Clusters of Excellence and Science Spillovers to Industry: Evidence from Additive Manufacturing*

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Abstract

Competitive public research funding is an important policy instrument to foster scientific progress. The effective design of such funding schemes and whether they generate knowledge spillovers to industrial inventions, however, remains debated. In this paper, we investigate the impacts of geographically localized forum grants—Clusters of Excellence—awarded for additive manufacturing research under Germany's Excellence Initiative from 2006–2012. Using synthetic difference-in-differences estimation, we find that Clusters increased local scientific output in funding-related domains in the right tail of the scientific impact distribution—as measured by article citations—compared to non-funded applicant groups in similar locations. While patenting by nearby firms remained unaffected at the extensive margin, we find evidence for significant knowledge spillovers to local industry. These manifested as a rise in the number of high-impact firm patents confined to related technical areas, and Clusters receiving a significantly larger number of prior art citations from industry patents, compared to the control group, which were geographically localized and confined to top publications. Our findings support the effectiveness of forum-based funding programs for top science and provide dual implications for research and industrial policy.

Keywords: Frontier science, research funding, knowledge spillovers, industry-science linkages

JEL codes: I23, O31, O38.

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1 Introduction

Universities are substantial drivers of economic growth. Being the principal breeding grounds of scientific knowledge and open loci of science transfer, they provide important spillovers to the broader economy (Jaffe, 1989; Mansfield, 1995; Henderson et al., 1998; Cohen et al., 2002; Bikard and Marx, 2020; Hausman, 2022). Prior literature has emphasized the direct link between scientific knowledge and commercial applications (Audretsch and Stephan, 1996; Gittelman and Kogut, 2003; Fleming and Sorenson, 2004; Krieger et al., 2024), in particular between scientific excellence and technological progress in industry (Hicks et al., 2000; Iaria et al., 2018; Poege et al., 2019; Schaper et al., 2025). A key question for science policy is, therefore, whether targeted research funding can foster the production of scientific knowledge relevant to business and society (Scherer and Harhoff, 2000; European Commisson, 2024). A growing body of work in the economics of science and innovation has established that competitive research funding can increase scientific output (Carayol and Matt, 2004; Jacob and Lefgren, 2011b; Hottenrott and Lawson, 2017; Heyard and Hottenrott, 2021), that the type of funding matters for the type of output (Azoulay et al., 2011; Myers, 2020; Veugelers et al., 2022), and that public research and development (R&D) grants spur industry patenting (Azoulay et al., 2019). However, it remains unclear which specific design of funding schemes would be (most) effective, both in terms of scientific advancement and industry spillovers.

This paper contributes to a better understanding of this link by studying the impacts of Germany's Clusters of Excellence, a flagship funding program aimed at supporting cutting-edge research in specific areas at the frontier of science through geographically localized forum-based grants. Introduced in 2006, this program has funded more than 106 Clusters of Excellence across Germany, with renewable up to seven-year terms.[1] It is one of the central pillars of the German Excellence Strategy—a large-scale funding scheme for German universities, administered by the German Research Foundation (DFG), with the goal of strengthening their competitiveness on a national and international level (Möller et al., 2016; Schiermeier, 2017; Schubert et al., 2017). Clusters of Excellence, specifically, aim to foster the agglomeration of frontier scientific human capital through financing groups of researchers who dedicate joint research efforts to a specific topic (Deutsche Forschungsgemeinschaft, 2015). In this analysis, we focus on Clusters in the broader area of additive manufacturing (AM). Researchers in this domain have received multiple Cluster grants, and emerging technological applications in this area were strongly reliant on fundamental science and still in their infant diffusion stage in the manufacturing industry during the first funding round of the Excellence Strategy (still carried out under its pre-

[1] A comprehensive list of all Clusters of Excellence, detailing their research focuses, participating institutions, and funding structures under Germany's Excellence Strategy, is available on the GEPRIS platform of the German Research Foundation. See https://gepris.dfg.de/gepris/OCTOPUS accessed on 09/01/2025.

decessor, the Excellence Initiative) (Campbell et al., 2023). Additive manufacturing was also defined as one of the Key Enabling Technologies (KET) by the European Commission the early 2010s (European Commisson, 2012). Spurring knowledge spillovers from science to industry appeared, therefore, crucial to promote technological progress and the diffusion of new scientific knowledge to applications for businesses and consumers in this area.

In this paper, we address the question of whether there are significant scientific and broader economic returns to frontier research funding in localized clusters. In particular, we investigate whether Clusters of Excellence generate more important and impactful scientific results and to what extent these would spill over (more) to industrial inventions, compared to other types of funding. The expectations on the direction of the impact of targeted research funding on industrial innovation are ambiguous. On the one hand, funding may increase the quality of R&D by co-located firms due to knowledge spillovers from increased scientific activity and agglomeration effects (Jaffe, 1989; Bikard and Marx, 2020). However, it is not obvious that basic research funding results in transferable knowledge (Rosenberg et al., 1990; Colen et al., 2022). Moreover, Clusters of Excellence may increase the independence of university research, thereby reducing collaborative ties with firms and decreasing their absorptive capacity towards new scientific findings produced (Cockburn and Henderson, 1998; Babina et al., 2023).

Studying the effects of Clusters of Excellence in a research area such as additive manufacturing is challenging for several reasons. First, AM is not a field in its own right, but rather a meta-area encompassing discoveries and inventions spanning multiple domains. At the same time, no domain or field is exclusive to AM-related science and technology alone. This makes it difficult to empirically map and trace output in this area. To overcome this issue, we classify all scientific articles in the Elsevier SCOPUS database and all patents granted by the United States Patent and Trademark Office(USPTO) based on the semantic content of their abstracts and patent text bodies using expert-curated vocabularies of keywords and word/class combinations specific to AM. This allows us to measure the exact publications and patents, their authors, inventors, and institutions of origin, as well as their impact on subsequent science and invention in the area of additive manufacturing worldwide.

The second challenge relates to the statistical inference of the (isolated) effects of Clusters of Excellence: the grant application process is highly competitive, and a successful application requires the involvement of top scientists and collaboration with eminent peers in related disciplines. The grant of a Cluster is therefore widely ex-ante determined by prior scientific excellence, and distinguishing its marginal impact from selection effects is non-trivial. To tackle this challenge, we provide matched case-control-based evidence derived from a synthetic difference-in-differences estimation (Arkhangelsky et al., 2021), carefully comparing locations with cluster funding to a weighted, dynamic counterfactual of university locations that had received funding from another large funding scheme provided by the DFG, the so-called Collaborative Research Centers (CRC). To test the robustness of our results, we further restrict the synthetic counterfactual to include only locations that had successfully submitted a first-round proposal for a Cluster of Excellence, were invited to the second and final round of evaluation, but were ultimately not selected for funding (runner-ups).

When comparing scientific publications and industry patenting across locations (counties) with prior CRCs with and without Clusters of Excellence, before and after the grant, we find that—in line with expectations—the latter did not significantly affect scientific production at the extensive margin, evidenced by a near constant rate of the number of yearly scientific articles relating to AM published in both groups. Importantly, however, we find that Clusters of Excellence had a strong positive influence on scientific output in the top 10% and top 5% of the distribution, defined as articles entering the 90^{th} and 95^{th} percentiles of article-to-article citations in a field-year worldwide, implying a substitution effect towards scientific production of higher quality and scientific importance. These effects are sharply confined to scientific articles related to AM and concentrated among top publications by universities and public research organizations, rather than firms, in Cluster locations. We, furthermore, find evidence for (although limited) crowding-out of top publications from collaboration with local industry. Following this rise in research output in the right tail of the scientific quality distribution, further results show a concomitant, significant increase in high-impact patents by nearby firms in Cluster regions, defined as patents entering the 90^{th} and 95^{th} of patent-to-patent citations in their CPC class-year worldwide; following the grant of Clusters of Excellence, the number of high-impact patents by firms in Cluster locations approximately doubled over a six-year period compared to the synthetic control based on other regions with CRCs in AM. These effects are again confined to the intensive margin and to firm patents covering inventions in AM-technology.

In order to strengthen the credibility of these findings reflecting knowledge spillovers from Clusters of Excellence to local industry, rather than differences in industrial agglomeration and skilled inventors, we further show a significant and large increase in the inflow of firm patent citations to high-quality scientific articles in AM originating from counties of Clusters of Excellence following the establishment of the Clusters, relative to CRC counties without Clusters. This increase is significantly larger than the proportional increase in high-quality articles, and its effects are heterogeneous and geographically localized. These findings are in their entirety robust when comparing Clusters of Excellence to only the subset of counties with applications for AM-related Clusters that were selected for the final round of evaluation during the Excellence Initiative but were ultimately rejected.

Taken together, our results provide strong support for the effectiveness of Clusters of Excellence in the science and technology fields analyzed by fostering frontier scientific research. At the same time, they illustrate the suitability of research clusters as a policy instrument capable of spurring significant knowledge spillovers from top science to successful industrial applications.

2 Research Funding & Knowledge Spillovers

Scientific research has long been understood as an important driver of knowledge and innovation (Nelson, 1959; Mansfield, 1995; Cohen et al., 2002). The growing reliance of technology on scientific inputs underscores the increasing importance and impact of science-based inventions (Narin et al., 1997; Fleming and Sorenson, 2004; Krieger et al., 2024). However, as already emphasized by Nelson (1959), the incentives to engage in scientific research are fundamentally constrained by the limited appropriability of knowledge. Thus, the levels of investment in scientific research by individuals and private organizations may be below the social optimum. This basic insight has led to a strong focus on the economics of science and particularly the role of publicly funded research in both scientific and economic progress (Stephan, 2012). In this discussion, a central question is how to promote the creation and diffusion of knowledge from science to industry, ultimately benefiting society (Jaffe, 1989; Hausman, 2022).

One prominent policy tool for promoting scientific research is grant competitions for allocating public research funding (Stephan, 1996; Azoulay et al., 2011; Froumin and Lisyutkin, 2015; Oancea, 2019; Hottenrott et al., 2021). The idea behind such funding instruments is that—unlike in the case of block grants—they incentivize competition for achievements among scientists and allocate scarce funding resources to those ideas and investigators likely to have the highest returns. Given the rising use of competitive funding allocation instruments, for instance, in European national funding systems (Krücken et al., 2021), it appears crucial to understand not only whether funding competitions indeed result in additional, relevant research and whether they can generate desired knowledge spillovers, but also which types of funding schemes may be particularly effective in this.

2.1 Types & effects of grant-based funding instruments

Grant-based science funding instruments usually aim to fund scientists, groups of scientists, or entire institutions. Unlike block funding, research grants are typically awarded on the basis of a specific project proposal and undergo a peer-review process which leads to an evaluation-based decision. The scientific quality of the proposed project and the characteristics of the applicants are typically relevant criteria for a positive evaluation. In most of such funding designs, the award process is administered by a funding agency and relies on collaboration with the scientific community which supports the review and assessment process. The idea of such a competitive funding process is that researchers need to dedicate effort towards the application and that the 'best' proposals 'win'. In the sociological perspective of Simmel (1908), such contests can be viewed as triads with the focal applicant being described as 'ego', the competitors as 'alter' and the funding agency constituting a third party ('tertius') that takes the role of a prize-giver (Buenstorf et al., 2025). Such a competitive, contest-style design is thought to ensure funding allocation to projects that are most likely to generate relevant outcomes (through peer review) and to encourage individual scientists to remain motivated and productive over the life-cycle by participating and succeeding in these contests (Stephan, 1996; Van der Meulen, 1998; Schubert, 2009).

Researchers have studied the impact of such grant-based instruments on knowledge production at multiple levels. At the individual level, most commonly, scientists are granted funding for clearly specified research projects in which they serve as principal investigators. Such projects are typically smaller in scale and span a period of one to four years (Hottenrott and Lawson, 2017; Heyard and Hottenrott, 2021). Studies evaluating the outcomes of such individual grants typically find small increases in research outcomes following the funding (Arora and Gambardella, 2005; Jacob and Lefgren, 2011a,b; Heyard and Hottenrott, 2021) but also stress that the sources of funding and the overall amount matter (Azoulay et al., 2011; Hottenrott and Lawson, 2017; Myers, 2020). Several of these studies show that funding positively affects scientific output.

At the institutional level, funding is typically allocated to the university or a larger part of it. Such funding is often not dedicated to specific research projects but rather supports larger infrastructure investments or institutional developments. A few authors have studied the impact of such institutional funding in the context of the German Excellence Initiative on aggregate, institutional-level scientific output (Gawellek and Sunder, 2016; Schubert et al., 2017). While, overall, their results suggest no to moderate positive aggregate effects on research outcomes, there is strong variability among findings across studies, depending on specific samples and methods employed. Schubert et al. (2017), using fixed effects panel regressions, do not find a strong impact of the institutional funding on publication performance once accounting for time-invariant heterogeneity across universities, yet a significant positive impact of Clusters of Excellence on university-wide publications in engineering sciences. Using a dynamic matched case-control study design to evaluate the impacts of institutional development strategies under the German and French excellence initiatives, Carayol and Maublanc (2025) find moderate positive effects on overall scientific output from excellence funding at the university level, in particular strong impacts on international collaborations and co-publications with industry. In addition, there is evidence on the impact of similar funding instruments in other countries, for example China's 985 project (Zhang et al., 2013; Zong and Zhang, 2019), Russia's

5–100 project (Agasisti et al., 2020; Turko et al., 2016), or Taiwan's World Class University project (Fu et al., 2020). Yet, also these studies found mixed performance effects from excellence initiatives. Obviously, funding at the institution may affect not only research outcomes but also university characteristics more generally. Concerning the impact on students, Bruckmeier et al. (2017) as well as Fischer and Kampkötter (2014) find that funded universities manage to attract more students and that students perceive the quality of teaching and supervision as better.

More recently, funding at the group or forum level has gained more attention, particularly regarding team-level outcomes. Here, grants are awarded to groups of researchers, labs, or regional, collaborative clusters. Studies investigating such team-level grants are still rare: Encaoua et al. (2000) find a positive link between science funding and research output also for research teams in the field of biotechnology in Italy, while Carayol and Matt (2004) do not find a significant link between science funding and team productivity for a set of labs at Louis Pasteur University in France, a large and well-ranked European research university. Bornmann (2016) documents a discipline-specific effect on co-authorship networks and publication performance from German Clusters of Excellence limited to solely the natural sciences. At the same time, a study by Möller et al. (2016) suggests that large-scale, group-level funding can have a substantial impact on measurable outputs. They estimate, based on aggregate bibliometric data, that about half of the increase in Germany's publication performance in the years after 2007 can be attributed to publications by the Clusters of Excellence. Thus, the findings for funding teams are less clear than those for individual researchers. On the one hand, collaboration within teams and the pooling of complementary skills may enhance motivation, creativity, research productivity, and quality of outcomes. On the other hand, teamwork involves coordination and communication costs, the disclosure of ideas to others, and conflicts. Moreover, most groups or teams in academia are fluid in the sense that there are considerable fluctuations, and funding periods are usually limited. The latter characteristic could potentially promote knowledge diffusion through increased mobility. Likewise, the involvement of different individuals could contribute to both knowledge creation and knowledge diffusion. Because of this ambivalence and fundamental difference as compared to individual grants, such group-level funding instruments are, therefore, particularly interesting, and previous insights are still very limited.

2.2 Clusters of Excellence

Clusters of Excellence were introduced in Germany as a science funding instrument as part of the German Excellence Initiative, which was first implemented in 2005 with the first funding round (2006-2012) distributing €1.9 billion and the second round (2012-2017) assigned another €2.7 billion (Deutsche Forschungsgemeinschaft, 2015). With the introduction, the German Federal Government adopted a stance on promoting top-level research through the competitive allocation of large grants, aiming to improve the international standing of German research institutions and make Germany a more attractive location for top researchers. Besides Germany, several other countries have implemented similar science funding programs and have generally moved towards larger-scale, performance-based allocation of science funding (Salmi, 2016; Hottenrott et al., 2021).

The funding instrument assigned funding through three funding lines. First, universities could apply to establish graduate schools (up to about €2.5 million per year). Graduate schools provide a structured training program for doctoral students and a place of interdisciplinary and cross-faculty scientific exchange to promote young researchers. They improve the cooperation within the university and with non-university research institutions. Second, Clusters of Excellence fund collaborative research in specific, often interdisciplinary, domains (up to about €8 million per year). Clusters of Excellence are allocated to large researcher consortia with up to 25 main principal investigators to foster expertise on specific topics to promote frontier research. Lastly, universities that were successful in these pillars could also apply for funding at the institutional level (institutional strategy) for developing the general university-level infrastructure without having to define particular research projects (up to €12.5 million per year). Thus, this funding line aims to strengthen the institution and its research (and education) as a whole.

This study focuses on the Clusters of Excellence as the central funding pillar. In this context, it can be expected that funding has positive effects on knowledge spillovers within academia and from science to industry, given their pan-organizational design. Such clusters can be quite large and comprehensive, spanning several universities and institutes from the large research associations (Leibniz Association, Max-Planck Society, Helmholtz Association, Fraunhofer Society), other research units, and, in a few cases, firms as collaboration partners.[2]

The first funding round covered the period between 1^{st} November 2006 and 31^{st} October 2012 and included two tendering rounds (2006 and 2007). In this phase, the total funding volume comprised 1.9 billion euros. 60% of this amount was allocated to 37 Clusters of Excellence. The second and third funding rounds took place between 2012 and 2017, and between 2019 and 2024, respectively. Besides the direct effects on knowledge production and research outputs, it is a relevant and interesting question whether—assuming that the funding results in additional knowledge—it also generates spillovers to actors not directly involved in the research funded by the grant. Often, such spillovers are referred to as justification for promoting cutting-edge research (Azoulay et al., 2019). Scientific research funded by the Excellence Initiative could be expected to create such spillovers through increased collaboration and exchange, as well as researcher mobility

[2]None of the Clusters of Excellence examined in this paper involved industry as direct funding recipients.

between organizations and teams. The local nature of most such clusters, i.e., relevant actors located within a certain spatial range, may foster spillovers within the region but also limit spillovers that reach other research locations and firms.

2.3 Localization of knowledge spillovers

Previous literature has long argued that knowledge spillovers are highly localized due to agglomeration advantages (Jaffe et al., 1993; Saxenian, 1996), the role of tacit knowledge—i.e., the complexity of inventions creating human capital characterized by 'natural excludability' (Zucker et al., 1998), and labor mobility within certain proximity (Palomeras and Melero, 2010). Based on these insights, Clusters intentionally focus on local collaboration to facilitate knowledge spillovers within their consortia. Adams and Griliches (1996), for example, show that co-location in interpersonal links between scientists and firms is contingent on the characteristics and role (intensity of connection and importance of task) of the scientists—suggesting a complex interdependence and heterogeneity in the relationship between spillovers, network, and geography.

Research on science-industry interactions has also traditionally focused on the spatial dimension of clustering of spillovers. Jaffe (1989) provides time-series evidence that university research generates a positive spillover effect on corporate R&D investment and patenting of firms located in the same U.S. state. Furthermore, Belenzon and Schankerman (2013) show, based on citation links, that firm patent citations to university patents are strongly clustered within state borders. However, they also document that this localization is much less sharp and widely released for firm patent citations to university publications. Moreover, research has examined institutional arrangements that facilitate science-industry spillovers, some of which relate to aspects of clustering. Based on variation within twin papers pairs, covering the same discovery but emerging in different locations independently, Bikard and Marx (2020) show that geographic hubs, where universities and industry are co-located, are not only a strong predictor for spillovers in terms of patent-to-article citations, but they also function as amplifiers of the geographic reach of spillovers.

The literature on absorptive capacity through collaboration between companies and (star) scientists (e.g., Cockburn and Henderson, 1998; Zucker et al., 1998; Colen et al., 2022) highlights the importance of the network dimension. Such networks form through direct collaboration, employee mobility, or informal exchanges (Fudickar and Hottenrott, 2019).

2.4 Research gap & contribution

Only a few studies have investigated the effects of Excellence Cluster funding on localized industry spillovers. Closely related to our analysis are those by Bergeaud et al. (2025)

and Krieger (2024).

Bergeaud et al. (2025) examine knowledge spillovers from the French Excellence Cluster program (Laboratoire d'Excellence) to industry. Exploiting variation in technological proximity to Clusters among local industries within commuting zones, and using a dynamic difference-in-differences approach, their results show that the increase in science funding led to a significant increase in firms' R&D activities and to additional R&D outputs as measured in patents and the establishments of plants. In terms of knowledge spillover channels, their results suggest that R&D outsourcing through public-private partnerships, labor mobility from the public to the private sector, and informal contacts explain their findings.

Adding to these insights on Clusters of Excellence in France, Krieger (2024) studies the effect of their counterparts under the German Excellence Initiative on regional innovativeness. In contrast to Bergeaud et al. (2025), this study relies on a survey-based measurement of knowledge spillovers and firms' innovative activities, using data from the Community Innovation Survey for Germany. Results from two-way fixed effects estimations indicate that significant science spillovers to industry from the German EI emerged only in two major metropolitan regions—Berlin and Munich—each of which received more than three Clusters of Excellence, while effects in all other Cluster locations were statistically indistinguishable from zero. Overall, the findings highlight the importance of regional context, as the impact of funding seems to vary significantly across different regions. The results further suggest that regions with more established universities and higher funding levels are better positioned to leverage additional funding, potentially with higher innovation spillovers.

While these insights stress the value of 'cluster funding' as a science policy instrument, it remains unclear whether these effects are driven by scaling through more university funding and therefore more human capital and collaboration opportunities or by a quality effect through pushing research within clusters closer to the research frontier, or a combination of the two. In addition, we still know little about the nature of the innovations benefiting from Clusters of Excellence—it is not straightforward that top science, insofar as produced by Clusters of Excellence, would automatically translate into top technology, which will likely be largely dependent on the (development of) top-science absorptive capacity of local industry. Our study adds to this line of research by explicitly differentiating between scaling (more publications) and quality effects (more relevant research as indicated by citations). By differentiating between scientific publications and patents as outcomes and between university/public research organization and industry-based authors, we aim to further examine the link between science funding and the origin of research outputs. Our analyses add to the findings by Bergeaud et al. (2025) and Krieger (2024) by investigating both the number and the relevance of inventions generated in the immediate vicinity of funded Clusters. Importantly, we can trace the actual relevance of scientific publications to patenting activity by focusing on a single technology area that we can capture with high granularity—both in terms of its scientific underpinnings and associated technological activities—using expert-curated semantic vocabularies and patent class combinations. This unique set-up allows us to examine whether technology-oriented Clusters of Excellence indeed foster cutting-edge research, as indicated by increases in highly cited publications, and whether they generate spillovers to industry in the form of high-impact inventions, rather than mere appropriation by firms. In doing so, we also reorient the analysis from private to social returns of Clusters of Excellence.

3 Empirical Context: Additive Manufacturing

Additive manufacturing (AM) refers to a group of production technologies that transform digital models into physical three-dimensional objects by adding material layer upon layer. AM consolidates technologies from different fields, such as computer-aided design (CAD), computer numerical control (CNC) machining, and laser technology (Cavallo et al., 2023). It is a science-based technology (Meyer-Krahmer and Schmoch, 1998; Ahmadpoor and Jones, 2017), relying heavily on progress in various research areas within the natural and engineering sciences—such as optics, material sciences, and mechanical engineering—and exhibiting a strong connection between basic research and technical progress. Universities and research organizations have played a pivotal role in advancing AM technologies and applications. Several landmark innovations in this area trace back to academic environments. For instance, Direct Shell Production Casting (DSPC) and inkjet printing for 3D fabrication—both foundational to modern AM—were pioneered at MIT. Another major figure in the early development of AM is Hideo Kodama of the Nagoya Municipal Industrial Research Institute, who in 1980 filed one of the first patent applications for a method to fabricate 3D objects using a layer-by-layer approach (Kodama). His work laid the groundwork for stereolithography and is widely recognized as a key milestone in the emergence of AM technology (Campbell et al., 2023). Still in 2022, academic institutions accounted for 12% of all international patent family applications in technology classes associated with AM (Cavallo et al., 2023). Unsurprisingly, industrial activity in AM—firms and start-ups developing and using AM technologies for commercial applications—tends to be clustered in proximity to universities with strong expertise in the field.

AM was initially used primarily for rapid prototyping, enabling quick iterations and facilitating the development of complex geometries (Gebhardt and Hötter, 2016). This early application made AM a powerful tool for testing and refining product ideas with relatively low upfront investment. In recent years, however, the focus has shifted increasingly towards end-use production. Nowadays, AM plays a central role in manufacturing customized products—most notably in healthcare, where it is used to produce patientspecific implants and prosthetics (Campbell et al., 2023).

Given its strong reliance on scientific underpinnings, advances in fundamental research on additive manufacturing are likely to spill over rapidly into industrial applications. Moreover, given the high patent intensity of AM, the use of science in industrial applications will likely leave traces in patent documents (namely, in prior art references and text), which allows us to measure knowledge spillovers in codified output (Ahmadpoor and Jones, 2017; Iaria et al., 2018; Schaper et al., 2025).

4 Data & Measures

Our analyses are based on a comprehensive dataset that includes information on science funding, scientific publications, patents, and regional demographic and industry characteristics for Germany from 1995 to 2013.

We obtain science funding information, including research area, applicant and participating institutions, as well as the funding periods for Clusters of Excellence and Collaborative Research Centres (CRC) from the GEPRIS database provided by the German Research Foundation (DFG).[3] For the Clusters of Excellence, we consider all first funding round clusters in the years 2006 and 2007. We identify whether a Cluster is related to AM based on its description, specifically when the investigation and discovery of phenomena relevant for AM technology is explicitly stated or can be inferred from context. In total, four universities located in three different regions—Aachen, Erlangen, and Hanover—hosted Clusters of Excellence related to AM. The regions of Aachen and Hanover received funding in 2006, while Erlangen followed in 2007. For comparison, we identified all AM-related CRCs between 1995 and 2005 analogously. In addition, from DFG press releases, we obtained a list of runner-up Cluster of Excellence applications related to AM that were selected for the second evaluation round but ultimately remained unsuccessful (Deutsche Forschungsgemeinschaft, 2006, 2007). We define counties in which the recipient universities or research organizations are located as beneficiary regions of Clusters. All counties that received Clusters of Excellence as well as all those with rejected applications were hosting previously granted CRCs in the area of AM, making the former two distinct sub-groups of the latter.

Our primary source for publication data is the Elsevier SCOPUS database, from which we obtain information about scientific articles, journals, authors, and affiliations, as well as publication years and, importantly, abstract texts for more than 50 million scholarly articles worldwide. To identify articles related to AM, we conduct a semantic search of article abstracts by authors with German affiliations, using technology-specific

[3]GEPRIS is a publicly available database indexing all funded research projects by the DFG, including information about the funding terms, the principal investigators and their institutions, and summaries of the content and aim of the funded projects.

keywords derived from established standards such as ISO/ASTM 52900 and VDI 3405, as well as recent literature (see Appendix A.2). This yields a publications sample of 13,432 AM-related articles in Germany between 1995–2013. Articles are assigned to Clusters of Excellence and CRCs based on the affiliation address information of the authors as listed on the publications. This results in a total of 1,789 AM-related articles assigned to counties that received Clusters of Excellence and 6,116 to counties of the other sixteen CRCs related to AM between 1995–2013. The four counties with ultimately rejected Cluster of Excellence applications account for a total of 1,604 AM-related articles.[4] We aggregate article counts to the county-year, which constitutes our unit of analysis. Articles with multiple assigned counties are counted separately for each county.

To quantify scientific excellence and cumulative impact on scientific research, articles in SCOPUS are linked via digital object identifiers (DOIs) to citations and field boundaries in Microsoft Academic Graph (MAG) (Sinha et al., 2015). In order to infer about scientific fields at the article-level, we leverage article concepts provided by MAG.[5] These concepts are abstract ideas about the content of scientific works which are generated by a machine-learning model based on information derived from titles, abstracts, and outlets (journals) of publications (Wang et al., 2019, 2020). Concepts themselves are based on external Wikidata Identifiers for scientific knowledge, and branch out from 19 root-level concepts across six layers of descendants to over 65k sub-level concepts (Shen et al., 2018). For our purpose, we extracted all concepts at Level 1 (i.e., the second-tier layer of aggregation), resulting in 284 distinct concepts. Subsequently, we manually map this list of concepts to 145 Clarivate Web of Science (WOS) Subject Categories.

To measure industrial inventions, AM-specific patents are identified among all patents filed at the United States Patents and Trademarks Office (USPTO). U.S. patents cover the largest share of inventions worldwide (also for Germany) among all patent offices and have the advantage of providing public full-text data, as well as several curated metadata on inventors and, in particular, links to science through disambiguated scientific non-patent references (SNPRs). Our primary data source for patent data is the EPO PATSTAT global (2022 autumn edition) database, which we link via U.S. patent numbers to PatentsView in order to retrieve full texts and geo-coded inventor and applicant locations. In order to identify AM-related patents, we adopt the approach and search key based on combinations of IPC/CPC classes and expert-curated technical terms from Pose-Rodriguez et al. (2020), querying the 'summary of the invention' sections in the full-text of all U.S. patents. Finally, we rely on the dataset provided by Marx and Fuegi

[4] A list of regions with respective science funding programs is listed in Appendix A.1.

[5] A known limitation of scientific publication databases such as SCOPUS or Web of Science is that they assign fields at the journal level. Since journals are typically linked to one (of few) fields, this can misclassify individual articles and result in an under-representation of smaller fields. To address this, we use a granular article-level classification that reflects each article's content rather than its journal assignment.

(2020) to identify citations from all U.S. patents to scientific articles in MAG.

Finally, to study the impact of Clusters of Excellence on scientific research and industrial inventions, we construct a panel data set of all German counties for the years 2000–2013, thereby restricting the observation period to about eight years prior to the funding of Clusters of Excellence during the first round and six years post-grant.[6] To assess the impacts of Clusters, we construct the following variables:

Number of articles. This is the count of AM-related scientific articles within a county in a given year. An article is assigned to a county if at least one author-affiliation address listed on the publication is located in the specific county.

Number of citation-weighted articles measures the sum of total scientific article citations to AM-related articles from a given year in a county, measured over a forward moving window of eight-years from publication. Article citations are a widely established measure to quantify the usefulness of an article for cumulative scientific progress (e.g., Garfield, 1955; Price, 1965).

Hit articles. This measure counts the number of AM-related articles in a county that rank among the most cited within their WOS field-year cohorts, based on the global distribution of citations. To capture the upper tail of the citation distribution, we construct indicators for whether an article falls into the 90^{th} percentile (top 10% articles) and, respectively, the 95^{th} percentile (top 5% articles) of citations. This is a widely used indicator for quantifying 'high-gain science' and scientific breakthroughs (cf. Wang et al., 2013; Ahmadpoor and Jones, 2017; Wang et al., 2017).

Number of firm patents. This is the count of corporate patents for AM-related inventions with at least one inventor location in a given county per year. The timing of patents is based on the worldwide first application date (priority date). Information about firm applicants is based on the PATSTAT Standardized Names (PSN) sector classification.

Number of citation-weighted firm patents measures the sum of total five-year patent forward citations within the USPTO to AM-related firm patents in a given country in the year of observation. Patent citations are a widely recognized and established indicator in the literature (Trajtenberg, 1990; Harhoff et al., 1999). They serve as a measure of technological impact, indicating how often an invention serves as a foundation for subsequent patents. For each focal patent, we consider forward citations over a five-year moving window, based on the priority filing year.

Hit firm patents. Similarly to the measure for hit articles, this counts the number of AM-related firm patents in a given county in each year that belong to the top 10% and top 5% most highly cited patents worldwide in their CPC-class-year five-year citations distribution, based on a patent's first-listed CPC class (subgroup-level). The underlying measure is a binary indicator for top-impact (or technological breakthrough) and has

[6] More recent years are excluded because of the possibly confounding effects from a second funding round in 2012, where some of the control units received funding, and others applied but were unsuccessful.

been widely used in the literature (e.g., Trajtenberg, 1990; Ahmadpoor and Jones, 2017; Pezzoni et al., 2022).

Number of firm patent citation-weighted articles. This measure counts the number of citations by AM-related firm patents worldwide to AM-related articles in a county in a given year. That is, it measures how often articles have been cited directly as prior art in firm patent documents in the relevant domain. Thereby, it provides an explicit account of the input of a scientific idea for the underlying citing inventions (cf. Tijssen, 2001; Roach and Cohen, 2013; Callaert et al., 2014). We measure the cumulative number of citing firm patents for each article over a five-year window. We distinguish between patent citations to all articles, top 10% articles, and top 5% articles.

For all outcomes, we construct identical measures for non-AM-related articles and patents.[7] To normalize patent output, we collected population data for each county for the year 2005—i.e., the last year pre-treatment—from the German Federal Statistical Office (Destatis) and divided patents by 100,000 inhabitants in a county to account for any differences in county size. Given that publication and patent outcomes are heavily skewed, and many county-year observations are zeros, we apply the inverse hyperbolic sine (IHS) transformation to all outcome variables for parametric estimation.

Table 1 compares the raw numbers for our main outcomes across counties with Clusters of Excellence and CRCs related to AM (with and without rejected cluster applications) for the pre-treatment period between 2000 and 2006. Given the small number of treated units, conventional balance tests have low power in this setting. We therefore use exact Fisher randomization inference, enumerating all possible treatment assignments and comparing the observed pre-period treated-control differences to the resulting randomization distribution. The reported p-values indicate whether the treated counties are unusually different from control counties compared to what would be expected under random assignment of treatment. Counties with Clusters of Excellence are relatively similar to other counties with CRC, both in the yearly number of AM-related scientific articles, as well as in their cumulative impact and the number of hit articles. However, there are considerable differences between the locations of Clusters of Excellence and the comparison regions with regard to the uptake of AM articles in patent references, suggesting that countries that received Clusters of Excellence were already ex-ante publishing more relevant scientific output for AM-related industry technology. This difference is particularly large with regard to firm patent reliance on the top 5% articles. When it comes to local AM-related patenting, it appears that counties of Clusters showed higher pre-grant rates in terms of the volume and citation-weighted number of patents compared to all other counties with prior CRCs, but were very similar to those counties with rejected

[7] We further distinguish articles by institution types—i.e., between universities/public research organizations (PROs) and firms. We further account for co-publications from university/PRO–industry collaborations.

Table 1: Pre-period summary statistics

	Clusters of Excellence	Other Collaborative Research Centres		Cluster Runner-ups	
Variables	Mean	Mean	Fisher p-val	Mean	Fisher p-val
AM articles	26.24	20.15	0.53	21	0.40
Citation-weighted AM articles	461	394	0.74	421	0.80
Top 10% AM articles	5.38	4.64	0.73	5.18	1.00
Top 5% AM articles	2.81	2.38	0.72	2.57	0.91
Pat cit-wtd AM articles	3.10	1.03	0.12	0.82	0.29
Pat cit-wtd top 5% AM articles	1.57	0.27	0.06	0.57	0.46
AM patents/ 100k	3.12	1.48	0.34	3.50	0.91
Cit-wtd AM patents/ 100k	7.89	3.57	0.30	7.64	0.97
Top 10% AM patents/ 100k	0.12	0.11	0.75	0.25	0.57
Top 5% AM patents/ 100k	0.05	0.05	0.91	0.11	0.51
Non-AM articles	2,120	2,007	0.65	1,801	0.51
Top 5% non-AM articles	255	260	0.66	244	0.74
Pat cit-wtd non-AM articles	944	757	0.61	627	0.29
Non-AM patents/ 100k	138	37.36	0.07	67.55	0.51
Top 5% AM patents/ 100k	3.48	1.08	0.07	2.19	0.57

Notes: This table compares group means at the region-level for yearly outcomes across counties receiving Clusters of Excellence (treated group), all other counties with Collaborative Research Centres granted between 1995–2005 (comparison group), and only counties with rejected final round applicants for a Cluster of Excellence (subset of comparison group) in the area of additive manufacturing (AM) over the pre-period of the Excellence Initiative from 2000–2006. Top 10% / top 5% articles (patents) are scientific articles (firm patents) that enter the 90^{th} / 95^{th} percentile of citations within a field–year (CPC class–year) worldwide. Reported p-values for differences in means are exact permutation (Fisher randomization) p-values computed from the full randomization distribution (two-sided). Patent outcomes are normalized by 100,000 population.

applications for Clusters in the final round—underscoring the importance of the latter sub-group for adequate comparison. With regard to hit patents—defined as the top1 10% and top 5% most highly cited patents—the group of rejected applicants even exhibits a seemingly higher intensity than counties that ultimately received a Cluster.

Considering scientific production and firm inventive activity outside of AM (bottom panel of Table 1), the three county groups again appear broadly similar in terms of article volume and hit articles. However, regions that received Clusters exhibit greater ex-ante technology-relevance overall and, in particular, substantially stronger industry patenting activity, as well as a higher volume of top-cited firm patents—especially relative to all other counties with prior CRCs, and to a lesser extent compared to those with rejected applicants. This represents a key ex-ante difference across regions, which may point to specific selection criteria underlying the awarding of Clusters of Excellence. The general R&D capacity of a region—the aggregate research output of its university and industry—appears to have played a significant role in funding decisions, independent of a region's performance in the specific scientific focus area of a Cluster. However, it is important to note that due to the small number of independent observations in our sample, none of these differences in group means can be interpreted with certainty as systematic, as also reflected in the consistently large Fisher randomization p-values.

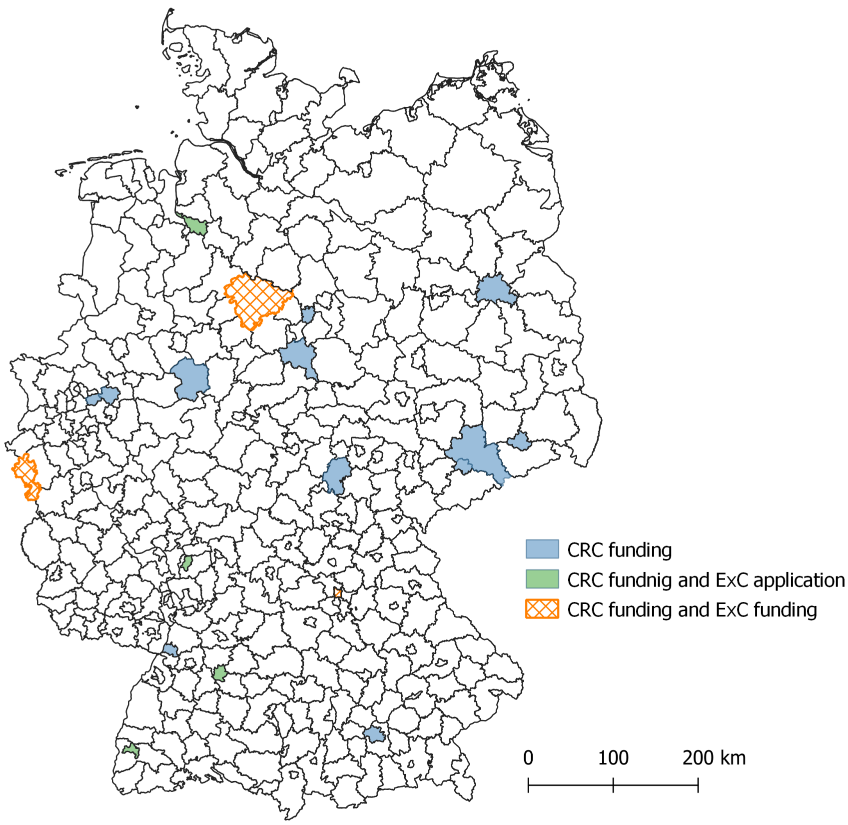
Table A.3 examines university-level differences in greater detail and shows that universities in counties that received Clusters in AM, on average, had substantially larger endowments—both in terms of basic funding and third-party funds—ranked higher, and produced more graduates, particularly in medicine, natural sciences, and engineering. However, they did not differ in terms of overall academic staff, including faculty, nor in the number of university spin-offs.

5 Estimation

5.1 Empirical strategy

The main objective of introducing the Clusters of Excellence was to advance the research frontier through targeted funding for consortia that can convince the review panel the feasibility of their plans. Hence, we can expect the funding to be allocated to top research groups that were already close to the frontier. This implies that there is likely a strong positive selection of highly able and highly productive researchers into the funding scheme. Similarly, Clusters of Excellence were designed to promote translational collaborative research and technology transfer. As a result, regions with strong university-industry linkages may be particularly likely to receive this type of funding. Even more, firms that are especially 'able' at generating high-impact inventions may often co-locate with top research universities, which are more likely to host Clusters of Excellence. In fact, as discussed in Section 4, the descriptive statistics reported in Table 1 provide some evidence in support of this prediction. To isolate the marginal impact of the policy from pre-existing characteristics of the involved scientists, regions, and firms, our empirical model must account for this non-random selection in order to produce unbiased estimates.

Figure 1: Regional distribution of Clusters of Excellence and comparison regions



Notes: This figure shows the regional distribution of counties with Collaborative Research Centers (CRC) granted between 1995 and 2005 related to additive-manufacturing (AM) across Germany, highlighting recipients of Clusters of Excellence (ExC) as well as rejected applicants in the final round of the Excellence Initiative of 2006/2007.

To address this, we aim to construct a plausible counterfactual for Clusters of Excellence based on counties at comparable levels of scientific performance and industrial inventions relating to AM prior to the Cluster grants. Following this objective, we draw a first comparison group from counties of all universities that had previously received a CRC in the area of AM between 1995 and 2005 but that did not receive a Cluster of Excellence during the first funding round of the Excellence Initiative in 2006–2007. CRCs are university-based research groups that can be funded for up to 12 years. They comprise a large number of projects and involve multiple PIs and partners from other research institutions and industry. There are a few key differences between CRCs and Clusters of Excellence: while also being topic-centered, highly selective funding schemes (although not as competitive as Clusters), CRCs are structurally embedded at lower levels of the university, usually at the faculty or department level. They have significantly shorter funding and reporting cycles before evaluation of only 4 years in the initial funding period, compared to seven years for Clusters of Excellence. Finally, CRCs involve smaller yet still considerable funding amounts of 2–4 million euros per year, compared to 6–8 million euros annually for Clusters of Excellence. Often, universities strategically align their CRCs to help prepare applications for Cluster proposals as thematic predecessors.[8] We infer the link to AM semantically from the 'thematic focus' section in the description of all 37 CRCs funded by the DFG included in the GEPRIS database (for a list of all CRCs, see Table A.1), by identifying CRCs with a strong focus on mechanical and production engineering or material engineering and material science. This choice is grounded on the rationale that research concerning production methods and material properties was particularly salient within the domain of AM in the early 2000s. Figure 1 shows the geographic location of the 12 regions with only CRCs (blue), four regions with CRCs and ultimately rejected cluster applications (green), and three regions that received Clusters of Excellence (yellow).

5.2 Synthetic difference-in-differences approach

The econometric analysis entails further methodological challenges. First of all, the focus of our study on a very specific research area (i.e., AM) determines a relatively small sample size. This is potentially problematic for inference—due to a lack of statistical power and the high likelihood of imprecise estimates—making it particularly difficult to reliably reject any null hypotheses. Second, even after refining the sample to only regions with similar characteristics regarding scientific research activities in AM, we still observe several differences across treated and comparison groups which could reveal to be systematic in larger samples, for instance, with regard to local industry patenting, university endowments and student numbers in relevant fields, as discussed above (cf. Tables 1 and A.3). These could imply differences in pre-trends with regard to the amount and intensity of knowledge spillovers to industry, which would violate the standard assumption in difference-in-differences estimation.

To address these challenges, we adopt a synthetic difference-in-differences (SDID) estimator as proposed by Arkhangelsky et al. (2021). SDID estimation combines features from synthetic control methods and conventional difference-in-differences estimation. The

[8] Indeed, as expected, all universities with Clusters of Excellence associated with AM had received a CRC related to AM between 1995 and 2005.

underlying estimator uses both unit-specific and flexible time weights to construct a synthetic, dynamic counterfactual for the treated units, which considerably relaxes the need for parallel trend assumptions. Moreover, in contrast to the synthetic control method, it does not require the treated units to lie in a convex hull of control units and is highly robust to level differences between treated and control units.

To estimate the effect of Clusters of Excellence on scientific output and industrial inventions, we minimize the following equation using the computational implementation described in Clarke et al. (2023):

$$\left(\hat{\tau}^{SDID}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - Cluster_{it-1}\tau)^2 \hat{w}_i^{SDID} \hat{\lambda}_t^{SDID} \right\}$$

In this minimization problem, $\hat{\tau}^{SDID}$ represents the average treatment effect (ATT) of Excellence Clusters. The ATT corresponds to the change in the differences in means of scientific output and industrial patenting between the periods before and after the treatment. $Cluster_{it-1}$ is a binary variable indicating whether a county i hosts a Cluster recipient university in the year prior to the observation year t. In line with prior literature (e.g., Jacob and Lefgren, 2011b; Krieger, 2024), we assume a time lag of one year for first treatment effects to materialize, i.e., for first research results to be produced and spillovers to industrial invention to become measurable. Accordingly, we consider 2007 as the first post-treatment year for Clusters awarded in 2006, and 2008 for those awarded in 2007. The variables $\hat{w}_i^{SDID}$ and $\hat{\lambda}_t^{SDID}$ correspond to the optimal region and time weights for control group units. Y_{it} is the indicator of scientific output and industrial patenting in county i and year t. Parameters α_i and β_t represent fixed effects for regions (counties) and years, respectively. Given the distributional properties of the underlying publication and patent data, we apply the inverse hyperbolic sine (IHS) transformation to all outcome variables in the SDID estimation. To conduct statistical inference for the ATT, we implement the placebo approach suggested by Arkhangelsky et al. (2021), and estimate standard errors from the distribution of 2,000 placebo reassignments of the treatment across units.

6 Results

6.1 Scientific output

To evaluate the impact of Clusters of Excellence on their hosting regions, we first analyze effects on scientific publication outcomes. Table 2 presents the results from the synthetic difference-in-differences estimation. The ATT coefficients in columns (1) and (2) imply that Clusters of Excellence had no significant impact on the overall volume nor on the citation-weighted output of scientific articles related to AM in counties that received

Clusters, relative to the (synthetic counterfactual) of the comparison group of (all other) counties with prior CRCs in the area of AM. Although point estimates for both outcomes are positive, they lie within the bounds of the placebo-derived standard errors. However, and importantly, coefficients in columns (3) and (4) reveal that Clusters had a sizable and in magnitude increasing effect on scientific production when moving towards the right tail of the scientific quality distribution: considering that IHS-transformed values here can be interpreted similar to logs (semi-elasticities), the point estimate of +0.51 (significant below the 5%-level) in column (3) suggests that counties with Clusters of Excellence increased their number of hit articles—i.e., articles above the 90^{th} percentile in field-year citations distribution—related to AM by about 65–70% following the establishment of Clusters, compared to counties with 'only' CRCs in AM-related fields. Evaluated at the sample mean ($\text{asinh}(y) = 2.19$), this corresponds to an increase from roughly 4.4 to 7.4 hit articles (3 additional hits) per year in the thematic area of the funded Cluster. The effect of Clusters is economically even larger when considering 'big hits'—the number of articles entering the top 5% most highly cited in their field—in column (4): the ATT of +0.67 (significant at the 5%-level) suggests that the number of such articles approximately doubled (+95%) relative to the baseline. Taken together, these first results provide evidence for a strong, non-uniform impact of Clusters of Excellence on scientific production, which was concentrated in the upper tail of the distribution and thus largely confined to science at the knowledge frontier.

Table 2: Impact of Clusters of Excellence on scientific publication output

	Synthetic difference-in-differences estimates							
	AM articles				Non-AM articles			
DV	(1) No. Articles	(2) Cit-wtd Articles	(3) Top10% Articles	(4) Top5% Articles	(5) No. Articles	(6) Cit-wtd Articles	(7) Top10% Articles	(8) Top5% Articles
Cluster_{t-1}	0.22	0.40	0.51^{**}	0.67^{**}	0.03	0.02	0.06	0.05
	(0.23)	(0.36)	(0.24)	(0.31)	(0.08)	(0.09)	(0.07)	(0.10)
DV mean	3.67	6.53	2.19	1.60	8.07	11.18	6.65	5.98
Observations	266	266	266	266	266	266	266	266

Notes: This table reports the estimates for the impact of Clusters of Excellence in the area of additive manufacturing (AM) on scientific publication output between 2000–2013. The comparison group consists of all other counties of universities with AM-related Collaborative Research Centres (CRC) granted between 1995 and 2005. The dependent variable measures the inverse hyperbolic sine (IHS) of the number of AM-related articles in column (1), citation-weighted articles in column (2), and articles that enter the 90^{th} (column (3)) and 95^{th} percentile (column (4)) of citations within a field–year worldwide. Columns (5)–(8) report estimates of the same outcomes for non-AM articles. Standard errors (reported in parentheses) are derived from placebo variance estimation with 2,000 repetitions. Significance levels: $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

We investigate the robustness and sensitivity of this result in several ways. First, we evaluate how plausibly these effects can be attributed Clusters in AM by re-estimating the same outcomes for scientific articles not related to-AM—which should not have been (or to a much lesser extent) affected by AM-specific Clusters—in the same regions. Results reported in columns (5)–(8) of Table 2 show that there was indeed no concomitant change in the volume, number of citation-weighted articles, or hit articles in counties with Clusters of Excellence in areas outside of AM-related research, relative to the comparison group. Point estimates of ATTs across all outcomes are very small and statistically indistinguishable from zero. This further alleviates concerns that the observed effects for AM-related articles could be influenced by positive selection relating to overall academic quality in counties of Clusters.

Second, with the same objective, we conduct a placebo test in time, exploiting the long lag of our data before the start of the funding line, by shifting the treatment five years back to a hypothetical arrival of Clusters in 2001/2002. Estimation results reported in Table A.4 show no significant differences between counties that received Clusters of Excellence and other counties with CRCs in AM on any of the scientific production outcomes considered between 1995–2008 in the absence of any actual Clusters. This reinforces our interpretation that the observed effects (in Table 2) are in fact attributable to funding of Clusters of Excellence.

Finally, in Table A.5 we evaluate robustness when holding constant the choice of participation in the Clusters of Excellence competition, by comparing counties of Clusters against a synthetic counterfactual consisting of a more narrow group of only those counties with prior CRCs in AM whose universities applied for a Cluster of Excellence, were selected for the final round of evaluation, but did ultimately not receive the grant. Results are qualitatively robust, implying roughly a doubling of scientific articles related to AM above the 90^{th} percentile of citation impact, as well as an augmentation by 3/4 of citation-weighted articles in AM, in regions of Clusters relative to the final round rejected applicants. The point estimate for top 5% articles in AM is similarly positive and sizable, but not statistically significant, likely due to the even smaller sample size in this comparison, the fairly low baseline probability of the dependent variable, and the resulting large standard errors. Results are further fully robust in showing no effects on non-AM-related articles.

In Table 3, we investigate potentially differential effects of Clusters of Excellence by type of institutional origin. As expected, effects are widely concentrated onto publications by universities and public research organizations (PRO): while there is no change in their overall number scientific articles related to AM (column 1), universities and PRO in Cluster counties achieve an additional of 3 hit articles in the top 5% of citations in this area after the establishment of Clusters, relative to the weighted comparison units (column (2), point estimate of +0.86, significant at the 1%-level). At the same time, there is no statistically tractable response of scientific publishing by firms in AM science, in terms of articles authored exclusively by firms (columns (3) – (4)). However, the ATT of -.16 in column (6), significant at the 5%-level, indicates a small relative decline

Table 3: Impact on scientific publication output by type of institution

	Synthetic difference-in-differences estimates					
	Universities & PROs		Firms		Univ/PRO–firm collab.	
	(1) No. Articles	(2) Top5% Articles	(3) No. Articles	(4) Top5% Articles	(5) No. Articles	(6) Top5% Articles
Cluster_{t-1}	0.16	0.86^{***}	-0.38	-0.04	0.06	-0.16^{**}
	(0.21)	(0.31)	(0.34)	(0.05)	(0.33)	(0.07)
DV mean	3.55	1.52	0.76	0.11	1.16	0.63
Observations	266	266	266	266	266	266

Notes: The table reports the estimates for the impact of Clusters of Excellence in the area of additive manufacturing (AM) on scientific publication output between 2001–2013. The comparison group consists of all other counties of universities with AM-related Collaborative Research Centres (CRC) granted between 1995 and 2005. The dependent variable measures the inverse hyperbolic sine (IHS) of the total number of AM-related articles in column (1), and AM-related articles that enter the 95^{th} percentile of citations within a field–year worldwide by universities and public research organizations in column (2). Columns (3)–(6) report estimates of the same outcomes for firms and for university–industry collaborations. Standard errors (reported in parentheses) are derived from placebo variance estimation with 2,000 repetitions. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

in the number of top 5% articles authored jointly by universities or PROs and firms. This suggests that, at least in terms of measurable output, recipient universities and PROs reduced their direct collaboration with the private sector, specifically in the kind of scientific production mainly targeted by the Clusters of Excellence, namely, frontier science. One possible interpretation of this observation is that public excellence funding partly crowded out corporate ties by increasing independence of academic scientists and reducing their reliance on industry funding, consistent with the findings by Babina et al. (2023) regarding federal research funding to U.S. universities.

6.2 Spillovers to local industrial inventions

After assessing the direct effects of Clusters of Excellence on scientific production by academic scientists in recipient counties in the previous section, we now turn to evaluating their impact on knowledge spillovers to local industrial R&D. Table 4 reports the results from SDID estimation of the effect of Clusters on local firm patenting outcomes.

Similar to the findings on scientific output (cf. Table 2), Clusters of Excellence do not seem to have affected the volume of firm patents related to AM (column (1)), nor the five-year citation-weighted patent output in AM (column (2)) by firms in the counties of Clusters, compared to the synthetic counterfactual drawn from all other counties with CRCs in the area of AM. However, and importantly, the ATT estimate of +0.25 (significant at the 1%-level) in column (3) implies a strong and sizable impact of Clusters on the number of hit patents by firms in the thematic area of the Clusters, as measured by patents entering the 90^{th} of the citations distribution of their primary CPC class-year.

Considering that for small numbers, IHS-transformed values can be interpreted directly in levels, the coefficient in column (3) implies nearly a tripling of such hit patents by industry in counties with Clusters of Excellence following the establishment of Clusters relative to the sample mean. Column (4) shows that this effect holds significantly and in nearly unchanged magnitude also with regard to 'big hit patents'—i.e., firm patents related to AM that enter the 95$^{\text{th}}$ percentile of citations in their class-year.

To investigate how specific these effects are to AM-technology, we examine responses to Clusters by firm patents regarding inventions that are unrelated to AM in counties of Clusters and their synthetic counterfactuals in columns (5)–(8). Across these estimation models, coefficients remain consistently small and are statistically not significant for all outcomes considered. This reinforces our interpretation that the observed increase in top-patenting by local industry in AM is likely related to an increase in knowledge spillovers created by the Clusters of Excellence.

Table 4: Impact of Clusters of Excellence on industry patenting

	Synthetic difference-in-differences estimates							
	AM patents				Non-AM patents			
DV	(1) No. Pats	(2) Cit-wtd Pats	(3) Top10% Pats	(4) Top5% Pats	(5) No. Pats	(6) Cit-wtd Pats	(7) Top10% Pats	(8) Top5% Pats
Cluster_{t-1}	-0.11	0.44	0.25^{***}	0.16^{***}	-0.08	-0.22	-0.11	0.01
	(0.14)	(0.38)	(0.06)	(0.05)	(0.09)	(0.27)	(0.20)	(0.12)
DV mean	1.04	1.36	0.13	0.07	4.20	4.87	1.46	0.95
Observations	266	266	266	266	266	266	266	266

Notes: The table reports the estimates from the receipt of an excellence cluster in the area of additive manufacturing (AM) on firm patents between 2000–2013. The comparison group consists of all other counties of universities with AM-related Collaborative Research Centres (CRC) granted between 1995 and 2005. The dependent variable measures the inverse hyperbolic sine (IHS) of the number of AM-related patents in column (1), citation-weighted patents in column (2), and patents that enter the 90$^{\text{th}}$ (column (3)) and 95$^{\text{th}}$ percentile (column (4)) of citations within a CPC class–year worldwide. All outcomes are normalized by 100,000 population. Columns (5)–(8) report estimates of the same outcomes for non-AM patents. Standard errors (reported in parentheses) are derived from placebo variance estimation with 2,000 repetitions. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We show the robustness of these findings when comparing counties that received Clusters to only those counties with AM-CRC that applied for a Cluster of Excellence and were rejected in the final round of the EI in Table A.6. Estimates therein show that the entire set of coefficients is robust against specifying this alternative subset as the comparison group. The magnitude of ATTs on the number of top 10% and top 5% is slightly smaller than that of ATTs from our default estimation sample, yet sizable and significant at the 1%-level and, respectively, 5%-level. Also in this comparison, there is no response from firm patenting in areas other than AM in counties that received Cluster relative to those with rejected applicants.

In sum, the results reported in this section provide evidence for economically significant and high-quality spillovers from Clusters of Excellence to local industry R&D. The uneven impact of Clusters on local firm patenting—concentrated in the upper tail of the patent citation distribution—matches the uneven distribution of direct effects of Clusters for scientific knowledge, and is in line with expectations on the general link between top-science and high-impact invention (Ahmadpoor and Jones, 2017; Poege et al., 2019; Schaper et al., 2025).

6.3 Paper trails from patents to scientific articles

Still unclear, at this point, is to what extent the observed spillovers to local firm patenting would directly build on scientific discoveries produced by Clusters of Excellence (i.e., be knowledge spillovers) or would originate from other types of agglomeration effects related to Clusters. To investigate this, in this section, we trace knowledge flows from science to industry by assessing the acumen of incoming patent citations to scientific articles published by academic researchers in our sample. Similar to article-to-article citations, inventors (or applicants or examiners) include references to scientific prior art that has provided relevant input for the underlying inventions in patent documents. Given that patent documents additionally provide rich information regarding the timing, institutional context, and addresses of inventors, we are thus able to trace actual knowledge spillovers accurately in time, space, and content of industrial applications.

Table 5: Impact of Excellence Clusters on firm patent citations to scientific articles

	Synthetic difference-in-differences estimates							
	Citations from firm AM-patents		By origin of citing patent: Same state		Other domestic		International	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV [Articles subset]	[All]	[Top5%]	[All]	[Top5%]	[All]	[Top5%]	[All]	[Top5%]
Cluster_{t-1}	0.20	0.53^{***}	-0.01	0.06^{***}	0.10	0.09^{*}	0.05	0.37^{***}
	(0.26)	(0.15)	(0.03)	(0.02)	(0.08)	(0.05)	(0.28)	(0.11)
DV mean	0.49	0.26	0.02	0.01	0.11	0.03	0.40	0.23
Observations	266	266	266	266	266	266	266	266

Notes: This table reports the estimates for the impact of Clusters of Excellence in the area of additive manufacturing (AM) on the number of firm patent citations to scientific articles between 2000–2013. The comparison group consists of all other counties of universities with AM-related Collaborative Research Centres (CRC) granted between 1995 and 2005. The dependent variable measures the inverse hyperbolic sine (IHS) of the number of patent citations to all AM-related articles, in column (1), and to AM-related articles that enter the 95^{th} percentile of article citations within a field-year worldwide in column (2). Columns (3)–(8) report estimates of the same outcomes for patent citations originating from within the same state (column (3)–(4)), from other states in Germany (columns (5)–(6)), and from abroad (columns (7)–(8)). Standard errors (reported in parentheses) are derived from placebo variance estimation with 2,000 repetitions. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 reports the corresponding results from the SDID estimation of differences in patent citations to scientific articles produced by Clusters of Excellence and counties with CRC in AM. Across all models, we consider incoming patent citations over a five-year moving window, based on the timing of publication of scientific articles and the priority filing date of patents. Columns (1) and (2) consider citation counts from patents related to AM worldwide to scientific articles in counties in our sample: while there is no statistically detectable difference in citation rates between regions of Clusters and CRCs with regards to the overall output of scientific articles in AM (column (1)), the point estimate in column (2) indicates a large and significant increase in the number of AM-patent citations to hit articles (entering the top 5% of the article-to-article citation distribution) related to AM in counties that received Clusters of Excellence. It is worth noting that the coefficient of +0.53 (significant at the 1%-level) implies an increase in the magnitude of about +235%, evaluated against the dependent variable sample mean, and is thereby approximately double the size of the increment in top 5% articles itself (cf. Table 2, column (4)). In other words, the estimated impact of Clusters of Excellence on knowledge spillovers from top science to firm patents largely exceeds what can be explained by a pure volume effect—i.e., an increase in top scientific output alone. Such a mechanism could be, for example, a shift toward more relevant top science for industrial application or increased visibility of frontier research induced by Cluster, making it more accessible to firms.

In columns (3)–(8), we further assess the extent to which excess patent citations to AM-related science generated by Clusters of Excellence are geographically localized. To this end, we differentiate citing patents by their regional proximity to counties in which the cited articles were produced. Specifically, we distinguish between patents with at least one inventor located in the same federal state (*Land*) as the cited article (columns (3)–(4)), patents originating from other German states having at least one domestic inventor (columns (5)–(6)), and international citations—i.e., patents without any inventor based in Germany (columns (7)–(8)). The coefficients show that the ATTs of Clusters of Excellence are positive and statistically significant across all geographic distances between citing patents and cited articles considered, though the effects are consistently limited to hit articles. Comparing effect magnitudes across regional categories reveals a clear pattern of localization. Evaluated at the respective sample means, the ATT is largest for patent citations originating from within the same state as the Clusters (approximately seven-fold), followed by domestic citations (around four-fold), and international citations (roughly two- to three-fold). This pattern suggests that the magnitude of spillovers from Clusters of Excellence for corporate inventors declines with geographic distance.

In Table A.7, we extend the analysis of patent citations to scientific articles to assess heterogeneity of effects, mechanisms, and sensitivity. First, as the estimates in columns (1)–(2) show, we do not find evidence for any increase in citations from patents outside of AM-related inventions. This suggests that the impact of Clusters was confined to relevant technological areas and, thus, supports our assessment that the treatment effects estimated in Table 5 reflect actual knowledge spillovers. The fact that the point estimates in columns (1) and (2) are positive and non-zero may be indicative of possible moderate cross-domain spillovers. However, due to the large standard errors, we cannot reject the null hypothesis on this observation. Second, the science-technology spillovers from Clusters of Excellence are by no means limited to corporate patents, but accrue similarly to patented inventions by universities and PROs, as shown in columns (3) and (4). As could be expected, these effects are somewhat more pronounced than the ATTs on firm patents and, unlike those, are not limited to hit articles originating from Clusters of Excellence (cf. column (3)). Third, the increase in patent citations to scientific articles in Cluster counties after their establishment is limited to (top) AM-related articles. As shown by columns (5) and (6), the ATT estimates for citations to non-AM articles from non-AM firm patents are close to zero and statistically insignificant, both for all articles and for hit articles. Finally, the estimates reported in columns (7) and (8) show that our findings of increased firm patent citations to AM-related hit articles are fully robust and even larger in magnitude when comparing Cluster counties to a synthetic comparison group composed solely of rejected applicants from the final evaluation round.

7 Discussion & Conclusion

Links between public science and industrial invention are central to technical change and societal progress, yet they are non-uniform and do not arise in straightforward ways. Designing effective targeted policy instruments that foster spillovers from fundamental science into industrial applications therefore remains a key challenge and an open area of debate. In this paper, we contribute to this debate by examining the impact of Clusters of Excellence—large-scale, collaborative, thematically focused, and localized public research grants targeted at the promotion of frontier research—on scientific outcomes and the subsequent knowledge spillovers into industrial technological innovation. Using additive manufacturing (AM) as a relevant, representative science-based technological domain, our paper presents a detailed examination of the effects of the German Excellence Initiative of 2006/2007, which allocated—among others—funding to three AM-related Clusters of Excellence.

Comparing university-locations that won Clusters to those that hosted Collaborative Research Centres (CRC) related to AM immediately before to the start of the funding line, but did not receive a Cluster, our analyses show that funding of Clusters appears to have been particularly selective towards regions with strong existing industrial R&D capacities in the targeted thematic areas and with scientific production that was particularly relevant for industrial technology, as evidenced by local firm patenting and citations to AM-specific scientific articles from firm patents worldwide.

Using a synthetic difference-in-differences approach in order to isolate the marginal impact of the funding scheme, we find that the strong positive effect of Clusters of Excellence on scientific production is highly concentrated among hit articles in the far right tail of the scientific citations distribution—i.e., discoveries at the scientific frontier. This rise in top publications is attributed exclusively to university researchers and authors at public research organizations and is sharply confined to the topics and fields targeted by the Clusters.

Our analyses moreover revealed that Clusters of Excellence generated substantial and qualitatively important knowledge spillovers from frontier science to industry, at a level beyond what can be accounted for by the increase in hit articles alone. These became manifest in a strong increase in the number of high-impact patents (hit patents) topically related to AM by local firms in counties hosting Clusters of Excellence, as well as by a significantly larger inflow of citations by industry patents to scientific hit articles. These effects were geographically localized and thematically confined to articles and patents in the area of AM. These findings show that the Clusters of Excellence not only enhanced local frontier research capabilities but also catalyzed measurable and statistically significant advancements in the translation of scientific knowledge into high-impact technological outputs.

The observation that locations that received Clusters produced both more frontier science and high-impact firm patents indicates that the benefits of excellence funding extended beyond academic research, fostering spillovers into industrial applications with superior technological importance and, alongside with this, most likely also significant private economic value. Importantly, our results suggest a pattern of substitution in which perhaps more mediocre science and invention outcomes were replaced by hit articles and hit patents, without any changes in aggregate output. This points to a shift at the intensive rather than the extensive margin and a reconfiguration of the local innovation ecosystem toward frontier research and, in turn, more significant inventive outcomes, thereby accelerating technical progress in targeted domains. In this respect, Clusters of Excellence differed fundamentally from comparable funding instruments, such as Collaborative Research Centres, and proved substantially more effective in achieving the underlying policy objective. Thereby, our findings contribute to the small literature regarding the effectiveness of excellence funding on scientific research (Bornmann, 2016; Möller et al., 2016; Gawellek and Sunder, 2016; Schubert et al., 2017; Carayol and Maublanc, 2025), by documenting that Clusters of Excellence—thematically focused, forum-based excellence grants—exerted a strong positive impact on the production of top-science, which contrasts with prior observations for university-wide excellence policies by Carayol and Maublanc (2025). Here, our findings suggest that Clusters may be particularly effective at promoting scientific excellence. With these insights, we add new evidence also to the more general literature on the returns to competitive research funding (Azoulay et al., 2011; Jacob and Lefgren, 2011b; Hottenrott and Lawson, 2017; Myers, 2020; Heyard and Hottenrott, 2021), in particular regarding team-level outcomes (Encaoua et al., 2000; Carayol and Matt, 2004). Our analysis also provides further support for the findings of Babina et al. (2023) that federal research funding may reduce the dependence of public university research on the private sector, by showing an increase in frontier scientific output alongside a decline in the share of industry collaborations among top-science publications in regions hosting Clusters of Excellence.

Our findings further contribute to the body of prior work that has evaluated real economic effects and industry spillovers from public science funding (e.g., Li et al., 2017; Azoulay et al., 2019), and excellence funding in particular (Bergeaud et al., 2025; Krieger, 2024), by showing that targeted excellence funding can effectively promote the accrual of high-quality knowledge spillovers from science to local firm R&D, as evidenced by an increase in the amount of industrial invention concentrated in the top of the technology impact distribution. By tracing knowledge flows from scientific publications to patented inventions, we further contribute to this literature by providing direct evidence of the reliance on and use of knowledge from scientific discoveries originating in Clusters of Excellence by industrial technology. In these respects, our findings also speak to the broader literature on the localization of knowledge spillovers from science to technology (e.g., Jaffe, 1989; Belenzon and Schankerman, 2013; Bikard and Marx, 2020), the heterogeneity of science-technology linkages across dimensions of scientific quality and technology impact (Ahmadpoor and Jones, 2017; Poege et al., 2019; Veugelers and Wang, 2019; Krieger et al., 2024), and the literature on institutions that effectively enhance spillovers from public science to private sector invention (Bryan and Ozcan, 2021; Schaper, 2021; Wernsdorf et al., 2022; Schaper et al., 2025).

Our analysis provides a focused, in-depth case study centered on AM-related science and technology, a setting particularly well suited to tracing knowledge spillovers through publications and patents at a highly granular level. Although the mechanisms documented here are likely relevant beyond additive manufacturing, an important avenue for future research would be to examine whether similar patterns arise in other scientific fields and technological domains. Extending the analysis to other disciplines would help assess the broader—and often less tangible—effects of research funding across different research environments. This may, however, require different indicators for knowledge transfer, especially in disciplines where patenting is uncommon.

A second priority would be to expand the analysis to substantially larger samples of individual researchers in order to investigate heterogeneity in the effects of excellence funding. Such heterogeneity is crucial for policy evaluation but has remained underexplored. In particular, future work should examine possible differential impacts by research profiles, career age, gender of principal investigators, or different institutional arrangements.

Future research should also consider broader and more nuanced dimensions of quality associated with frontier science, such as risk-taking, novelty, and breadth of impact, and extend the set of outcomes beyond academic science. While our analysis covers an extended period, it does not explicitly capture effects that may emerge only over longer horizons. Some consequences of excellence funding may materialize gradually, for example, through the mobility of researchers, such as doctoral graduates who transition into new academic or industrial roles, or through collaborative technology development, licensing, labor mobility, incumbent firms, or new venture creation. Exploring such channels in more detail and in different contexts would improve our understanding of the longer-run effects of excellence funding on scientific and technological ecosystems.

More generally, the mechanisms through which excellence funding generates its effects deserve further attention. Funding programs such as the Excellence Initiative confer considerable prestige, which may, in turn, increase the visibility and influence of research produced in funded locations. Greater visibility may facilitate the diffusion and recognition of new insights, as both researchers and their universities may leverage the Cluster funding to more effectively market their work. At the same time, it remains challenging to disentangle the effects of new, enhanced, or expanded collaborations from the mere infusion of additional resources into existing partnerships. Likewise, distinguishing research directly supported by the grant from other work conducted by the same investigators—or by other researchers in the same field and region—poses a non-trivial methodological challenge. These ambiguities highlight the need for future studies to explore the pathways through which such funding mechanisms generate their impacts.

Despite the limitations, our findings underscore that large-scale research funding can generate measurable effects that extend well beyond the immediate circle of funded researchers. In addition to advancing the scientific frontier, targeted funding programs appear capable of strengthening local innovation ecosystems, fostering high-impact knowledge spillovers from public to private sector, and enhancing regional technological capabilities.

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Appendix

Table A.1: List of Clusters of Excellence, runner-ups, and Coll. Research Centres

Location	Clusters of Excellence	Cluster runner-ups	Collaborative Research Centres
Aachen	EXC89, EXC128	-	289, 401, 442, 525, 532, 561
Berlin	-	-	281, 546, 605
Bochum	-	-	459, 526
Brunswick	-	-	420, 599
Bremen	-	✓	570, 637
Chemnitz	-	-	283, 379, 457
Clausthal	-	-	390
Darmstadt	-	✓	392, 595, 666
Dortmund	-	-	459, 559
Dresden	-	-	609, 639
Erlangen	EXC315	-	396
Freiberg	-	-	609
Freiburg	-	✓	499
Hanover	EXC62	-	516, 599, 653
Illmenau	-	-	622
Karlsruhe	-	-	483, 588
Munich	-	-	582
Paderborn	-	-	614
Stuttgart	-	✓	404, 467, 543

Notes: This tables shows outcomes across university cities with Collaborative Research Centres (CRC) in the area of additive manufacturing (AM) granted between 1995 and 2005 in the final round of the Excellence Initivative of 2006/2007 with regards to AM-related Clusters of Excellence. Collaborative Resaerch Centres considered are in the fields of mechanical & production engineering and material engineering & material sciences.

Table A.2: Keyword vocabulary for semantic search of AM-related articles

Source: Standard VDI 3405		
Additive Manufacturing	Additive Fertigung	Rapid Manufacturing
Rapid Prototyping	Rapid Tooling	Stereolithography
Stereolithografie	Laser Sintering	Laser-Sintern
Selective Laser Sintering	Selektives Laser-Sintern	Laser Beam Melting
Laser-Strahlschmelzen	Laser Forming	Laser Forming
Selective Laser Melting	Selective Laser Melting	LaserCUSING
Direct Metal Laser Sintering	Direktes Metall-Laser-Sintern	Electron Beam Melting
Elektronen-Strahlschmelzen	Fused Layer Manufacturing	Fused Layer Modelling
Fused Deposition Modelling	Filament Deposition	Strangablegeverfahren
Multi-Jet Modelling	Poly-Jet Modelling	3D-Printing
3D-Druck	Layer Laminated Manufacturing	Schicht-Laminat-Verfahren
Laminated Object Manufacturing	Digital Light Processing	Thermotransfer Sintering
Thermotransfer-Sintern		
Source: Standard ISO/ASTM 52900		
Binder Jetting	Freistrahl-Bindemittelauftrag	Directed Energy Deposition
Materialauftrag mit gerichteter Energieeinbringung	Material Extrusion	Materialextrusion
Material Jetting	Freistrahl-Materialauftrag	Powder Bed Fusion
Pulverbettbasiertes Schmelzen	Sheet Lamination	Schichtlaminierung
Vat Photopolymerization	Badbasierte Photopolymerisation	
Source: AMPower GmbH & Co. KG		
Metal Selective Laser Sintering	Laser Beam Powder Bed Fusion	Wire Feed Laser
Powder Feed Laser Energy Deposition	Continuous Fiber Sheet Lamination	Wire Arc
Plasma Arc Energy Deposition	Electron Beam Powder Bed Fusion	Liquid Metal Printing
Fiber Alignment Area-Wise Vat Polymerization	Electron Beam Energy Deposition	Ultrasonic Welding
Metal Filament Fused Deposition Modeling	Nanoparticle Jetting	Friction Deposition
Metal Pellet Fused Deposition Modeling	Metal Lithography	Powder Metallurgy Jetting
Continuous Fiber Thermoplastic Deposition	Electrographic Sheet Lamination	Thermal Powder Bed Fusion
Laser Powder Bed Fusion	Pellet Based Material Extrusion	Mold Slurry Deposition
Continuous Fiber Material Extrusion	Filament Based Material Extrusion	Coldspray
Area-Wise Vat Polymerization	Resistance Welding	Thermoset Deposition
Continuous Fiber Thermoset Deposition	Elastomer Deposition	Vat Vulcanization
Source: Recent scientific articles from journals such as *Additive Manufacturing*, *Rapid Prototyping Journal*, *Materials*, etc.		
Laser Chemical Vapor Deposition	Continuous Liquid Interface Production	Laser Metal Fusion
Selektives Laserschmelzen	Selective Mask Sintering	Selektive Maskensintern
Laser Engineered Net Shaping	ARBURG Kunststoff-Freiformen	Laserpulverformung
Maskless Masoscale Material Deposition	Foam Reaction Prototyping	Tool-Less Fabrication
Werkzeuglose Fertigung	Generative Manufacturing	Generative Fertigung
Digital Composite Manufacturing	Laserstrahlschmelzen	Laser Consolidation
Laserkonsolidierung	Ultrasonic Consolidation	Ultraschallkonsolidierung
Freeform Fabrication	Freiformherstellung	Layer Manufacturing
Schichtbauverfahren	Additive Layer Manufacturing	Additive Schichtherstellung
Additive Layer Manufacturing	Additive Schichtherstellung	Additive Techniques
Ultrasonic Additive Manufacturing	Additive Process	Additive Fabrication
Digital Light Synthesis	Continuous Digital Light Manufacturing	Two-Photon Polymerization
Programmable Photopolymerization	Direct Shell Production Casting	Thermal Polymerization
Directed Light Fabrication	Light Initiated Fabrication Technology	Additive Techniken
Ultraschalladditivherstellung	E-Manufacturing	Hot Lithography
Holographic Interference Solidification	Fused Filament Fabrication	Schmelzschichtung
Masked Stereolithography	Laser Metal Deposition	Laserauftragsschmelzen
Lithography-Based Ceramic Manufacturing	Robocasting	Direct Metal Deposition
Beam Interference Solidification	Ballistic Particle Manufacturing	Bioprinting
Solid Ground Curing	Solid Foil Polymerisation	Film Transfer Imaging
Cold Spraying	Selective Deposition Lamination	Kaltgasspritzen
Digital Manufacturing	Digitale Fertigung	Direct Ink Writing
Stereolithography Apparatus		

Notes: This table lists all AM-related keywords used for the semantic search of article abstracts. The keyword vocabulary is constructed from four sources: the standards VDI 3405 and ISO/ASTM 52900, the consulting firm AMPower GmbH & Co. KG, and technical terms from recent literature in journals such as *Additive Manufacturing*, *Rapid Prototyping Journal*, and *Materials*.

Table A.3: Pre-period summary statistics—University characteristics

	Clusters of Excellence	Other Collaborative Research Centres		Cluster Runner-ups	
Variables	Mean	Mean	Fisher p-val	Mean	Fisher p-val
Basic funding (k EUR)	381,150	266,733	0.52	229,051	0.11
Third-party grants (k EUR)	109,343	79,905	0.55	82,478	0.29
University rank (within DE)	18.89	29.45	0.33	26.13	0.03
Academic staff	3,572	3,672	0.78	3,411	0.97
Faculty staff	310	385	0.99	332	0.86
Graduates	3,133	2,686	0.61	2,153	0.11
Engineering	722	503	0.40	517	0.63
Natural Sciences	2,058	1,483	0.56	1,269	0.11
Medicine	595	287	0.38	171	0.23
University spin-offs	25.44	24.81	0.84	24.92	0.91

Notes: This table compares group means at the region-level for yearly outcomes across counties receiving Clusters of Excellence (treated group), all other counties with Collaborative Research Centres granted between 1995–2005 (comparison group), and only counties with rejected final round applicants for a Cluster of Excellence (subset of comparison group) in the area of additive manufacturing (AM) over the pre-period of the Excellence Initiative from 2000–2006. Reported p-values for differences in means are exact permutation (Fisher randomization) p-values computed from the full randomization distribution (two-sided).

Table A.4: Impact of Clusters of Excellence on scientific output—Placebo test

	Synthetic difference-in-differences estimates							
	AM articles				Non-AM articles			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV	No. Articles	Cit-wtd Articles	Top10% Articles	Top5% Articles	No. Articles	Cit-wtd Articles	Top10% Articles	Top5% Articles
PlaceboCl_{t-1}	0.08	0.15	0.16	0.09	-0.01	0.05	0.05	0.02
	(0.10)	(0.18)	(0.22)	(0.24)	(0.10)	(0.14)	(0.13)	(0.18)
DV mean	3.04	5.43	2.19	1.62	7.19	9.88	5.73	5.07
Observations	266	266	266	266	266	266	266	266

Notes: This table reports the estimates from a placebo test for the impact of Clusters of Excellence in the area of additive manufacturing (AM) on scientific publication output between 1995 and 2008, assuming a hypothetical establishment of Clusters in 2001/2002. The comparison group consists of all other counties of universities with AM-related Collaborative Research Centres (CRC) granted between 1995 and 2005. The dependent variable measures the inverse hyperbolic sine (IHS) of the number of AM-related articles in column (1), citation-weighted articles in column (2), and articles that enter the 90$^{\text{th}}$ (column (3)) and 95$^{\text{th}}$ percentile (column (4)) of citations within a field–year worldwide. Columns (5)–(8) report estimates of the same outcomes for non-AM articles. Standard errors (reported in parentheses) are derived from placebo variance estimation with 2,000 repetitions. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Impact of Clusters of Excellence on scientific output—Runner-ups only

	Synthetic difference-in-differences estimates							
	AM articles				Non-AM articles			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV	No. Articles	Cit-wtd Articles	Top10% Articles	Top5% Articles	No. Articles	Cit-wtd Articles	Top10% Articles	Top5% Articles
Cluster_{t-1}	0.20	0.55^{**}	0.80^{***}	0.39	0.05	0.07	0.11	0.13
	(0.33)	(0.22)	(0.30)	(0.35)	(0.17)	(0.14)	(0.17)	(0.18)
DV mean	4.06	7.04	2.60	1.95	8.49	10.67	6.07	5.44
Observations	98	98	98	98	98	98	98	98

Notes: This table reports the estimates for the impact of Clusters of Excellence in the area of additive manufacturing (AM) on scientific publication output between 2000–2013. The comparison group consists of counties of universities with applications for a Cluster of Excellence related to AM that were selected for the final round of the Excellence Initiative 2006/2007 but were ultimately rejected. The dependent variable measures the inverse hyperbolic sine (IHS) of the number of AM-related articles in column (1), citation-weighted articles in column (2), and articles that enter the 90^{th} (column (3)) and 95^{th} percentile (column (4)) of citations within a field–year worldwide. Columns (5)–(8) report estimates of the same outcomes for non-AM articles. Standard errors (reported in parentheses) are derived from placebo variance estimation with 2,000 repetitions. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Impact of Clusters of Excellence on industry patenting—Runner-ups only

	Synthetic difference-in-differences estimates							
	AM patents				Non-AM patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV	No. Pats	Cit-wtd Pats	Top10% Pats	Top5% Pats	No. Pats	Cit-wtd Pats	Top10% Pats	Top5% Pats
Cluster_{t-1}	-0.20	0.48	0.27^{***}	0.09^{**}	0.02	-0.32	-0.29	-0.09
	(0.30)	(0.77)	(0.06)	(0.04)	(0.18)	(0.39)	(0.26)	(0.26)
DV mean	1.59	1.84	0.21	0.11	4.89	5.68	2.08	1.48
Observations	98	98	98	98	98	98	98	98

Notes: The table reports the estimates for the impact of Clusters of Excellence in the area of additive manufacturing (AM) on firm patents between 2000–2013. The comparison group consists of counties of universities with applications for a Cluster of Excellence related to AM that were selected for the final round of the Excellence Initiative 2006/2007 but were ultimately rejected. The dependent variable measures the inverse hyperbolic sine (IHS) of the number of AM-related patents in column (1), citation-weighted patents in column (2), and patents that enter the 90^{th} (column (3)) and 95^{th} percentile (column (4)) of citations within a CPC class–year worldwide. All outcomes are normalized by 100,000 population. Columns (5)–(8) report estimates of the same outcomes for non-AM patents. Standard errors (reported in parentheses) are derived from placebo variance estimation with 2,000 repetitions. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Impact of Clusters of Excellence on firm patent citations to scientific articles—Sensitivity

	Synthetic difference-in-differences estimates							
	Citations from Non-AM patents		Citations from Univ/PRO patents		Citations to Non-AM articles		Only Runner-ups	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV [Articles subset]	[All]	[Top5%]	[All]	[Top5%]	[All]	[Top5%]	[All]	[Top5%]
Cluster_{t-1}	0.56	0.42	0.46^{***}	0.46^{***}	0.05	-0.04	0.40	0.98^{**}
	(0.53)	(0.53)	(0.17)	(0.08)	(0.18)	(0.25)	(0.52)	(0.39)
DV mean	2.02	1.11	0.30	0.18	6.58	5.57	0.70	0.47
Observations	266	266	266	266	266	266	98	98

Notes: This table reports the estimates for the impact of Clusters of Excellence in the area of additive manufacturing (AM) on the number of patent citations to scientific articles between 2000–2013. The comparison group in columns (1)–(6) consists of all other counties of universities with AM-related Collaborative Research Centres (CRC) granted between 1995 and 2005. The dependent variable measures the inverse hyperbolic sine (IHS) of the number of citations from non-AM firm patents to all AM-related articles, in column (1), and to AM-related articles that enter the 95$^{\text{th}}$ percentile of article citations within a field-year worldwide in column (2). Columns (3)–(4) report estimates of the same outcomes for AM-related patent citations originating from patents by universities and public research organizations (PRO). Columns (5)–(6) report estimates of the same outcomes for patent citations by non-AM firm patents to non-AM articles. Columns (7)–(8) report estimates for the number of citations from AM-related firm patents to AM-articles using an alternative comparison group consisting of only counties of universities with applications for a Cluster of Excellence related to AM that were selected for the final round of the Excellence Initiative 2006/2007 but were ultimately rejected. Standard errors (reported in parentheses) are derived from placebo variance estimation with 2,000 repetitions. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.