively. The ATT is the weighted average of the post-treatment event-study coefficients. All specifications include firm, year-by-two-digit-industry, and year-by-NUTS-3-region fixed effects. Standard errors clustered at the firm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

7 Discussion and Conclusion

We examine the causal direct and indirect effects of the German Leading-Edge Cluster Competition (LECC). Using geo-referenced firm-level data from Orbis, patent data from PATSTAT, and detailed information on the LECC between 2004 and 2016, we employ an event study design to estimate both the direct and indirect effects of the LECC on firms' inventive activity, joint patenting as a result of R&D collaboration, and firm size. First, we analyze the direct effect of the LECC on cluster firms. In addition to estimating the overall effect of the policy program, we are able to distinguish between firms that receive R&D subsidies and firms that do not receive financial support but are exposed to the policy's systemic components, such as cluster management, shared R&D infrastructure, intermediary organizations, and enhanced integration into regional innovation networks. These firms can directly benefit from knowledge transfer within existing cluster networks. This distinction allows us to disentangle the roles of targeted financial support and the systemic component of cluster policy. Second, we investigate whether the LECC generates indirect effects through localized knowledge spillovers to geographically proximate non-cluster firms. To

identify these spillovers, we define two geographic distance bands of 0–5 km and 5–10 km around cluster firms, then compare non-cluster firms located within these bands to non-cluster firms located farther away. Taken together, this empirical design provides a comprehensive assessment of both the direct and indirect effects of the LECC and allows us to assess if – and to what extent – direct funding is responsible for the program impact, to what degree the systemic component plays a role, and if the desired spillovers into the regional innovation system materialize. In this way, we contribute to the growing literature on cluster policy by providing causal evidence on one of the largest and most prominent cluster policy programs in Europe.

Our results provide partial support for Hypothesis 1 and show that the LECC had positive effects on inventive activity and firm size, measured by employment costs, among cluster firms. Across all cluster firms, regardless of whether they received R&D funding, we observe an average increase of about 6% in inventive activity measured by quality-adjusted patent counts and about 17% in employment costs. These findings suggest that the LECC not only stimulated firms’ inventive activities but also contributed to their economic expansion. The timing of these effects points to different underlying mechanisms. Employment costs respond immediately after cluster selection, indicating that firms rapidly expanded their workforce once the policy was implemented to conduct the proposed research activities. By contrast, the effect on inventive activity becomes most pronounced during the middle of the funding period, consistent with the time lag between R&D investments and observable inventive outputs (Hall et al., 1986; Wang & Hagedoorn, 2014). This temporal pattern supports the interpretation that the LECC first enabled firms to build innovation capacities, which subsequently translated into measurable inventive performance. Our findings are broadly consistent with previous evaluations of cluster policies at the regional level (Aranguren et al., 2013; Crass et al., 2019; Engel et al., 2019, 2013; The Danish Agency for Science, Technology and Innovation, 2011; Uyarra & Ramlogan, 2016) and serve as a micro foundation of these results. In terms of magnitudes, the estimated effects are comparable to earlier studies. For example, Falk (2012) report a 4.6%–5.7% increase in innovation output for the Bavarian High-Tech Cluster initiative, while Engel et al. (2013) find that winning regions in the BioRegio competition increased patents by 15% and regional employment by 12%. Taken together, these results indicate that cluster policies can simultaneously strengthen firms’ innovation performance and promote economic growth.

However, contrary to our expectation, we find a negative effect of the LECC on joint patenting. This effect is particularly pronounced during the second half of the funding period, albeit only statistically significant for the third funding cohort. This finding contrasts with project-level and survey-based evaluations of the LECC that document increases in the extent and intensity of collaboration (Cantner et al., 2013; Rothgang et al., 2017a; Töpfer et al., 2019) as well as the results of other cluster evaluations (e.g., Nishimura & Okamuro, 2011). At first glance, this appears inconsistent with one of the central objectives of cluster policies, namely fostering collaboration among participating organizations. However, formal R&D collaboration does not necessarily result in jointly owned patents. Firms may exchange knowledge, coordinate research activities, or collaborate within projects while choosing to protect intellectual property individually (Hagedoorn, 2003; Hagedoorn et al., 2003). Consequently, the decline in joint patenting should not be interpreted as evidence of declining collaboration *per se*. Nevertheless, the decline compared to the control group is puzzling. Several mechanisms may explain this pattern. First, the negative effect

becomes most pronounced during the second half of the funding period, suggesting that the potential for establishing new formal collaborations may diminish over time. Such an exhaustion of collaboration opportunities is also documented for another German cluster initiative by Graf and Broekel (2020). Second, LECC required applicants to demonstrate existing collaborative structures and complementarities before funding was awarded (Rothgang et al., 2014). Consequently, many participating firms already belonged to mature innovation networks, limiting the scope for additional formal collaborations. This interpretation is consistent with the fact that the selected clusters were generally at a mature stage of their life cycle (Menzel & Fornahl, 2010). A third explanation could be that successful collaboration within the cluster may have reduced the need for joint patenting as a way to control access to knowledge. As collaborative relationships become more established, firms may increasingly rely on contractual arrangements or trust (Gulati, 1995) that allocate intellectual property to individual partners rather than through joint patent applications. Such governance structures are common in strategic R&D alliances, where collaboration and knowledge exchange coexist with individually owned innovation outputs (Hagedoorn, 2003; Hagedoorn et al., 2000). The result that the LECC increased patenting in general supports this argument further. Overall, the findings provide only partial support for Hypothesis 1.

Distinguishing between cluster firms that receive R&D funding and those that benefit only from the systemic component of the LECC in Hypotheses 2a and 2b provides further insights into the mechanisms through which cluster policy affects firms. We observe several differences between firms that receive R&D funding and cluster members that receive no funding but nevertheless benefit from the systemic support provided by the LECC. First, cluster firms that receive R&D funding in addition to the general systemic support from the LECC exhibit a strong positive effect on firm size, indicating that funding triggers increased employment, similar to the aggregate results for Hypothesis 1. However, we find no overall treatment effect on inventive activity, with a positive effect only for the second funding cohort. This result contrasts with the broader literature on direct R&D support, which generally reports a positive effect on patenting (e.g., Bronzini & Piselli, 2016; Czarnitzki & Hussinger, 2018), but is consistent with the findings of Nishimura and Okamuro (2011). Similar to the aggregate results, the negative effect on joint patenting persists, which is surprising, since the R&D funding is provided mainly for collaborative research projects. Taken together with the pronounced increase in firm size, these results suggest that the additional financial resources primarily strengthen firms' R&D capacities by enabling investments in human capital, while only part of these investments translates into additional patentable output during the observation period or joint patenting. Thus, we find only partial support for Hypothesis 2a.

Second, the results for non-funded cluster firms highlight the importance of the systemic component of the LECC. Although these firms do not receive R&D funding, they still benefit from the cluster organizations, intermediary actors, networking activities, and the enhanced embeddedness in regional innovation networks fostered by the LECC. We find a positive effect on patenting activity, predominantly in the third funding cohort. This finding indicates that cluster firms benefit substantially from the systemic embeddedness in the cluster and can translate this into inventive activity. Furthermore, the effect of joint patenting is not statistically significant, indicating that formal collaborative patenting does not decline as observed for funded cluster firms. These findings together suggest that direct financial support is not a prerequisite for increasing inventive activity. Instead, they point to the importance of systemic support mechanisms that improve

firms' access to external knowledge, collaboration opportunities, and complementary innovation input, in line with the findings of Nishimura and Okamuro (2011), Töpfer et al. (2019), and the rationale for systemic innovation policy in general (Smits & Kuhlmann, 2004). The results may suggest that the systemic component of cluster policy constitutes an effective policy instrument in its own right rather than merely complementing direct R&D subsidies. However, as part of this systemic component, it seems also plausible that cluster firms profit from research activities of the funded firms as part of the cluster network. Thus, although the systemic component of cluster policies is inherently important, funding of R&D also influences the systemic component in a qualitative way by affecting the degree of within-cluster knowledge transfer. In addition to the expected effects, the results indicate that non-funded cluster firms also increase their firm size, although the estimated effects are substantially smaller than for funded firms. The increase in employment costs may reflect higher employment to support innovation activities and interactions within the cluster. Alternatively, it may result from rising local wages caused by increased demand for skilled labor following the implementation of the LECC, hinting towards another kind of agglomeration shadow or negative spillover effect as suggested by Audretsch et al. (2018) even within the cluster. Overall, we find only partial support for Hypothesis 2b.

Taken together, the results show that the LECC directly affects cluster firms through different policy mechanisms. While the aggregate analysis indicates that the LECC increases inventive activity and firm size, distinguishing between funded and non-funded cluster firms reveals that these gains originate from different components of the policy. Firms receiving direct R&D funding primarily use the additional resources to expand their human capital, but this is not reflected in additional patenting. In contrast, non-funded cluster firms, which benefit only from the systemic components of the LECC, exhibit significant increases in inventive activity despite not receiving any direct funding. Furthermore, these firms do not suffer from a substantial decline in joint patenting. This suggests that the systemic component of cluster policy plays an important role in addresses constraints to innovation beyond firms' financial resources. At the same time, the results provide little evidence that direct R&D funding and systemic support reinforce each other in terms of inventive output for funded firms. Instead, the two policy instruments appear to affect different dimensions, with R&D funding primarily fostering firm size and systemic support stimulating innovation and potentially collaboration. Overall, the findings imply that the effectiveness of cluster policies should not be assessed solely by the additionality of R&D subsidies or by formal collaboration outcomes, but also by their ability to strengthen the innovation system in which firms operate.

Hypothesis 3 postulates that cluster policy generates positive spillover effects for geographically proximate firms that are not members of a cluster but operate in cluster-targeted industries. This rationale for indirect effects of cluster policy receives little support from our assessment of the LECC. For neighboring firms, irrespective of their distance to the cluster firms, we find no effect on inventive activity, joint patenting, or firm size. Overall, the results provide little evidence that the LECC generated measurable localized spillovers to neighboring non-cluster firms along these indicators.

Several explanations may account for this finding. First, although the LECC supports collaboration and knowledge exchange among participating firms, these interactions may have remained largely confined to cluster members. Since the systemic support of the LECC was directed primar-

ily at participating firms, neighboring non-cluster firms might only have had limited opportunities to benefit from these resources. Second, geographic proximity alone may not be sufficient for knowledge spillovers to materialize. As argued by Boschma (2005), effective knowledge diffusion also depends on cognitive, organizational, and institutional proximity. The LECC specifically supported leading-edge high-technology clusters, implying that neighboring firms may have been geographically close but technologically too distant to absorb and exploit the knowledge generated within the cluster. Additionally, not being part of the cluster network will probably reduce the possibility of profiting from newly developed knowledge in the form of technology spillovers. Third, more generally, benefiting from external knowledge requires sufficient absorptive capacity (Cohen & Levinthal, 1990). Even if knowledge diffused beyond the cluster, neighboring non-cluster firms may have lacked the capabilities to recognize, assimilate, and exploit this knowledge. Finally, knowledge spillovers may occur through channels such as labor mobility, customer-supplier relationships, or informal interactions that are not immediately reflected in inventive activity, joint patenting, or firm size (Breschi & Lissoni, 2001). Consequently, while our results do not reject the existence of localized knowledge spillovers more generally, they suggest that such spillovers are neither an automatic consequence of geographic proximity nor a guaranteed outcome of cluster policy.

The results bear several theoretical implications. First, our causal evidence shows that cluster policy is effective in supporting cluster development. The analysis provides insights into the mechanisms through which it operates. Distinguishing between the funding component and the systemic component highlights the importance of the latter for stimulating innovative activity. Theoretically, this implies that cluster policy should not be viewed as a homogeneous treatment but rather as a combination of distinct elements that address different innovation constraints, including both market failures and systemic failures. Second, the results for non-funded cluster firms strengthen the theoretical claim that innovation depends not only on firms' own R&D investments but also on the quality of the innovation system in which they operate. The findings therefore provide firm-level support for innovation systems theory by showing that in clusters with funded R&D activities, supporting networking, intermediary organizations, and knowledge exchange can stimulate inventive activity in addition to direct financial support. The activities of the funded cluster organizations seem to foster the distribution of newly created knowledge. Third, the results suggest that the complementarity between the financial and systemic components is limited. While direct R&D funding primarily promotes firm size and capability building, the systemic component appears to be a core driver of inventive activity. This indicates that the two components affect different dimensions of firm performance rather than reinforcing one another uniformly, suggesting that theories of cluster policy should explicitly distinguish between resource-based and network-based mechanisms of innovation. Finally, we find no substantial evidence that the LECC generated spillovers to neighboring non-cluster firms. These findings suggest that the localized spillovers expected from cluster policy are not an automatic consequence of geographic proximity. Instead, they support theoretical perspectives emphasizing that knowledge diffusion depends on cognitive proximity, absorptive capacity, and participation in innovation networks. Consequently, arguments for indirect cluster policy effects should place greater emphasis on network embeddedness and firms' ability to absorb external knowledge than on spatial proximity alone.

The results and their implications give rise to several policy recommendations. First, the systemic component of cluster policy deserves greater attention. Supporting regional innovation systems through cluster organizations, knowledge brokers, collaborative platforms, and other innovation intermediaries can stimulate collaboration and inventive activity independently of direct R&D subsidies. Policymakers should recognize that systemic instruments (e.g., funding the activities of cluster organizations) are an important component in supporting networking, coordination, and knowledge exchange. Second, the findings suggest that financial and systemic support should be balanced. While R&D funding primarily contributes to firms' growth and capability building, the systemic component appears to be a core driver of interaction and knowledge exchange. Cluster policy should aim for an instrument mix that appropriately reflects the complementary and distinct roles of financial and systemic support. Third, the decline in joint patenting, despite positive effects on inventive activity and firm growth, suggests that collaborative dynamics evolve over the cluster life cycle. As clusters mature, firms may increasingly rely on established partnerships and there is the risk of exhausting collaborative potential. Consequently, cluster policy should become more adaptive over the life cycle of the cluster and the respective technology and, especially at the mature stage, encourage collaboration with new partners, including firms, research organizations, and institutions outside the cluster and the cluster region. Fourth, the absence of measurable spillovers to neighboring non-cluster firms indicates that broader regional benefits cannot be taken for granted. If policymakers aim to promote regional economic development beyond cluster participants, cluster policy should be complemented by measures that facilitate knowledge diffusion, strengthen the absorptive capacity of non-cluster firms, and lower barriers to participation in cluster networks. Fifth, the LECC's focus on supporting already leading-edge clusters raises broader questions about the design and efficiency of cluster policy. While concentrating resources on internationally competitive clusters may maximize excellence, it may also increase the risk of agglomeration shadows, including the crowding out of less competitive neighboring regions, labor market frictions, and widening regional disparities. Thus, future policy designs should carefully consider the trade-off between concentrating resources in existing leading-edge clusters and supporting emerging high-technology clusters that may generate broader innovation benefits. Finally, the findings underline the importance of systematic *ex-post* evaluations of large-scale innovation programs. Given the considerable time lag between policy interventions and measurable innovation outcomes, evaluations conducted five to ten years after program completion are essential for capturing medium- and long-term effects. Combining ongoing monitoring with *ex-post* evaluations can strengthen policy learning by identifying which policy instruments are effective, under which conditions, and for which types of firms, thereby supporting the design of more effective, inclusive, and regionally balanced innovation policy.

Our study has several limitations that also point to promising avenues for future research. First, the LECC supported not only firms but also universities, research institutes, and other organizations that cannot be captured in our empirical analysis. Consequently, our analysis focuses on firm-level effects and does not account for the effect on these organizations and potential second-order effects arising from basic research results. Future research should adopt a broader innovation system perspective by examining the effect on different types of organizations to provide an overall assessment of cluster policy. Second, our measures of innovative activity and collaboration capture these concepts only partially: patents do not necessarily translate into products

or processes, while joint patenting reflects only one specific form of collaboration. This limitation is particularly relevant given our counterintuitive finding of declining joint patenting. Future research should combine quantitative analyses with survey or interview data to better understand whether this pattern reflects an exhaustion of collaboration opportunities or an increase in trust among the partners that reduced the need for formal arrangements. Third, while our analysis distinguishes between the R&D funding and systemic components of the LECC, it cannot fully assess how these components interact. In particular, it would be worthwhile to look into the question why some cluster firms participate in the R&D funding component while others rely solely on the systemic support provided by the cluster. In case of the LECC, some of these firms had participated in a cluster-internal selection process and not been successful while others did not apply for program funding at all. A better understanding of firms' participation decisions, the complementarities between the policy components, and the heterogeneity of treatment effects would provide valuable insights for the design of cluster policy. Fourth, as the LECC is a complex policy program that provides impulses in a variety of sectoral and regional innovation systems, the individual effects may differ significantly from one cluster to another. Together with the disadvantages of the available quantitative indicators, there is a risk that the actual effects of cluster policy are not adequately measured or understood. Fifth, our results reveal little evidence of localized spillovers to neighboring non-cluster firms. However, the underlying mechanisms remain difficult to identify with administrative and patent data alone. More fine-grained analyses, for example, conducting surveys or interviews of neighboring firms, could provide deeper insights into whether knowledge spillovers occur through channels such as labor mobility, supplier relationships, or informal interactions. Finally, the LECC was an important core element of the German Hightech Strategy and, with respect to funding volume, one of the core cluster programs in Europe on a national level. While this makes it an important case for analyzing cluster policy, the extent to which our findings generalize to smaller, less technology-intensive, or less mature clusters remains an open question. Comparative studies across different cluster policy programs and institutional contexts would help establish external validity of our findings and identify which policy components are most effective under different conditions.

References

- Aboal, D., Perera, M., & Rovira, F. (2020). Cluster development policies and firms' performance: Evidence from an emerging economy in latin america. *Journal of Entrepreneurship in Emerging Economies*, 12(5), 687–726.
- Almeida, P. (1996). Knowledge sourcing by foreign multinationals: Patent citation analysis in the u.s. semiconductor industry. *Strategic Management Journal*, 17(S2), 155–165.
- Angelino, P., Czarnitzki, D., & Volckaert, A. (2026). Cluster policy, innovation, and firm productivity. an econometric assessment of the flemish spearhead cluster program. *Journal of Regional Science*, 66(2), 426–444.
- Aranguren, M. J., de la Maza, X., Parrilli, M. D., Vendrell-Herrero, F., & Wilson, J. R. (2013). Nested methodological approaches for cluster policy evaluation: An application to the basque country. *Regional Studies*, 48(9), 1547–1562.
- Audretsch, D. B., Lehmann, E. E., Menter, M., & Seitz, N. (2018). Public cluster policy and firm performance: Evaluating spillover effects across industries. *Entrepreneurship & Regional Development*, 31(1–2), 150–165.
- Autant-Bernard, C., Fadairo, M., & Massard, N. (2013). Knowledge diffusion and innovation policies within the european regions: Challenges based on recent empirical evidence. *Research Policy*, 42(1), 196–210.
- Autio, E., & Rannikko, H. (2016). Retaining winners: Can policy boost high-growth entrepreneurship? *Research Policy*, 45(1), 42–55.
- Baptista, R., & Swann, P. (1998). Do firms in clusters innovate more? *Research Policy*, 27(5), 525–540.
- Barbieri, N., Ramaciotti, L., & Rizzo, U. (2022). The relationship between r&d knowledge spillovers and employment entry. *The Annals of Regional Science*, 71(3), 671–695.
- Bioeconomy. (2024). Retrieved February 18, 2024, from <https://www.bioeconomy.de/en/>
- BioM Biotech Cluster Development GmbH. (2024). *Leading-edge cluster m4*. Retrieved February 18, 2024, from <https://www.bio-m.org/en/about-biom/history/leading-edge-clusterm4.html>
- BMBF. (2006). *Die Hightech-Strategie für Deutschland* (tech. rep.). BMBF - Bundesministerium für Bildung und Forschung / Federal Ministry of Education and Research (BMBF), Berlin.
- BMBF. (2009). *Leitfaden zur Antragstellung im Spitzencluster-Wettbewerb (2. Wettbewerbsrunde) des Bundesministeriums für Bildung und Forschung* (tech. rep.). Bundesministerium für Bildung und Forschung / Federal Ministry of Education and Research (BMBF), Berlin.
- Boeing, P., & Mueller, E. (2016). *Measuring patent quality and national technological capacity in cross-country comparison* (ZEW Discussion Papers No. 16-048). ZEW - Leibniz Centre for European Economic Research.
- Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, 39(1), 61–74.
- Brakman, S., & van Marrewijk, C. (2013). Reflections on cluster policies. *Cambridge Journal of Regions, Economy and Society*, 6(2), 217–231.
- Breschi, S., & Lissoni, F. (2005). "Cross-firm" inventors and social networks: Localized knowledge spillovers revisited. *Annales d'Économie et de Statistique*, (79-80), 189–209.

- Breschi, S., & Lissoni, F. (2009). Mobility of skilled workers and co-invention networks: An anatomy of localized knowledge flows. *Journal of Economic Geography*, 9(4), 439–468.
- Breschi, S., & Lissoni, F. (2001). Knowledge spillovers and local innovation systems: A critical survey. *Industrial and Corporate Change*, 10(4), 975–1005.
- Breschi, S., & Lissoni, F. (2004). Knowledge networks from patent data: Methodological issues and research targets. In H. F. Moed, W. Glänzel, & U. Schmoch (Eds.), *Handbook of quantitative science and technology research: The use of publication and patent statistics in studies on S&T systems* (pp. 613–643). Springer.
- Bronzini, R., & Piselli, P. (2016). The impact of r&d subsidies on firm innovation. *Research Policy*, 45(2), 442–457.
- Brown, R., Mawson, S., & Mason, C. (2017). Myth-busting and entrepreneurship policy: The case of high growth firms. *Entrepreneurship & Regional Development*, 29(5–6), 414–443.
- Cantner, U. (2013). Innovationsentscheidungen und innovationspfade: Zwischen unsicherheit und risiko. In S. Jeschke, E.-M. Jakobs, & A. Dröge (Eds.), *Exploring uncertainty: Ungewissheit und unsicherheit im interdisziplinären diskurs* (pp. 295–312). Springer.
- Cantner, U., Graf, H., & Hinzmann, S. (2013). Policy induced innovation networks: The case of the german “leading-edge cluster competition”. In *The geography of networks and r/d collaborations* (pp. 335–352). Springer International Publishing.
- Cantner, U., & Kösters, S. (2011). Picking the winner? Empirical evidence on the targeting of R&D subsidies to start-ups. *Small Business Economics*, 39(4), 921–936.
- Chatterji, A., Glaeser, E., & Kerr, W. (2014). Clusters of entrepreneurship and innovation. *Innovation Policy and the Economy*, 14(1), 129–166.
- Cluster for individualized immune intervention (ci3) e.v. (2024). Retrieved February 18, 2024, from <https://ci-3.de/>
- Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128–152.
- Crass, D., Rammer, C., & Aschhoff, B. (2019). Geographical clustering and the effectiveness of public innovation programs. *The Journal of Technology Transfer*, 44(6), 1784–1815.
- Czarnitzki, D., & Hussinger, K. (2018). Input and output additionality of r&d subsidies. *Applied Economics*, 50(12), 1324–1341.
- Dahl, M. S., & Pedersen, C. Ø. R. (2004). Knowledge flows through informal contacts in industrial clusters: Myth or reality? *Research Policy*, 33(10), 1673–1686.
- Dahl, M. S., & Pedersen, C. Ø. R. (2005). Social networks in the r&d process: The case of the wireless communication industry around aalborg, denmark. *Journal of Engineering and Technology Management*, 22(1–2), 75–92.
- Delgado, M., Porter, M. E., & Stern, S. (2016). Defining clusters of related industries. *Journal of Economic Geography*, 16(1), 1–38.
- Digital hub logistics – effizienzcluster. (2024). Retrieved February 18, 2024, from <https://digitalhublogistics.de/effizienzcluster/>
- Dimos, C., & Pugh, G. (2016). The effectiveness of r&d subsidies: A meta-regression analysis of the evaluation literature. *Research Policy*, 45(4), 797–815.
- Dobkins, L. H., & Ioannides, Y. M. (2001). Spatial interactions among U.S. cities: 1900–1990. *Regional Science and Urban Economics*, 31(6), 701–731.

- Duranton, G. (2011). California dreamin': The feeble case for cluster policies. *Review of Economic Analysis*, 3(2), 3–45.
- E-mobil south-west. (2024).
- Edler, J., & Fagerberg, J. (2017). Innovation policy: What, why, and how. *Oxford Review of Economic Policy*, 33(1), 2–23.
- Engel, D., Eckl, V., & Rothgang, M. (2019). R&D funding and private R&D: Empirical evidence on the impact of the leading-edge cluster competition. *The Journal of Technology Transfer*, 44(6), 1720–1743.
- Engel, D., Mitze, T., Patuelli, R., & Reinkowski, J. (2013). Does cluster policy trigger R&D activity? Evidence from German biotech contests. *European Planning Studies*, 21(11), 1735–1759.
- Falck, O., Heblich, S., & Kipar, S. (2010). Industrial innovation: Direct evidence from a cluster-oriented policy. *Regional Science and Urban Economics*, 40(6), 574–582.
- Falk, M. (2012). Quantile estimates of the impact of R&D intensity on firm performance. *Small Business Economics*, 39(1), 19–37.
- Figal Garone, L., Maffioli, A., de Negri, J. A., Rodriguez, C. M., & Vázquez-Baré, G. (2015). Cluster development policy, sme's performance, and spillovers: Evidence from brazil. *Small Business Economics*, 44(4), 925–948.
- Fritsch, M., & Slavtchev, V. The role of regional knowledge for innovation. eng. In: 45th Congress of the European Regional Science Association: "Land Use and Water Management in a Sustainable Network Society", 23-27 August 2005, Amsterdam, The Netherlands. Louvain-la-Neuve: European Regional Science Association (ERSA), 2005.
- Fromhold-Eisebith, M., & Eisebith, G. (2008). Looking behind facades: Evaluating effects of (automotive) cluster promotion. *Regional Studies*, 42(10), 1343–1356.
- Fujita, M., Krugman, P., & Mori, T. (1999). On the evolution of hierarchical urban systems. *European Economic Review*, 43(2), 209–251.
- Funke, M., Niebuhr, A., Funke, M., & Niebuhr, A. (2000). Spatial r&d spillovers and economic growth - evidence from west germany.
- Gallé, J., Overbeck, D., Riedel, N., & Seidel, T. (2024). Place-based policies, structural change and female labor: Evidence from india's special economic zones. *Journal of Public Economics*, 240, 105259.
- Gambardella, A., Harhoff, D., & Verspagen, B. (2008). The value of European patents. *European Management Review*, 5(2), 69–84.
- Gilbert, B. A., McDougall, P. P., & Audretsch, D. B. (2008). Clusters, knowledge spillovers and new venture performance: An empirical examination. *Journal of Business Venturing*, 23(4), 405–422.
- Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy*, 100(6), 1126–1152.
- Graf, H., & Broekel, T. (2020). A shot in the dark? Policy influence on cluster networks. *Research Policy*, 49(3), 103920.
- Grashof, N. (2021). Putting the watering can away – Towards a targeted (problem-oriented) cluster policy framework. *Research Policy*, 50(9), 104335.

- Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, 28, 1661–1707.
- Grossman, G. M., & Helpman, E. (1991). Trade, knowledge spillovers, and growth. *European Economic Review*, 35(2-3), 517–526.
- Gulati, R. (1995). Does familiarity breed trust? the implications of repeated ties for contractual choice in alliances. *Academy of Management Journal*, 38(1), 85–112.
- Görg, H., & Mulyukova, A. (2024). Place-based policies and firm performance: Evidence from special economic zones in india. *European Economic Review*, 165, 104752.
- Hagedoorn, J. (2003). Sharing intellectual property rights - an exploratory study of joint patenting amongst companies. *Industrial and Corporate Change*, 12(5), 1035–1050.
- Hagedoorn, J., Link, A. N., & Vonortas, N. S. (2000). Research partnerships. *Research Policy*, 29(4-5), 567–586.
- Hagedoorn, J., van Kranenburg, H., & Osborn, R. N. (2003). Joint patenting amongst companies – exploring the effects of inter-firm R&D partnering and experience. *Managerial and Decision Economics*, 24(2–3), 71–84.
- Hall, B. H., Griliches, Z., & Hausman, J. A. (1986). Patents and r and d: Is there a lag? *International Economic Review*, 27(2), 265–283.
- Harhoff, D., Narin, F., Scherer, F. M., & Vopel, K. (1999). Citation frequency and the value of patented inventions. *Review of Economics and Statistics*, 81(3), 511–515.
- Harhoff, D., Scherer, F. M., & Vopel, K. (2003). Citations, family size, opposition and the value of patent rights. *Research Policy*, 32(8), 1343–1363.
- Hinzmann, S., Cantner, U., & Graf, H. (2019). The role of geographical proximity for project performance: Evidence from the German Leading-Edge Cluster Competition. *The Journal of Technology Transfer*, 44(6), 1744–1783.
- Iacus, S. M., King, G., & Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Association*, 106(493), 345–361.
- Iacus, S. M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, 20(1), 1–24.
- Intelligent Technical Systems OstWestfalenLippe (it’s OWL). (2024). *Strategy / it’s owl*. Retrieved February 18, 2024, from <https://www.its-owl.com/about-us/>
- Jacobs, J. (1969). *The economy of cities*. Vintage.
- Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108(3), 577–598.
- Jaffe, A. B., & de Rassenfosse, G. (2017). Patent citation data in social science research: Overview and best practices. *Journal of the Association for Information Science and Technology*, 68(6), 1360–1374.
- Kiese, M., & Hundt, C. (2014). Cluster policies, organising capacity and regional resilience: Evidence from German case studies. *Raumforschung und Raumordnung / Spatial Research and Planning*, 72(2), 117–131.
- Kuhlmann, S., & Edler, J. (2003). Scenarios of technology and innovation policies in europe: Investigating future governance. *Technological Forecasting and Social Change*, 70(7), 619–637.

- Lehmann, E. E., & Menter, M. (2018). Public cluster policy and neighboring regions: Beggar-thy-neighbor? *Economics of Innovation and New Technology*, 27(5–6), 420–437.
- Liu, X., Zhang, A., & Xie, Y. (2023). Industrial policy and cluster development: A literature review. *International Journal of Technology, Policy and Management*, 23(2), 187–215.
- Lucas, R. E., Jr. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22(1), 3–42.
- Lychagin, S., Pinkse, J., Slade, M. E., & Reenen, J. V. (2016). Spillovers in space: Does geography matter? *The Journal of Industrial Economics*, 64(2), 295–335.
- MAI Carbon – Composites United cluster. (2020). Retrieved February 18, 2024, from <https://composites-united.com/cluster/mai-carbon/>
- Martin, P., Mayer, T., & Mayneris, F. (2011). Public support to clusters: A firm level study of french “Local Productive Systems”. *Regional Science and Urban Economics*, 41(2), 108–123.
- Medical valley EMN. (2020). Retrieved February 18, 2024, from <https://www.medical-valley-emn.de/>
- Menzel, M.-P., & Fornahl, D. (2010). Cluster life cycles—dimensions and rationales of cluster evolution. *Industrial and Corporate Change*, 19(1), 205–238.
- Michel, J., & Bettels, B. (2001). Patent citation analysis. A closer look at the basic input data from patent search reports. *Scientometrics*, 51(1), 185–201.
- MicroTEC Südwest. (2024). *Microtec südwest*. Retrieved February 18, 2024, from <https://www.microtec-suedwest.de/en/>
- Moodysson, J. (2008). Principles and practices of knowledge creation: On the organization of “buzz” and “pipelines” in life science communities. *Economic Geography*, 84(4), 449–469.
- Müller, S., & Korsgaard, S. (2018). Resources and bridging: The role of spatial context in rural entrepreneurship. *Entrepreneurship & Regional Development*, 30(1–2), 224–255.
- Nishimura, J., & Okamuro, H. (2011). Subsidy and networking: The effects of direct and indirect support programs of the cluster policy. *Research Policy*, 40(5), 714–727.
- OECD. (1997). *National innovation systems*. OECD.
- OECD. (2007). *Oecd reviews of regional innovation: Competitive regional clusters*. OECD.
- Partridge, M. D., Rickman, D. S., Ali, K., & Olfert, M. R. (2009). Do new economic geography agglomeration shadows underlie current population dynamics across the urban hierarchy? *Papers in Regional Science*, 88(2), 445–467.
- Peri, G. (2005). Determinants of knowledge flows and their effect on innovation. *Review of Economics and Statistics*, 87(2), 308–322.
- Porter, M. E. (1998). Clusters and the new economics of competition. *Harvard Business Review Nov-Dec*, 77–90.
- Romer, P. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, 94(5), 1002–37.
- Rothgang, M., Cantner, U., Dehio, J., Engel, D., Fertig, M., Graf, H., Hinzmann, S., Linshalm, E., Ploder, M., Scholz, A. M., & Töpfer, S. (2017a). Cluster policy: Insights from the German leading-edge cluster competition. *Journal of Open Innovation: Technology, Market, and Complexity*, 3(1).

- Rothgang, M., Cantner, U., Dehio, J., Engel, D., Fertig, M., Graf, H., Hinzmann, S., Linshalm, E., Ploder, M., Scholz, A.-M., & Töpfer, S. (2014). *Begleitende Evaluierung des Förderinstruments "Spitzencluster-Wettbewerb" des BMBF* (tech. rep.).
- Rothgang, M., Dehio, J., & Lageman, B. (2017b). Analysing the effects of cluster policy: What can we learn from the German leading-edge cluster competition? *The Journal of Technology Transfer*, 44(6), 1673–1697.
- Rothgang, M., Lageman, B., & Scholz, A.-M. (2021). Why are there so few hard facts about the impact of cluster policies in germany? a critical review of evaluation studies. *Review of Evolutionary Political Economy*, 2(1), 105–139.
- Ruffner, J., & Spescha, A. (2018). The impact of clustering on firm innovation. *CESifo Economic Studies*, 64(2), 176–215.
- Shaver, J. M., & Flyer, F. (2000). Agglomeration economies, firm heterogeneity, and foreign direct investment in the united states. *Strategic Management Journal*, 21(12), 1175–1193.
- Smits, R., & Kuhlmann, S. (2004). The rise of systemic instruments in innovation policy. *International Journal of Foresight and Innovation Policy*, 1(1-2), 4–32.
- Software-Cluster. (2024). Retrieved February 18, 2024, from <https://software-cluster.org/en/>
- Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175–199.
- The Danish Agency for Science, Technology and Innovation. (2011). *The impacts of cluster policy in denmark: An impact study on behaviour and economical effects of innovation network denmark* (Available online). Ministry of Science, Technology and Innovation. Denmark.
- Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. *The RAND Journal of Economics*, 21(1), 172–187.
- Töpfer, S., Cantner, U., & Graf, H. (2019). Structural dynamics of innovation networks in German Leading-Edge Clusters. *The Journal of Technology Transfer*, 44(6), 1816–1839.
- Uyarra, E., & Ramlogan, R. (2016). The impact of cluster policy on innovation. In J. Edler, P. Cunningham, A. Gök, & P. Shapira (Eds.), *Handbook of Innovation Policy Impact* (pp. 196–238). Edward Elgar Publishing.
- Wang, N., & Hagedoorn, J. (2014). The lag structure of the relationship between patenting and internal r&d revisited. *Research Policy*, 43(8), 1275–1285.
- Wolf, T., Cantner, U., Graf, H., & Rothgang, M. (2017). Cluster ambidexterity towards exploration and exploitation: Strategies and cluster management. *The Journal of Technology Transfer*, 44(6), 1840–1866.
- Woolthuis, R. K., Lankhuizen, M., & Gilsing, V. (2005). A system failure framework for innovation policy design. *Technovation*, 25(6), 609–619.

Appendix

A Institutional background: Leading-Edge Cluster Competition

A.1 Program objectives and design

The "Leading-edge Cluster Competition" (LECC) was launched in 2007 as part of Germany's "High-Tech Strategy 2006"⁵. With a total budget of 600 million euros, LECC stands as the largest cluster program established by the government to date (Rothgang et al., 2017a), resulting in over 40 business startups, 300 patents, and 900 innovations (Lehmann & Menter, 2018). The primary objective of the program was to foster innovative capabilities and promote the development of efficient, highly productive clusters in Germany by offering financial support to collaborative R&D projects in selected cluster regions (Lehmann & Menter, 2018). Various strategies were employed to create an innovative ecosystem and to enhance regional innovation performance, including strengthening R&D collaboration among diverse stakeholders such as firms, universities, and research institutes (Töpfer et al., 2019).

Specifically, the LECC sought to generate positive impacts across six target levels: (1) projects, (2) actors, (3) cluster organizations, (4) clusters, (5) cluster regions, and (6) the national economy. As such, the program established a wide range of objectives concerning the future development of the Leading-Edge Clusters (Rothgang et al., 2017a).

- Enhancing the technological and economic competencies of Leading-Edge Clusters based on their strategic plans.
- Leveraging regional innovative potential to foster sustained value creation, with a focus on promoting novel forms of R&D collaboration, particularly in innovative domains.
- Elevating the international visibility and competitiveness of the clusters as premier technology hubs, while attracting innovative foreign enterprises to establish operations in cluster regions.
- Prioritizing the training of highly skilled professionals and workers.

In total, the cluster competition consisted of three rounds (in 2008, 2010, and 2012), during which the Federal Ministry selected 15 clusters based on the recommendations of an expert jury. These clusters, designated as Leading-Edge Clusters, received funding of up to 40 million euros per cluster over a five-year period (Hinzmann et al., 2019). The funding for the third wave of the LEC concluded in 2017 (Rothgang et al., 2017b). The awarded funds were utilized by the winning clusters to execute research and development projects in collaboration with partners sharing the same thematic focus (Hinzmann et al., 2019).

Unlike other political initiatives that concentrated on the identification and financing of specific regions through a top-down approach, the "Leading-edge cluster competition" encouraged self-selection processes among German regions. In this scenario, regions had to independently apply for financial and governmental support, thereby fostering a political bottom-up approach. This

⁵The "High-Tech Strategy 2006" was initiated by the German Federal Ministry of Education and Research (BMBF) with the objective of allocating public funding to foster innovation, and entrepreneurship, while also enhancing productivity and prosperity across German regions by leveraging their unique factors and resources (Lehmann & Menter, 2018)

approach aided regions in identifying and leveraging their unique regional factors and resources, ultimately contributing to successful outcomes and enhancing the overall efficiency of the cluster (Lehmann & Menter, 2018).

In summary, the overarching objective of the LECC was to bolster the German economy through multifaceted regional development. Consequently, policymakers focused on fostering collaboration between the public and private sectors and elevating the involvement of universities as active partners within funded clusters. These clusters, in turn, were tasked with cultivating an enabling environment, especially for small- and medium-sized enterprises, facilitating groundbreaking innovation and regional expansion (Lehmann & Menter, 2018).

A.2 Selection process and characteristics of funded clusters

As outlined earlier, the LECC designated funding for 15 cluster initiatives. Figure A1 depicts the geographical dispersion of these Leading-Edge Clusters alongside approximately 640 cluster programs established at the national or Länder (state) level in 2013. This visualization underscores the pivotal role of cluster support in Germany’s innovation policy. While all German Länder endorse clusters, there are notable variations in the number of clusters funded and the extent of support provided. Moreover, it is important to note that Leading-Edge Clusters are integrated into the cluster structures and networks sanctioned by the Länder. Typically, the Länder offer financial backing to clusters for a limited duration, occasionally leveraging funding avenues from the European Fund for Regional Development (EFRE) (Rothgang et al., 2017a).

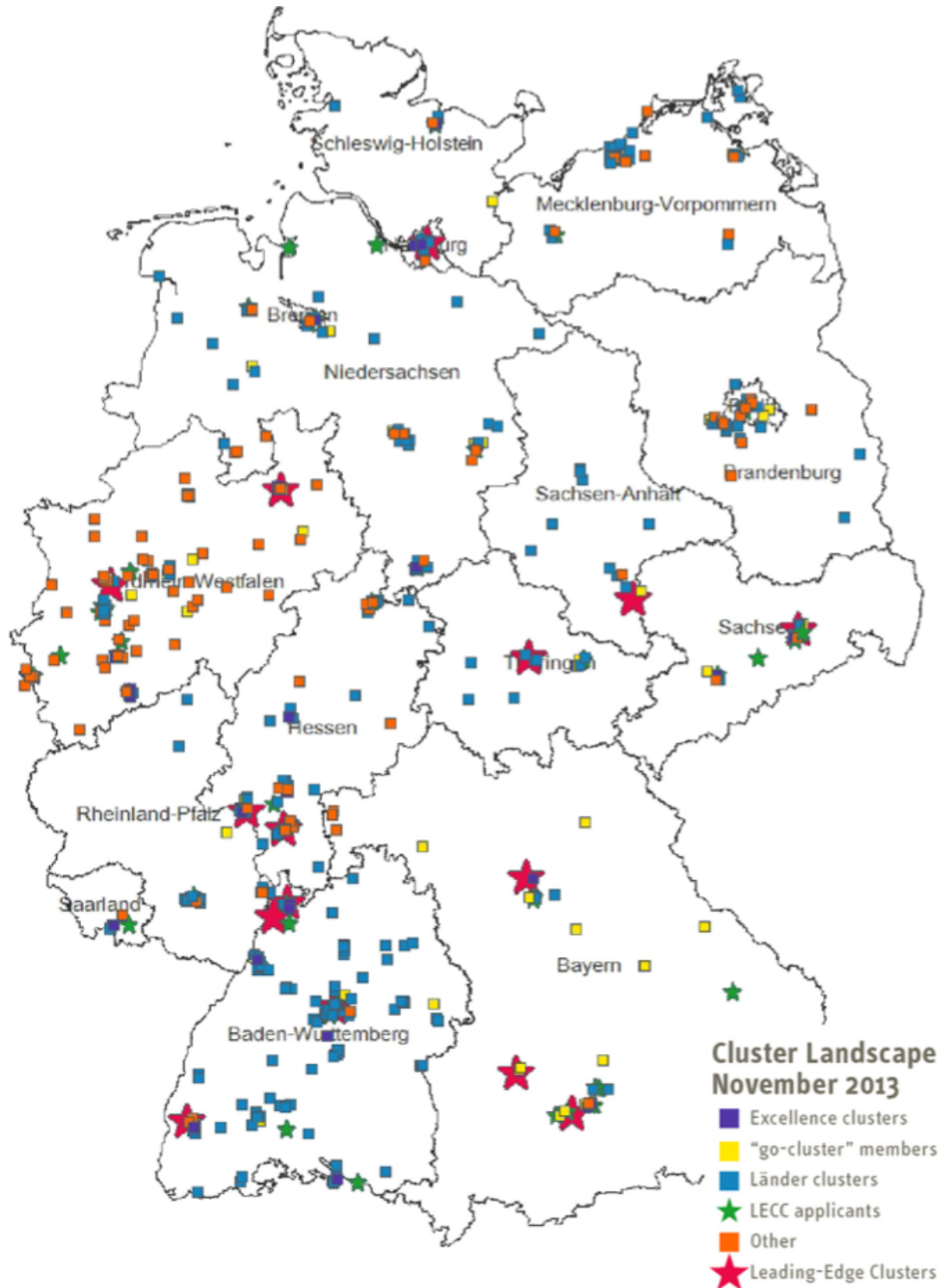
The selection process within the LECC involved a two-step selection mechanism overseen by a jury comprising representatives from both industry and academia. Notably, the competition welcomed proposals from all technology domains. The funding was allocated across three rounds, with the evaluation outcomes of the initial stage influencing the distribution of funds for the subsequent phase (Rothgang et al., 2017a).

The LECC’s selection process was transparent and well-structured, with clear proposal deadlines and thorough selection criteria. Figure A2 illustrates how LECC participants were distributed across three waves. The figure demonstrates that the LECC effectively encouraged new cluster initiatives in both the second and third rounds. Furthermore, the program played a role in enhancing the organizational and strategic processes of initially unsuccessful clusters, some of which succeeded in subsequent rounds. For example, in the second wave, 7 out of 10 finalists had previously been unsuccessful applicants in the first wave. Additionally, three applicants from the first wave and five from the second wave participated in the third wave of the cluster competition (Rothgang et al., 2017a).

The BMBF outlined specific requirements to uphold the innovative success of clusters, with the two key stipulations being:

- The presence of effective cluster management capable of coordinating activities within the cluster and facilitating connections between cluster participants by promoting collaboration between academia and industry (Töpfer et al., 2019).
- The cluster management, in collaboration with the cluster members’ committee, was tasked with pre-selecting projects and devising a collective cluster strategy that balanced exploration (new research) and exploitation (previous research) (Wolf et al., 2017). To achieve

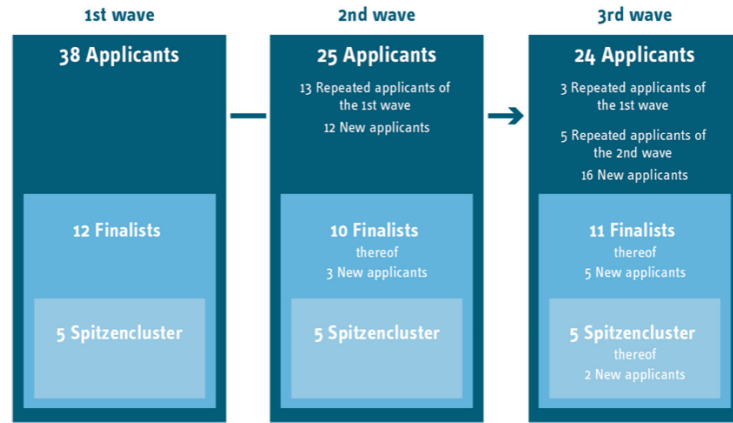
Figure A1: Geographical distribution of German cluster initiatives, 2013.



Notes: The map presents the geographical distribution of German cluster initiatives as of November 2013. Symbols distinguish Excellence Clusters, members of the federal “go-cluster” initiative, clusters supported by the German Länder, LECC applicants, other cluster initiatives, and the 15 clusters selected for funding through the LECC.
Source: Adapted from Rothgang et al. (2017a), p. 4.

this strategy, a strong emphasis was placed on fostering cooperation among all stakeholders. According to Töpfer et al. (2019), social cohesion notably improved during the LECC project phase, attributed to various initiatives organized by cluster management, such as regular formal and informal gatherings, as well as open seminars.

Figure A2: Applicants and selected clusters across three LECC competition waves



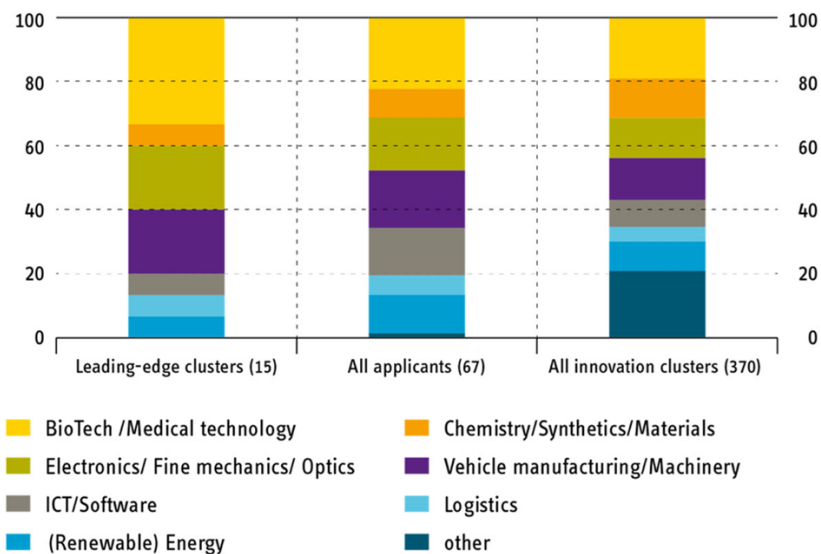
Notes: The figure summarizes the three selection waves of the LECC. The nested boxes represent the successive stages of the selection process: applicants, finalists, and the five Leading-Edge Clusters selected in each wave. The first wave received 38 applications, the second 25, and the third 24. The figure also distinguishes new applicants from applicants that participated again after an earlier wave.

Source: Adapted from Rothgang et al. (2017a), p. 2.

As previously mentioned, the LECC welcomed participation from all sectors and technological domains, which could explain its engagement across various industries. Additionally, the regional composition of industries and diversity play significant roles in determining the geographical distribution of cluster initiatives. Regions with higher levels of industrial development tend to host more cluster initiatives and networks. In essence, the prevalence of cluster initiatives correlates positively with the degree of regional industrialization. Consequently, nine out of fifteen Leading-Edge Clusters are situated in the more industrialized southern regions of Germany (Rothgang et al., 2017a).

Figure A3 illustrates the sectoral breakdown of the LECC compared to all applicants of the LECC and other innovative clusters in Germany. It is noticeable from this figure that, within the LECC, the biotechnology and medical technology sectors are prominent, with an average higher number of cluster applications. This prominence may be attributed to the existence of previous funding programs for networks and clusters, such as BioRegio, which facilitated the development of structures conducive to LECC candidacy. Additionally, other notable industries in the LECC include Electronics/Fine Mechanics/Optics and ICT/Software, which also exhibit a greater representation than other comparison groups (Rothgang et al., 2017a).

Figure A3: Sectoral composition of selected LECC clusters, LECC applicants, and German innovation clusters



Notes: The stacked bars report the percentage distribution of clusters across eight technology and industry categories for the 15 selected Leading-Edge Clusters, all 67 LECC applicants, and 370 German innovation clusters. Each bar sums to 100%, with the numbers in parentheses indicating the size of the corresponding group.

Source: Adapted from Rothgang et al. (2017a), p. 5.

Shifting the focus to those regions receiving support, the following is a brief overview of 15 unique clusters spanning different industries funded within the framework of the LECC:

1. **The "BioRN"** cluster, situated in the Rhein-Neckar region, specializes in red biotechnology. SMEs primarily lead this cluster, with significant involvement from large firms as major consumers. The cluster boasts a substantial presence of actors from the pharmaceutical industry, supplemented by knowledge-intensive services in life sciences and software development (Töpfer et al., 2019).
2. **"Cool Silicon"** operates across Dresden and Chemnitz, prioritizing enhanced energy efficiency within information and communication technology, particularly in microelectronics. As a result, cluster participants maintain close ties with electronic semiconductors and devices, medical technology, as well as industrial process and control technology sectors. Notably, unlike other major IT clusters globally (e.g., Silicon Valley in the USA), research and development activities are integrated with productive operations within this cluster (Töpfer et al., 2019).
3. The cluster **"Forum Organic Electronics" (FOE)**, situated in the Rhein-Neckar region, focuses on organic electronics, a cross-sectional technology offering a wide range of potential applications for the processing industry. The participants specialize in advanced and high-tech applications, mainly comprising large firms, renowned research institutes, and universities due to the innovative technology and significant emphasis on basic research. In contrast, the representation of SMEs is relatively lower compared to other selected clusters. Research objectives within FOE include organic LED and photovoltaic technologies, organic sensors, memories, and circuits (Töpfer et al., 2019).

4. **"Hamburg Aviation"** is located in the Hamburg region. This cluster encompasses two facets of the aviation industry. Primarily, it involves activities related to aerospace technology and engineering, such as the design and production of cabin systems, as well as innovative applications for fuel cells. Additionally, it encompasses a wide array of services associated with aeronautical techniques and air traffic management. "Hamburg Aviation" comprises a significant number of SMEs, alongside a few large firms, research organizations, and universities (Töpfer et al., [2019](#)).
5. **"Solar Valley"**, situated in Middle Germany encompassing Saxony, Saxony-Anhalt, and Thuringia, specializes in silicon-based photovoltaic and thin-film technology. The cluster participants are intricately involved in the semiconductor industry, with a particular emphasis on the production of electronic semiconductors, electronic and fine mechanical optical devices, as well as optical instruments, among others (Töpfer et al., [2019](#)).
6. **The Effizienz Cluster Logistic Ruhr**, located in Ruhr, serves as a global hub for pioneering the development of efficient and effective logistic services. Currently, the cluster comprises 160 companies alongside 12 scientific and educational institutions actively engaged in various projects. In addition to the cluster partners, the Effizienz Cluster Logistic Ruhr receives support from numerous other firms and organizations beyond the cluster's immediate scope ("Digital Hub Logistics – Effizienzcluster", [2024](#)).
7. Since 2010, **Medical Valley EMN** has been integrated into the LECC, covering the Nürnberg region. It focuses on developing efficient products and services in the realms of prevention, diagnosis, therapy, and rehabilitation, aiming to enhance overall healthcare structures. Within the LECC framework, Medical Valley partners have executed 45 R&D projects between 2010 and 2015, concentrating on five main areas: ophthalmology, diagnostics, imaging, horizontal innovation, as well as intelligent sensors and therapy systems. These endeavors have notably contributed to improving the efficiency of the healthcare system ("Medical Valley EMN", [2020](#)).
8. **The Munich Biotech Cluster**, situated in the Munich region, received LECC funding from 2010 to 2015. Specializing in personalized drugs and targeted therapies, the cluster engages over 100 partners from both industry and academia (BioM Biotech Cluster Development GmbH, [2024](#)).
9. One of the pioneering internationally renowned Leading-Edge Clusters (LECs) is **MicroTEC Southwest**, located in the Baden-Württemberg region. The primary objective of this cluster is to offer intelligent microsystem solutions in the domains of production and life sciences, with the aim of boosting the competitiveness of manufacturing companies while simultaneously enhancing safety, security, resource efficiency, and overall quality of life (MicroTEC Südwest, [2024](#)).
10. **The Software Cluster** stands as Europe's most robust network of companies and research institutions in the realm of software development. Encompassing a wide area in the southwest of Germany, including the cities of Darmstadt, Kaiserslautern, Karlsruhe, Saarbrücken, and Walldorf, along with their surroundings, the cluster places particular emphasis on enterprise software. It aims to bolster its technological leadership in cloud-based platforms

and Industry 4.0 solutions. To realize these objectives, since 2017, the cluster has forged strong collaborations with partners from the world’s most innovative regions, such as Silicon Valley (USA), Singapore, and Bahia (Brazil). These partnerships offer exceptional living laboratories for data-driven projects, capitalizing on vast amounts of diverse data (“Software-Cluster”, 2024).

11. Since its designation as a Leading-Edge Cluster in 2012, **the BioEconomy Cluster** has received funding from the German Federal Ministry of Education and Research until 2017. Operating across the regions of Sachsen-Anhalt and Sachsen, it brings together industry and scientific stakeholders to advance the material foundation and energetic utilization of non-food biomass. The BioEconomy cluster serves as a regional hub of expertise in bioeconomics, engaging a diverse range of industries including timber and forestry, chemicals, plastics, and plant engineering. Through the incorporation of upscaling methods, the cluster facilitates the swift transition of processes from laboratory-scale to industrial-scale development (“Bioeconomy”, 2024).
12. **The Cluster for Individual Immune Intervention (Ci3)** is situated in the Rhine-Main region, spanning across Rheinland-Pfalz, Hessen, and Baden-Württemberg. Similar to other Leading-Edge Clusters of the third wave, Ci3 received government funding from 2012 to 2017. The cluster is dedicated to consolidating exceptional and innovative expertise in individualized immune intervention, covering a spectrum of knowledge in drugs, diagnostics, and therapeutic approaches, with the overarching aim of positioning the region as a global leader in this field. Ci3’s projects predominantly address challenges associated with oncology, infections, and autoimmune diseases (“Cluster for Individualized Immune Intervention (Ci3) e.V.”, 2024).
13. **The Electric Mobility South-West Cluster** extends across the regions of Karlsruhe, Mannheim, Stuttgart, and Ulm, engaging over 120 stakeholders from both industry and science. The cluster’s primary objective is to drive technological advancements in the automotive sector, focusing on reducing pollution, enhancing efficiency, and promoting the acceptance of electric mobility in the market. To achieve these goals, the cluster management has formulated a comprehensive strategy that includes targets such as "Markets and Costs" (aiming to create competitive life-cycle expenditures), "Handling and Comfort" (meeting customer demands for electric vehicles), and "Connected Mobility" (improving the availability of transportation modes) (“e-mobil South-West”, 2024).
14. **It’s OWL (Intelligent Technical Systems Ostwestfalen-Lippe)** is among the five Leading-Edge Clusters of the third wave, situated in the Nordrhein-Westfalen region. The primary objective of this cluster is to create solutions for Intelligent Technical Systems, encompassing intelligent products and production methods. These systems emerge from the convergence of engineering sciences and information technology, characterized by their adaptability to the environment, robustness, user-friendliness, and high predictive capabilities. To achieve its overarching goal, the cluster fosters the development of new technological fields within its network, including machine intelligence, the design of socio-technical systems, digital infrastructure, safety and security, value-added networks, and advanced Systems Engineering (Intelligent Technical Systems OstWestfalenLippe (it’s OWL), 2024).

15. **MAI Carbon** stands as the final Leading-Edge Cluster endorsed by an independent jury during the third round (2012) of the LECC. Positioned strategically within the triangle of Munich, Augsburg, and Ingolstadt, the cluster benefits from a highly advantageous location. Leveraging quantum leap innovation, MAI Carbon endeavors to harness the lightweight construction potential of CFRP technology (Carbon fiber reinforced plastics), aiming to establish it as a standard not only in the automotive and aerospace sectors but also in the realm of mechanical engineering (“MAI Carbon – Composites United Cluster”, 2020).

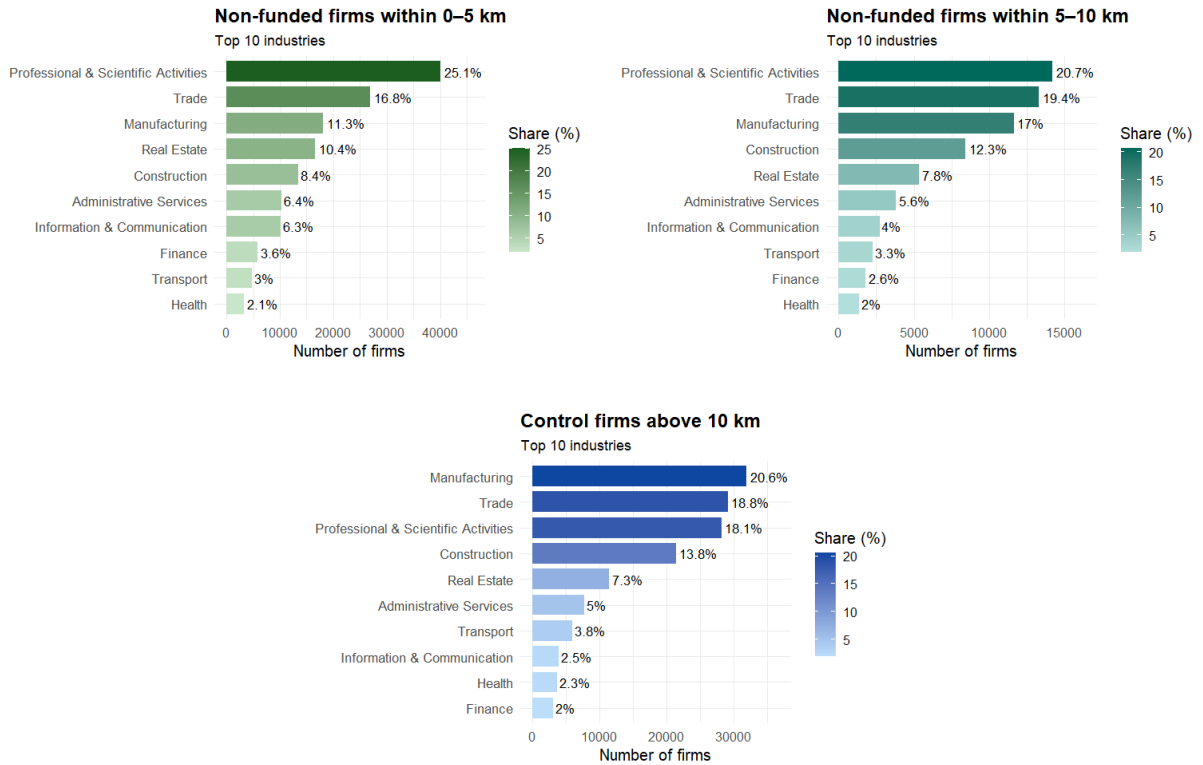
B Pre-treatment characteristics of neighboring non-cluster firms by distance

Table B1: Descriptive statistics for neighboring non-cluster firms by distance, 2007

	Firms within 0–5 km (N=159,999)	Firms within 5–10 km (N=68,711)	Control firms: above 10 km (N=155,555)	Overall (N=384,265)
Firm age	17.3 (20.8)	18.8 (21.7)	18.6 (23.1)	18.1 (21.9)
Log total assets	13.4 (2.17)	13.3 (1.96)	13.4 (1.92)	13.4 (2.04)
Log employment costs	14.7 (1.93)	14.5 (1.83)	14.5 (1.73)	14.6 (1.83)
Log adjusted patents	0.0214 (0.229)	0.0244 (0.236)	0.0201 (0.207)	0.0214 (0.222)
Log joint patents	0.00595 (0.107)	0.00581 (0.104)	0.00440 (0.0845)	0.00530 (0.0979)

Notes: The table reports descriptive statistics for non-cluster firms in 2007, grouped according to their distance from the nearest LECC cluster firm. The control group comprises non-cluster firms located more than 10 km away. Reported values are means, with standard deviations in parentheses. Variables labeled “Log” are transformed as $\log(1 + x)$. N denotes the total number of distinct firms in each distance group.

Figure B1: Industry composition of neighboring non-cluster firms by distance, 2007



Notes: The figure presents the ten largest aggregated NACE-based industry groups among non-cluster firms in 2007, separately for firms located within 0–5 km, within 5–10 km, and more than 10 km from the nearest LECC cluster firm. Industry shares are calculated separately within each distance group among firms with available industry information. Because only the ten largest industries are displayed, the reported shares do not sum to 100%.

C Coarsened Exact Matching (CEM)

C.1 Coarsened Exact Matching: Funded and non-funded cluster members

The same Coarsened Exact Matching (CEM) procedure is additionally implemented separately for funded and non-funded cluster members using the same set of pre-treatment covariates: firm age, firm size (log total assets), and 2-digit NACE industry classification (see Section 5.1 of the main paper for details). For both subsamples, funded and non-funded cluster members are matched to firms from the previously constructed pool of matched non-LECC firms.

Tables C1 and C2 report descriptive statistics before and after matching for funded and non-funded cluster members, respectively. Before matching, both funded and non-funded cluster members differ substantially from non-LECC firms, particularly in firm size, patenting activity, and collaborative innovation outcomes. Funded cluster members are, on average, older, larger, and substantially more innovative than non-LECC firms, while non-funded cluster members also exhibit higher levels of adjusted and joint patenting.

Table C1: Descriptive statistics before and after matching: Funded cluster members

Variable	Before matching			After matching		
	Funded LECC (N = 275)	Non-LECC (N = 751)	p-value	Funded LECC (N = 266)	Non-LECC (N = 266)	p-value
	mean (SD)	mean (SD)		mean (SD)	mean (SD)	
Firm age	23.4 (30.9)	19.4 (26.3)	0.054	23.4 (31.15)	22.9 (29.2)	0.822
Log total assets	16.3 (2.92)	15.5 (2.64)	0.001	16.3 (2.92)	16.2 (2.71)	0.644
Log employment costs	16.9 (1.99)	16.3 (1.90)	0.001	16.9 (1.95)	16.4 (1.97)	0.020
Log adjusted patents	1.05 (1.86)	0.31 (1.03)	0.001	1.05 (1.86)	0.45 (1.27)	0.001
Log joint patents	0.54 (1.29)	0.13 (0.61)	0.001	0.54 (1.29)	0.18 (0.77)	0.001

Notes: This table presents means and standard deviations (in parentheses) for funded LECC members and Non-LECC firms before and after matching. p-values are based on two-sided t-tests of mean differences. The pre-matching sample includes 275 treated and 751 control firms, while the matched sample includes 266 treated and 266 control firms. Total assets, employment costs, adjusted patents, and joint patents are transformed using $\ln(1 + x)$.

After matching, differences in the matching covariates become negligible, indicating that the matching procedure successfully improves comparability between treated and control firms. In the funded subsample, out of 275, 266 funded cluster firms are successfully matched to 266 non-LECC firms, while in the non-funded subsample, out of 476, 466 non-funded cluster firms are matched to 466 non-LECC firms. Differences in pre-treatment outcomes nevertheless remain, particularly for patenting activity. This is not unexpected because these outcomes are not used as matching variables and reflect the stronger pre-treatment innovative orientation of cluster firms. Overall, the matching procedure produces substantially more comparable control groups for the subsequent analysis.

Table C2: Descriptive statistics before and after matching: Non-funded cluster members

Variable	Before matching			After matching		
	Non-funded LECC (N = 476)	Non-LECC (N = 751)	p-value	Non-funded LECC (N = 466)	Non-LECC (N = 466)	p-value
	mean (SD)	mean (SD)		mean (SD)	mean (SD)	
Firm age	17.4 (24.8)	19.4 (26.3)	0.183	16.7 (23.5)	16.4 (21.6)	0.837
Log total assets	15.1 (2.70)	15.5 (2.64)	0.024	15.1 (2.72)	15.0 (2.55)	0.679
Log employment costs	16.4 (1.84)	16.3 (1.90)	0.483	16.4 (1.86)	16.2 (1.86)	0.340
Log adjusted patents	0.46 (1.22)	0.31 (1.03)	0.022	0.47 (1.23)	0.24 (0.89)	0.001
Log joint patents	0.19 (0.72)	0.13 (0.61)	0.085	0.20 (0.73)	0.11 (0.52)	0.025

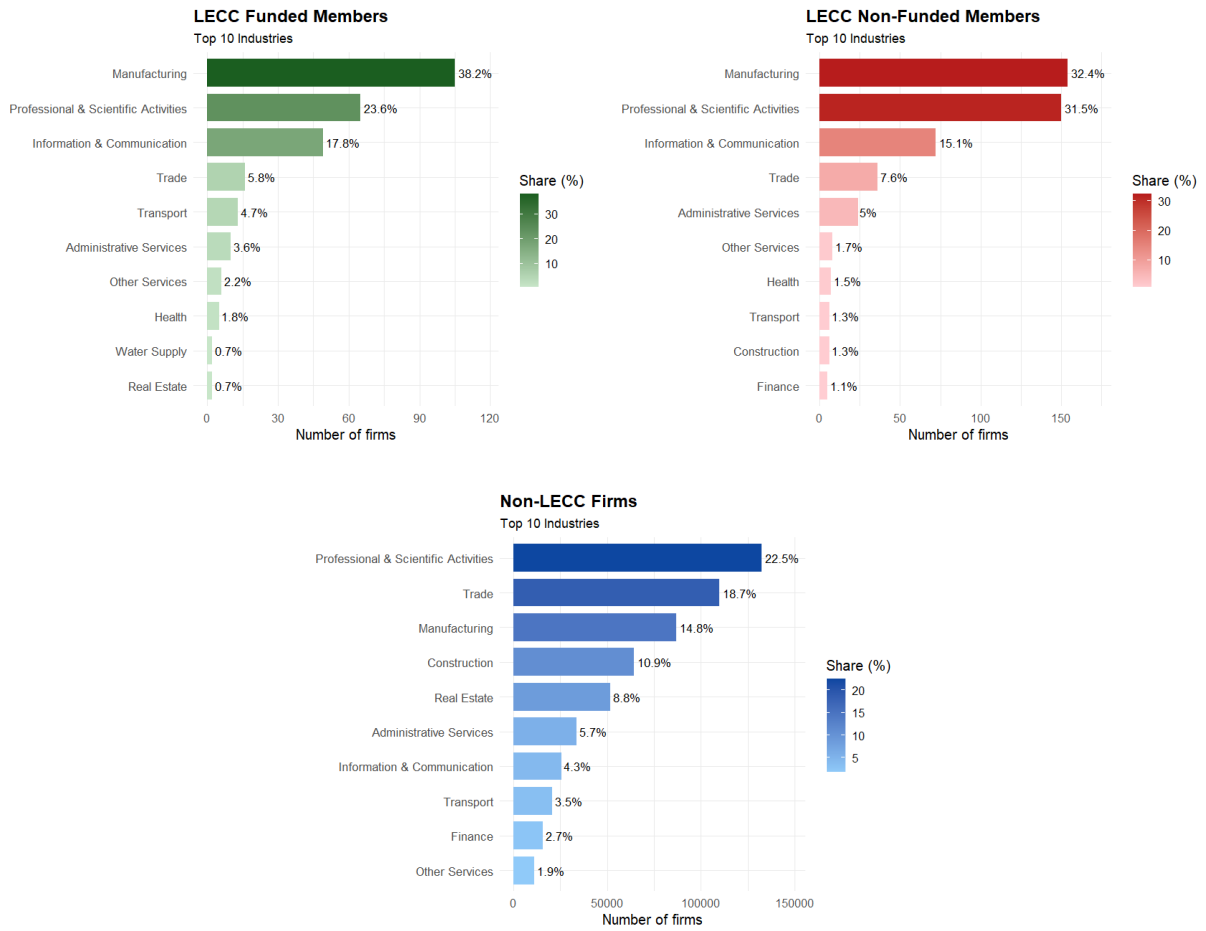
Notes: This table presents means and standard deviations (in parentheses) for non-funded LECC members and Non-LECC firms before and after matching. p-values are based on two-sided t-tests of mean differences. The pre-matching sample includes 476 treated and 751 control firms, while the matched sample includes 466 treated and 466 control firms. Total assets, employment costs, adjusted patents, and joint patents are transformed using $\ln(1 + x)$.

Figure C1 illustrates the industry composition of funded cluster members, non-funded cluster members, and non-LECC firms before matching. Both funded and non-funded LECC members are heavily concentrated in manufacturing and knowledge-intensive activities. Among funded cluster members, Manufacturing represents the largest industry group (38.2%), followed by Professional and Scientific Activities (23.6%) and Information and Communication (17.8%). Together, these three sectors account for almost 80% of all funded cluster firms. Non-funded cluster members exhibit a similar pattern, with Manufacturing (32.4%) and Professional and Scientific Activities (31.5%) accounting for nearly two-thirds of firms, while Information and Communication represents an additional 15.1%.

In contrast, non-LECC firms are more broadly distributed across industries. Professional and Scientific Activities (22.5%), Trade (18.7%), and Manufacturing (14.8%) constitute the largest sectors, while Construction (10.9%) and Real Estate (8.8%) are substantially more prevalent than among cluster members. Information and Communication accounts for only 4.3% of non-LECC firms, compared with 17.8% and 15.1% among funded and non-funded cluster members, respectively.

These differences highlight the strong sectoral specialization of cluster members in manufacturing and technology-intensive industries. Since industry affiliation is likely correlated with innovation performance, patenting activity, and collaborative behavior, we match both groups (funded vs non-funded cluster members) separately to non-cluster 2-digit NACE industry classifications to ensure comparability between treated and control firms. After the matching, the industry distribution of both groups (funded and non-funded cluster members) and non-cluster firms is identical.

Figure C1: Industry composition before matching, by firm group



Notes: The figure presents the industry composition of funded cluster members, non-funded cluster members, and non-LECC firms in 2007, prior to matching. Industry groups are constructed by aggregating two-digit NACE classifications into broader sectors. Shares are calculated separately within each group among firms with available industry information. The distribution of non-LECC firms therefore refers to the unmatched pool of potential comparison firms rather than to the final matched estimation sample.

D Robustness Checks

In this section, we assess the robustness of our baseline results by augmenting the empirical specification with additional high-dimensional fixed effects. Specifically, we sequentially introduce Industry-Year and State-Year fixed effects to account for time-varying unobserved heterogeneity at the industry and regional levels. This approach allows us to control for shocks and trends that may simultaneously affect treated and control firms within industries or states, thereby reducing concerns about omitted variable bias. We apply these robustness checks to the analysis of direct effects, as well as to the analyses for funded and non-funded cluster members.

D.1 Overall direct effect of the LECC

Table D1 reports the results across three specifications. The estimated average effects on employment costs remain positive and statistically significant at the 1% level throughout, with ATT estimates ranging from 0.1640 to 0.1907.

For innovation outcomes, the ATT for adjusted patents remains positive and statistically significant at the 5% level across all specifications, with estimates ranging from 0.0625 to 0.0859. The average effect on joint patents becomes less negative as additional fixed effects are introduced: the ATT changes from -0.0629 in Specification I to -0.0449 in Specification II and -0.0349 in Specification III. It is significant at the 1% level in Specification I and the 10% level in Specification II, but is no longer statistically significant in Specification III. Nevertheless, the negative coefficient for the pooled period four or more years after treatment remains significant across all three specifications.

The cohort-specific results show that the 2008 cohort has the largest employment-cost point estimates across specifications, although its estimate is significant only at the 10% level in Specification III. The 2012 cohort has the largest point estimates for adjusted patents, but these are not statistically significant in every specification. Its estimated effects on joint patenting remain negative and statistically significant throughout, although the significance level varies across specifications.

These checks support the robustness of the positive average effects on employment costs and adjusted patents. The evidence for a negative average effect on joint patenting is more sensitive to the fixed-effects specification.

Table D1: Direct LECC effects on cluster firms: Alternative fixed-effects specifications

	I			II			III		
Dependent Variables:	Patent (adjusted)	Joint patents	Employment costs	Patent (adjusted)	Joint patents	Employment costs	Patent (adjusted)	Joint patents	Employment costs
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Variables</i>									
Year = -4	0.0068 (0.0315)	-0.0117 (0.0203)	-0.0589 (0.0479)	-0.0155 (0.0362)	-0.0230 (0.0253)	-0.0844 (0.0639)	-0.0121 (0.0387)	-0.0321 (0.0272)	-0.0558 (0.0662)
Year = -3	0.0217 (0.0290)	-0.0059 (0.0190)	-0.0346 (0.0316)	0.0361 (0.0344)	-0.0055 (0.0221)	-0.0386 (0.0421)	0.0462 (0.0391)	-0.0147 (0.0249)	-0.0231 (0.0451)
Year = -2	0.0314 (0.0246)	0.0092 (0.0177)	-0.0311 (0.0321)	0.0328 (0.0287)	-0.0015 (0.0197)	-0.0357 (0.0339)	0.0284 (0.0313)	-0.0018 (0.0215)	-0.0426 (0.0356)
Year = 0	0.0550** (0.0243)	-0.0078 (0.0209)	0.0892*** (0.0310)	0.0613** (0.0289)	0.0011 (0.0248)	0.0803** (0.0371)	0.0630** (0.0316)	0.0060 (0.0277)	0.0832** (0.0372)
Year = 1	0.0381 (0.0288)	-0.0069 (0.0219)	0.1140*** (0.0316)	0.0524 (0.0345)	0.0116 (0.0259)	0.1240*** (0.0392)	0.0486 (0.0414)	0.0190 (0.0319)	0.1163** (0.0481)
Year = 2	0.0877*** (0.0337)	-0.0364 (0.0283)	0.1697*** (0.0392)	0.1160*** (0.0422)	-0.0172 (0.0307)	0.1861*** (0.0518)	0.1413*** (0.0476)	0.0081 (0.0373)	0.1895*** (0.0552)
Year = 3	0.1071*** (0.0394)	-0.0606** (0.0304)	0.1706*** (0.0390)	0.1249*** (0.0466)	-0.0555 (0.0338)	0.2120*** (0.0523)	0.1284** (0.0515)	-0.0442 (0.0390)	0.2039*** (0.0547)
Year = 4	0.0499 (0.0388)	-0.1170*** (0.0341)	0.2088*** (0.0528)	0.0546 (0.0472)	-0.0912** (0.0370)	0.2548*** (0.0682)	0.0744 (0.0507)	-0.0842** (0.0404)	0.2131*** (0.0725)
ATT	0.0625** (0.0288)	-0.0629*** (0.0241)	0.1640*** (0.0371)	0.0742** (0.0354)	-0.0449* (0.0259)	0.1907*** (0.0475)	0.0859** (0.0391)	-0.0349 (0.0295)	0.1731*** (0.0491)
CATT (cohort = 2008)	0.0360 (0.0743)	-0.0648 (0.0499)	0.2116*** (0.0627)	0.0216 (0.0851)	-0.0240 (0.0533)	0.2484*** (0.0830)	0.0646 (0.0900)	-0.0466 (0.0607)	0.1908* (0.1049)
CATT (cohort = 2010)	0.0592* (0.0318)	-0.0362 (0.0275)	0.1314*** (0.0434)	0.0864** (0.0395)	-0.0334 (0.0313)	0.1595*** (0.0616)	0.0846* (0.0472)	-0.0036 (0.0369)	0.1665*** (0.0581)
CATT (cohort = 2012)	0.1246** (0.0607)	-0.1830*** (0.0669)	0.1829** (0.0886)	0.1108 (0.0715)	-0.1347* (0.0730)	0.1882* (0.0985)	0.1297* (0.0769)	-0.1583** (0.0762)	0.1631 (0.1037)
<i>Fixed-effects</i>									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year				Yes	Yes	Yes	Yes	Yes	Yes
State-Year							Yes	Yes	Yes
<i>Fit statistics</i>									
Observations	16,109	16,109	7,071	16,109	16,109	7,071	16,109	16,109	7,071
Number of firms	1502	1502	1502	1502	1502	1502	1502	1502	1502
R ²	0.89070	0.79082	0.95806	0.91166	0.84115	0.97281	0.91287	0.84470	0.97408
Within R ²	0.00344	0.01183	0.01751	0.00413	0.00646	0.02372	0.00466	0.00780	0.01564

Notes: The table reports event-study estimates following Sun and Abraham (2021) for all LECC cluster firms relative to matched non-cluster comparison firms. Treatment timing is defined by the year in which the respective cluster received LECC funding. All dependent variables are transformed as $\log(1 + x)$. Event time $t = -1$ is the omitted reference period, while the endpoints at $t = -4$ and $t = 4$ pool event times $t \leq -4$ and $t \geq 4$, respectively. Specification I includes firm and year fixed effects. Specification II additionally includes year-by-industry fixed effects, and Specification III further includes year-by-state fixed effects. The ATT is the weighted average of the post-treatment effects across cohorts and event periods. The CATTs report the average post-treatment effect separately for the 2008, 2010, and 2012 treatment cohorts. Standard errors clustered at the firm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

D.2 The effect on funded and non-funded cluster members

Tables D2 and D3 present the results separately for funded and non-funded cluster members. Across the three specifications, the signs of the ATT estimates remain unchanged, although their magnitudes and statistical precision changes when year-industry and year-state fixed effects are added.

For funded cluster members, the estimated effects on employment costs are positive and statistically significant at the 1% level across all specifications, with ATT estimates ranging from 0.1929 to 0.2142. By contrast, the estimated effects on quality-adjusted patents are positive, but statistically not significant throughout. The ATT for joint patents is negative and statistically significant at the 5% level in Specification I (-0.0902) but becomes smaller and statistically insignificant after the additional fixed effects are included.

For non-funded cluster members, the estimated effect on employment costs remains positive across all specifications, although it is only weakly significant in Specifications I and III (at the 10% level). The ATT estimates for quality-adjusted patents are also positive, but their statistical significance weakens as additional fixed effects are introduced. The ATT estimates for joint patents remain negative and statistically insignificant in all specifications. At the cohort level, the positive adjusted-patent effect for non-funded members in the 2012 cohort remains significant at the 5% level or better throughout.

In terms of R-squared values, the inclusion of extra fixed effects does lead to slight improvements in some cases. For example, in Models II and III for both funded and non-funded cluster members, there are small increases in the R-squared values compared to Model I. This indicates that the additional fixed effects may capture some additional variation in the outcomes, leading to a slightly better model fit.

Overall, while the inclusion of extra fixed effects does improve the explanatory power of the models marginally, it doesn't significantly alter the estimated coefficients for the LECC policy. Thus, the additional fixed effects contribute to better explaining variations in the outcomes without changing the overall interpretation of the LECC policy effects.

Table D2: Direct LECC effects on funded cluster members: Alternative fixed-effects specifications

	I			II			III		
Dependent Variables: Model:	Patent (adjusted) (1)	Joint patents (2)	Employment costs (3)	Patent (adjusted) (4)	Joint patents (5)	Employment costs (6)	Patent (adjusted) (7)	Joint patents (8)	Employment costs (9)
<i>Variables</i>									
Year = -4	0.0416 (0.0579)	0.0430 (0.0403)	-0.0304 (0.0842)	0.0514 (0.0721)	0.0849 (0.0533)	-0.0932 (0.0947)	0.0026 (0.0767)	0.0261 (0.0505)	-0.1067 (0.0998)
Year = -3	-0.0095 (0.0522)	0.0096 (0.0360)	-0.0689 (0.0555)	0.0750 (0.0672)	0.0861* (0.0471)	-0.1126 (0.0742)	0.0220 (0.0774)	0.0392 (0.0506)	-0.1009 (0.0722)
Year = -2	0.0158 (0.0460)	0.0392 (0.0314)	0.0145 (0.0438)	0.0519 (0.0638)	0.0605 (0.0382)	-0.0142 (0.0412)	0.0149 (0.0704)	0.0354 (0.0411)	-0.0245 (0.0485)
Year = 0	0.0574 (0.0447)	0.0070 (0.0376)	0.1341*** (0.0511)	0.0388 (0.0566)	0.0346 (0.0451)	0.1049** (0.0479)	0.0508 (0.0622)	0.0253 (0.0479)	0.1107** (0.0511)
Year = 1	0.0026 (0.0485)	-0.0133 (0.0370)	0.1667*** (0.0518)	0.0252 (0.0629)	0.0386 (0.0457)	0.1359** (0.0569)	-0.0158 (0.0730)	0.0082 (0.0512)	0.1728** (0.0759)
Year = 2	0.1020* (0.0591)	-0.0018 (0.0470)	0.2158*** (0.0610)	0.1324* (0.0755)	0.0501 (0.0527)	0.1795*** (0.0660)	0.1216 (0.0826)	0.0461 (0.0590)	0.1968*** (0.0836)
Year = 3	0.1236* (0.0683)	-0.0863* (0.0518)	0.2333*** (0.0586)	0.1429* (0.0859)	-0.0922 (0.0565)	0.1843*** (0.0690)	0.0854 (0.0891)	-0.1122* (0.0608)	0.1878** (0.0907)
Year = 4	0.0382 (0.0643)	-0.1855*** (0.0621)	0.2528*** (0.0751)	0.0496 (0.0816)	-0.1450** (0.0713)	0.2532** (0.1065)	0.0416 (0.0838)	-0.1380* (0.0799)	0.2627** (0.1187)
<i>Fixed-effects</i>									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year				Yes	Yes	Yes	Yes	Yes	Yes
State-Year							Yes	Yes	Yes
ATT	0.0569 (0.0491)	-0.0902** (0.0417)	0.2142*** (0.0560)	0.0692 (0.0622)	-0.0549 (0.0455)	0.1929*** (0.0675)	0.0519 (0.0658)	-0.0613 (0.0515)	0.2062*** (0.0753)
CATT (cohort = 2008)	-0.0803 (0.1098)	-0.1236 (0.0763)	0.1997** (0.0858)	-0.0300 (0.1357)	-0.0473 (0.0882)	0.2364* (0.1219)	-0.0267 (0.1461)	-0.0798 (0.1045)	0.2942** (0.1482)
CATT (cohort = 2010)	0.1391*** (0.0483)	-0.0201 (0.0493)	0.2061*** (0.0586)	0.1355** (0.0600)	-0.0188 (0.0597)	0.2032** (0.0865)	0.1071 (0.0666)	-0.0085 (0.0637)	0.2100** (0.0931)
CATT (cohort = 2012)	0.0753 (0.1141)	-0.2634** (0.1110)	0.2687 (0.1692)	0.0585 (0.1492)	-0.1998 (0.1231)	0.0695 (0.1313)	0.0342 (0.1504)	-0.2067 (0.1310)	0.0045 (0.1321)
<i>Fit statistics</i>									
Observations	5,902	5,902	3,189	5,902	5,902	3,189	5,902	5,902	3,189
R ²	0.90999	0.82590	0.95475	0.93531	0.88841	0.97694	0.93811	0.89459	0.97979
Within R ²	0.00765	0.02598	0.02594	0.00697	0.02047	0.02757	0.00798	0.01389	0.02538

Notes: The table reports event-study estimates following Sun and Abraham (2021) for funded LECC cluster members relative to separately matched non-cluster comparison firms. Treatment timing is defined by the year in which the respective cluster received LECC funding. All dependent variables are transformed as $\log(1+x)$. Event time $t = -1$ is the omitted reference period, while the endpoints at $t = -4$ and $t = 4$ pool event times $t \leq -4$ and $t \geq 4$, respectively. Specification I includes firm and year fixed effects. Specification II additionally includes year-by-industry fixed effects, and Specification III further includes year-by-state fixed effects. The ATT is the weighted average of the post-treatment effects across cohorts and event periods. The CATTs report the average post-treatment effect separately for the 2008, 2010, and 2012 treatment cohorts. Standard errors clustered at the firm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D3: Direct LECC effects on non-funded cluster members: Alternative fixed-effects specifications

	I			II			III		
Dependent Variables: Model:	Patent (adjusted) (1)	Joint patents (2)	Employment costs (3)	Patent (adjusted) (4)	Joint patents (5)	Employment costs (6)	Patent (adjusted) (7)	Joint patents (8)	Employment costs (9)
<i>Variables</i>									
Year = -4	-0.0165 (0.0377)	-0.0460** (0.0230)	-0.0940* (0.0559)	-0.0460 (0.0453)	-0.0703** (0.0295)	-0.1777** (0.0819)	-0.0382 (0.0467)	-0.0617** (0.0314)	-0.1463* (0.0829)
Year = -3	0.0399 (0.0351)	-0.0098 (0.0223)	-0.0093 (0.0372)	0.0421 (0.0429)	-0.0296 (0.0262)	-0.0323 (0.0577)	0.0645 (0.0497)	-0.0237 (0.0311)	-0.0430 (0.0701)
Year = -2	0.0455 (0.0288)	-0.0053 (0.0220)	-0.0727 (0.0497)	0.0239 (0.0333)	-0.0297 (0.0252)	-0.0883 (0.0584)	0.0243 (0.0361)	-0.0146 (0.0276)	-0.1021 (0.0629)
Year = 0	0.0561* (0.0292)	-0.0094 (0.0260)	0.0467 (0.0411)	0.0605* (0.0360)	-0.0146 (0.0314)	-0.0044 (0.0629)	0.0311 (0.0401)	-0.0054 (0.0390)	-0.0101 (0.0648)
Year = 1	0.0658* (0.0370)	0.0050 (0.0274)	0.0486 (0.0408)	0.0791* (0.0454)	0.0126 (0.0342)	0.0704 (0.0563)	0.0534 (0.0589)	0.0271 (0.0476)	0.0566 (0.0892)
Year = 2	0.0930** (0.0415)	-0.0455 (0.0357)	0.1178** (0.0535)	0.1089** (0.0524)	-0.0446 (0.0390)	0.1446* (0.0859)	0.1215* (0.0637)	-0.0135 (0.0521)	0.1681* (0.0921)
Year = 3	0.1144** (0.0483)	-0.0420 (0.0381)	0.1021* (0.0552)	0.1410** (0.0574)	-0.0286 (0.0451)	0.1968** (0.0873)	0.1458** (0.0684)	0.0023 (0.0541)	0.2044** (0.0916)
Year = 4	0.0562 (0.0496)	-0.0694* (0.0402)	0.1405* (0.0765)	0.0804 (0.0628)	-0.0496 (0.0450)	0.2743*** (0.1026)	0.0863 (0.0741)	-0.0436 (0.0478)	0.2177** (0.0996)
ATT	0.0714** (0.0362)	-0.0405 (0.0300)	0.1015* (0.0521)	0.0898* (0.0459)	-0.0303 (0.0339)	0.1651** (0.0757)	0.0858 (0.0557)	-0.0152 (0.0400)	0.1458* (0.0757)
CATT (cohort = 2008)	0.1591 (0.1018)	0.0233 (0.0635)	0.2184** (0.0958)	0.1340 (0.1114)	0.0240 (0.0666)	0.3112** (0.1356)	0.1839 (0.1218)	-0.0043 (0.0763)	0.1778 (0.1622)
CATT (cohort = 2010)	0.0286 (0.0415)	-0.0434 (0.0340)	0.0501 (0.0659)	0.0658 (0.0539)	-0.0326 (0.0390)	0.1212 (0.0984)	0.0446 (0.0723)	0.0050 (0.0485)	0.1521* (0.0923)
CATT (cohort = 2012)	0.1757*** (0.0671)	-0.1157 (0.0840)	0.1154 (0.0736)	0.1560** (0.0729)	-0.0955 (0.0896)	0.1137 (0.1584)	0.1669** (0.0806)	-0.1394 (0.0967)	0.0800 (0.2117)
<i>Fixed-effects</i>									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year				Yes	Yes	Yes	Yes	Yes	Yes
State-Year							Yes	Yes	Yes
<i>Fit statistics</i>									
Observations	9,782	9,782	3,636	9,782	9,782	3,636	9,782	9,782	3,636
R ²	0.86144	0.73100	0.95869	0.89830	0.81120	0.97733	0.90099	0.81788	0.97973
Within R ²	0.00649	0.00578	0.01454	0.00768	0.00588	0.03775	0.00839	0.00844	0.03077

Notes: The table reports event-study estimates following Sun and Abraham (2021) for non-funded LECC cluster members relative to separately matched non-cluster comparison firms. Treatment timing is defined by the year in which the respective cluster received LECC funding. All dependent variables are transformed as $\log(1 + x)$. Event time $t = -1$ is the omitted reference period, while the endpoints at $t = -4$ and $t = 4$ pool event times $t \leq -4$ and $t \geq 4$, respectively. Specification I includes firm and year fixed effects. Specification II additionally includes year-by-industry fixed effects, and Specification III further includes year-by-state fixed effects. The ATT is the weighted average of the post-treatment effects across cohorts and event periods. The CATTs report the average post-treatment effect separately for the 2008, 2010, and 2012 treatment cohorts. Standard errors clustered at the firm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.