Research Policy 55 (2026) 105393

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

The effect of publicly co-funded industry-science collaboration on scientific production

Paul Hünermund [a,b], Cindy Lopes-Bento [c,e,*], Maikel Pellens [c,d,f]

[a] Copenhagen Business School, Department of Strategy and Innovation, Kilevej 14A, 2000, Frederiksberg, Denmark
[b] Vilnius University, Faculty of Economics and Business Administration, Saulėtekio al. 9, 10222, Vilnius, Lithuania
[c] KU Leuven, Department of Managerial Economics, Strategy and Innovation, Naamsestraat 69, 3000, Leuven, Belgium
[d] ZEW – Leibniz Center for European Economic Research Mannheim. L7, 1, 68161, Mannheim, Germany
[e] FNR (Luxembourg National Research Fund), 2 avenue de l'Université, L-4365, Esch-sur-Alzette, Luxembourg
[f] Centre for R&D Monitoring (ECOOM) at KU Leuven, Naamsestraat 61, 3000, Leuven, Belgium

A R T I C L E I N F O

Keywords:
Innovation
Academic engagement
Industry-science collaboration
Science and technology policy
Joint programming initiative

A B S T R A C T

Competitive industry-science collaboration programs encourage academic scientists to co-develop innovation projects with firms. These programs combine attributes of competitive research funding and science commercialization policies. Because they demand more time and effort than traditional science funding, and may push applicants toward projects with higher commercial potential, the question arises whether they come at the expense of scientific productivity or alter the direction of research. Using data from a large-scale, cross-country R&D policy, we find no evidence of negative impacts on science. On the contrary, our analysis shows an increase in joint scientific publications with industrial partners, while the overall direction of research remains unchanged.

1. Introduction

Policymakers increasingly rely on "translational" programs in the design of public R&D support measures; initiatives that blend features of traditional R&D subsidies with elements of research commercialization. The driving logic behind such programs is that including commercialization in policy design increases the chances of market introduction of research results, thereby achieving economic and societal impact.[1] While the impact of such policies on firm growth and commercialization has been analyzed in the academic literature (Hünermund and Czarnitzki, 2019), we know little about the consequences of such programs on scientific productivity and direction. By analyzing the mechanisms at play in industry-science programs that are primarily aimed at enhancing the outcome of industry partners, in this paper we address a recent plea by Azoulay and Li (2022) on the scarcity of knowledge regarding the impact of translational programs on science and involved scientists (Azoulay et al., 2019b; Bonvillian, 2006; Van Atta, 2007). Understanding this impact is vital since scholars and policymakers agree that scientific findings are essential for contributing to welfare-enhancing innovations (Azoulay and Li, 2022; Dasgupta and David, 1994; Mokyr, 2002; Rosenberg, 1974).[2]

A primary example of a translational program is provided by the

* Corresponding author at: KU Leuven, Department of Managerial Economics, Strategy and Innovation, Naamsestraat 69, 3000, Leuven, Belgium.
E-mail address: cindy.lopesbento@kleuven.be (C. Lopes-Bento).

[1] Not only government programs encourage the commercialization of research. For instance, survey evidence finds that entrepreneurship is widely encouraged in U.S. university research labs (Roach, 2017).

[2] Roughly 40 % of grants funded by the National Institute of Health (NIH) are cited in private sector patents, and each dollar of NIH-funded research money translates into spillovers worth twice as much for the private sector, without accounting for the value generated for academic research and training (Azoulay et al., 2019a; Azoulay and Li, 2022; Li et al., 2017). A drug like Gleevec, an efficient treatment for chronic myelogenous leukemia, or a general-purpose project like "concrete computational complexity," which led to the first public-key cryptosystem, are only two of numerous examples of life-changing discoveries derived from basic research projects (Azoulay and Li, 2022; Rivest et al., 1978).

https://doi.org/10.1016/j.respol.2025.105393
Received 16 September 2024; Received in revised form 18 November 2025; Accepted 2 December 2025
Available online 20 December 2025

famous ARPA-E (Advanced Research Projects Agency) research funding in the U.S., oriented toward commercialization and societal impact.[3] Also in Europe, policymakers go a long way in encouraging collaboration between scientists and firms, one of the most important initiatives being the EU's famous flagship program *Eurostars*. Eurostars is a program targeting R&D active firms, SMEs in particular, that encourages cross-country collaboration as well as collaboration with science to increase innovativeness and competitiveness of the European private sector (more details on the program are provided in section 3). While Eurostars has translational objectives, this paper focuses specifically on the impact of the program with respect to its *collaborative nature* – i.e., how structured interaction between scientists and industry partners affects academic research outcomes.

We empirically study the effect of participating in Eurostars on scientists' knowledge production by analyzing the program's impact on publications, citations, and the research agendas of first-time involved PIs. We further investigate whether the effects are moderated by factors such as seniority, the type of institution a scientist is active in, or the network structures that are likely to drive any productivity changes. In doing so, we are not only addressing a critical policy issue but also tackling endogeneity challenges faced by most existing studies in policy evaluation settings. Recent literature has endeavored to mitigate endogeneity issues in policy evaluation primarily by the use of regression discontinuity designs (RDD) (e.g., Bronzini and Iachini, 2014; Howell, 2017). While there are many advantages to using an RDD, the external validity of this method remains limited insofar as the evaluation is constrained to grants around a single funding threshold. To address this challenge, we go beyond the current state-of-the-art of evaluation techniques and use a unique budget allocation rule that creates plausibly exogenous variation in the funding of projects with similar quality. This approach relies on funding variation in a wide range of the program's evaluation ranking rather than a small neighborhood around the funding threshold. Consequently, it leads to a higher external validity than an RDD would and corroborates a method used in firm-level policy evaluation of the same program (Hünermund and Czarnitzki, 2019).

While our data are drawn specifically from the Eurostars program, it is important to highlight that Eurostars is not an isolated funding scheme within the EU. Instead, it serves as a flagship example of competitively co-funded industry-science collaborations, with a structure and objectives closely aligned to numerous other EU and global funding programs. This makes our findings broadly relevant beyond Eurostars itself. Illustrating the program's growing importance, its budget nearly doubled from €500 million in Eurostars-1 to €1.14 billion in Eurostars-2. Concerning its structure and policy objectives, Eurostars is comparable to other translational research initiatives such as ARPA-E (US), Innovate UK, and Germany's ZIM program. It should also be noted that while Eurostars targets SMEs, applicant firms can also collaborate with larger corporations. In that sense, about a fifth of the firms in our sample (17 % to be exact) form a consortium with a larger firm, leading to a representative size distribution of funded firms. Finally, by evaluating the impact of the Virtual Common Pot (VCP, see methodology section for more information) in fostering industry-science collaboration, knowledge spillovers, and commercialization outcomes, our findings contribute to broader EU policy discussions on designing effective multi-country funding models that balance flexibility with strategic coordination.

Our analysis does not reveal evidence of a negative impact on scientists' productivity, technological output, or research direction. While participation in Eurostars does not significantly increase the overall number of publications, it leads to a substantial rise in industry co-authored publications – by approximately 25 % – without affecting other types of research output. This suggests that the program fosters deeper collaboration between academia and industry rather than simply increasing overall research activity. Importantly, we find no evidence that participation shifts scientists' research agendas toward more applied topics, as measured by keyword introduction, journal diversification, and abstract similarity. Furthermore, our results indicate that the observed increase in industry collaboration is not driven by an expansion in co-author networks or research team size, ruling out a pure resource effect. Instead, knowledge spillovers from industry to academia appear to be the primary driver. The effects are particularly pronounced for scientists in public research organizations (as opposed to universities), early-career researchers, and those in ICT-related fields, where industry collaborations are less common. Additionally, larger grants amplify the program's impact on industry co-authored publications. Long-term analyses show that these effects persist beyond the program's duration, with Eurostars-funded scientists continuing to collaborate more frequently with industry partners even a decade after the end of the program.

2. Conceptual Background: substitution and complementarity in industry-science collaboration

Industry-science collaboration programs, such as Eurostars, involve tensions between commercialization objectives and academic research goals. These tensions can be understood through two overarching mechanisms*: substitution effects* and *complementarity effects*, which shape scientific outcomes in distinct ways.

Substitution effects occur when the emphasis on commercialization displaces traditional academic priorities. The traditional role of universities has been to produce and disseminate knowledge through the work of autonomous researchers who enjoy academic freedom in choosing their projects, methods, and modes of dissemination (Aghion et al., 2008). Translational programs, however, often challenge this model by requiring scientists to realign their research agendas to meet dual demands: the pursuit of academic excellence, as in competitive research funding, and the demonstration of commercialization potential, as in proof-of-concept funding. With increased collaboration between industry and science, scholars have thus expressed concerns about the trade-off between research and commercialization activities (Goldfarb, 2008; Toole and Czarnitzki, 2010); the distortion of institutional norms (Mowery et al., 2001); reduced scientific productivity and knowledge dissemination through publications (or publication delays) because of appropriation, secrecy, and intellectual property rights (Blumenthal et al., 1996, 1997; Czarnitzki et al., 2015; Evans, 2010a; Lee, 2000; Louis et al., 2001; Shibayama et al., 2012; Stephan, 1996; Thursby et al., 2001); and a shift from general to more direct forms of knowledge exchange (Shibayama et al., 2012). This may result in a shift away from purely academic pursuits, such as publishing, toward more practical applications. Scientists may also need to collaborate with new kinds of research partners, such as firms, which can impose restrictions on knowledge dissemination through corporate secrecy or competitive behavior, thereby hindering contributions to teaching, open science, and the broader dissemination of findings.

Complementarity effects, on the other hand, arise when commercialization activities reinforce academic research. Industry-science collaborations can stimulate new ideas and *knowledge spillovers* from industry to academia, enabling scientists to explore novel research

[3] ARPA-E was established in 2007 as part of the America COMPETES Act. It received an initial budget of USD 400 million in 2009 and has, as of fiscal year 2019, received approximately USD 3 billion in total (ARPA-E, 2020a). A 2017 assessment of ARPA-E concluded that "ARPA-E considers its 'technology-to-market (T2M)' activities to be an ongoing experiment, and the challenges of developing such a program may be greater than originally thought" (National Academies of Sciences, Engineering, and Medicine, 2017, p. 3–32). The report recommends that "ARPA-E should reconceptualize its 'technology-to-market (T2M)' program to account for the wide variation in support needed across programs and performers concerning prospective funding, commercialization, and development pathways" (National Academies of Sciences, Engineering, and Medicine, 2017, p. 3–33).

questions (Agrawal and Henderson, 2002; Azoulay et al., 2009; Lee, 2000; Mansfield, 1995; Perkmann and Walsh, 2009). Furthermore, *collaborations and networks* with industry can align with the interests of researchers who are drawn to downstream, application-oriented work, leading to greater personal and professional satisfaction (Roach and Sauermann, 2010). In line with these ideas, prior literature documents positive relations between engagement with industry and productivity (Gulbrandsen and Smeby, 2005; Perkmann et al., 2013; Bikard et al., 2019). Moreover, in some cases, the *additional resources* received from industry may lead to resource spillovers, allowing university departments to buy new equipment or hire graduate or post-graduate students to work in their labs, thus ensuring continued scientific output (D'Este and Perkmann, 2011; Tartari and Breschi, 2012).

Importantly, the co-development of a competitively funded project between industry and science necessitates both partners to work together closely, already when developing the proposal. Compared to other types of commercialization, where commercialization follows successful research results, competitively co-funded industry-science projects will generate knowledge spillovers between academic and industry partners regardless of the project's success, because knowledge exchange starts at the proposal stage. Therefore, this type of project might yield greater complementarities, since developing a proposal requires tight collaboration and knowledge sharing (Ayoubi et al., 2019). If the academic partner concentrates on bringing remote parts of technologies together to find novel solutions (Fleming and Sorenson, 2004) while leaving commercialization strategy to the industry partner, synergies may allow for increased specialization (Bikard et al., 2019). Since industry and academia differ in their approach to research (Evans, 2010b; Siegel et al., 2003), strong ties to industry can provide scientists with novel insights and knowledge, which are likely to increase their research output beyond the joint project (Hottenrott and Lopes-Bento, 2014). Indeed, research suggests that connecting diverse knowledge and perspectives through collaborations can help innovative teams to avoid intellectual lock-in and embark on explorations (Beck et al., 2019; Fleming et al., 2007; Reagans et al., 2004; Teodoridis, 2017; Uzzi and Spiro, 2005).

While prior literature has emphasized differences between scientific fields in terms of their orientation toward fundamental understanding versus applied use (e.g., as captured in Pasteur's Quadrant), we do not adopt this typology in our theoretical framework. The reason for this is that Eurostars projects are, by design, required to have a commercial and applied orientation across all technological fields. Consequently, even scientists from traditional basic-science fields engage in applied problem-solving when participating in translational programs such as Eurostars. As such, the framework's key dimensions (basic vs. use-oriented) are held constant by the program's structure. We thus focus on more practical and empirically grounded differences – such as the extent to which industry-science collaboration is prevalent in a given domain (e.g., lower in ICT, higher in biosciences). These differences may condition the effects of collaboration programs, particularly in how scientists build new ties or benefit from complementarities with industry partners.

Understanding these mechanisms – i.e., knowledge spillover effects, resource effects, and network effects – is crucial for assessing the impact of translational programs on scientific knowledge production and determining whether they advance or undermine science's contribution to societal welfare. However, to date, little empirical evidence is available to corroborate which of these mechanisms prevails for such programs. Fig. 1 graphically presents our research questions, with the various mechanisms and moderators at play.

3. Institutional setting

Our analysis is based on the Eurostars Joint Programming Initiative (JPI) – one of the EU's flagship science and technology programs. Eurostars promotes R&D and innovation in small and medium-sized enterprises (SMEs) and shares many features with similar grant schemes that combine academic research and commercialization, rendering our findings relevant for a large variety of translational programs, in and outside of the EU.

Eurostars was one of the first European JPIs, which are jointly organized and financed by several EU member states. In 2008, the European Commission (EC) proposed increased engagement in JPIs in a communication to the European Parliament and other stakeholders (European Commission, 2008) to address fragmented national R&D efforts and facilitate cross-border cooperation in research, thereby increasing the efficiency and impact of R&D policy initiatives in Europe. Article 185 of the *Treaty on the Functioning of the European Union* (TFEU) states that the EC is permitted to contribute financial resources from community budgets to research programs that are jointly undertaken by member states. Launched in September of 2008, Eurostars 1 pooled funds from 33 participating countries (the EU28, including the UK, plus Iceland, Israel, Norway, Switzerland, and Turkey) and had an estimated budget of EUR 500 million (Makarow et al., 2014), of which EUR 100 million were co-financed by the EC[4] (see Fig. 2 for a depiction of individual contributions by country). The program was organized by EUREKA, an international research network based in Brussels, and ran until 2013, with a total of ten biannual application rounds (so-called "cutoffs").

Projects that applied for funding under the Eurostars program were not restricted to a particular field of technology but had to be of an applied nature and for civilian purposes. Projects came in roughly equal parts from the fields of engineering, information and communication technologies, bioscience, and pharma and chemistry, and lasted an average of 28 months. Research consortia that applied for Eurostars funding had to consist of at least two SMEs from at least two participating countries.[5] The key criterion was that an SME had to be the main project applicant. Once these requirements were met, universities and research institutes (as well as larger companies) were allowed to join a project. The consortia consisted of an average of 3.3 partners from 2.5 countries. About 49 % of project applications were submitted with a co-applicant from academia. Because of their experience with grant applications, academic partners often played an important role in drafting the proposal and forming the project consortium (Hünermund et al., 2016). Applications with an academic partner were 18.7 % more likely to receive funding, corresponding to a success rate of 20.6 % compared to 17.3 % in absolute terms.

Since R&D activities in Eurostars had an applied and close-to-the-market character, academic partners were supposed to provide the technology transfer for turning research ideas into viable commercial solutions. An example of such an industry-science collaboration was the SILIBACTS project, a consortium of two SMEs from Germany and Hungary, together with the University Medical Center of the Johannes Gutenberg University in Mainz, Germany, and the Université Pierre et Marie Curie in Paris, France, which received EUR 900 thousand in funding from Eurostars 1 in 2008. The project's objective was to incorporate genetic material from marine sponges into bioactive enzymes and bacteria to make them more resilient to material stress in bio-industrial manufacturing processes. The estimated commercial potential of this technology in a global market for specialty enzymes was expected to exceed $4 billion in 2015 (Eurostars, 2014).[6] This example illustrates

[4] Until 2020, Eurostars (including the successor program Eurostars 2) assigned a total estimated budget of EUR 1.6 billion in public funding.

[5] The EU defines an SME as having fewer than 250 employees and either less than (or equal to) EUR 50 million in turnover or a balance sheet total of less than (or equal to) EUR 43 million (https://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition_en, last accessed September 5th, 2025).

[6] Other Eurostars success stories can be reviewed at https://www.eurekanetwork.org/impact-eureka/ (last accessed September 5th, 2025).

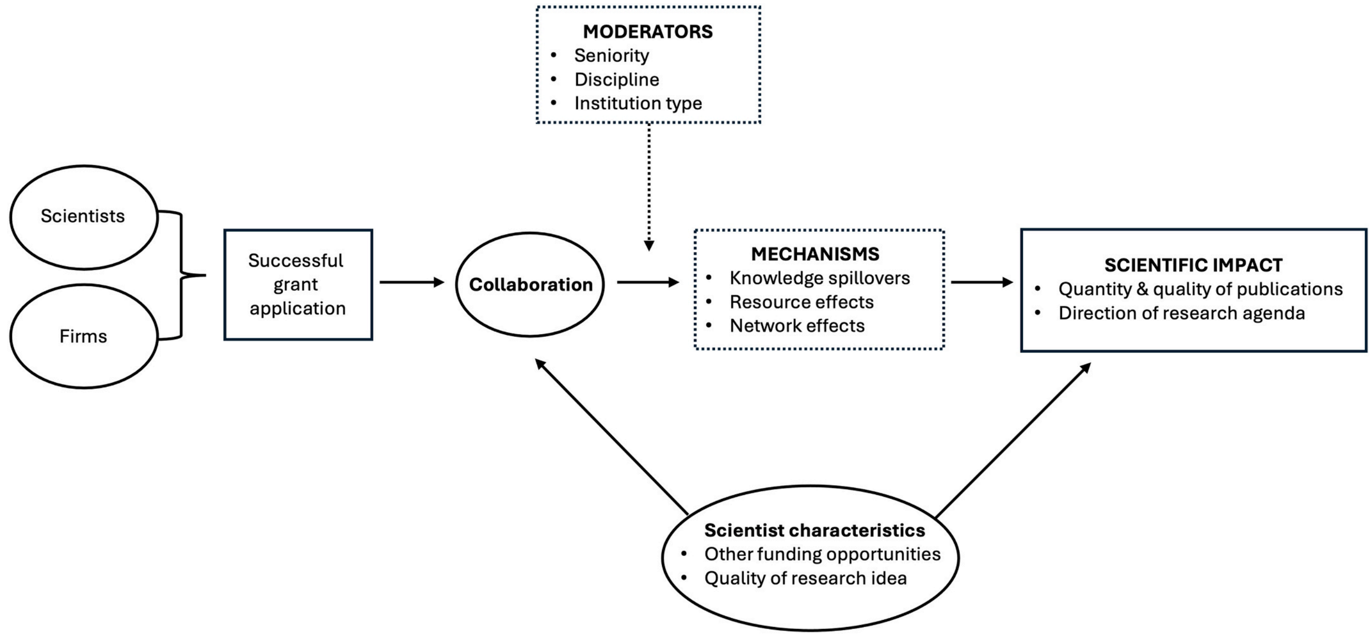

Fig. 1. Conceptual model.
Notes: Theoretical constructs related to the actors are represented as nodes with rounded borders, while observable performance-related factors are shown as square nodes. Dashed borders indicate both the theoretical mechanisms driving the observed performance outcomes and the moderating contingency factors within our model.

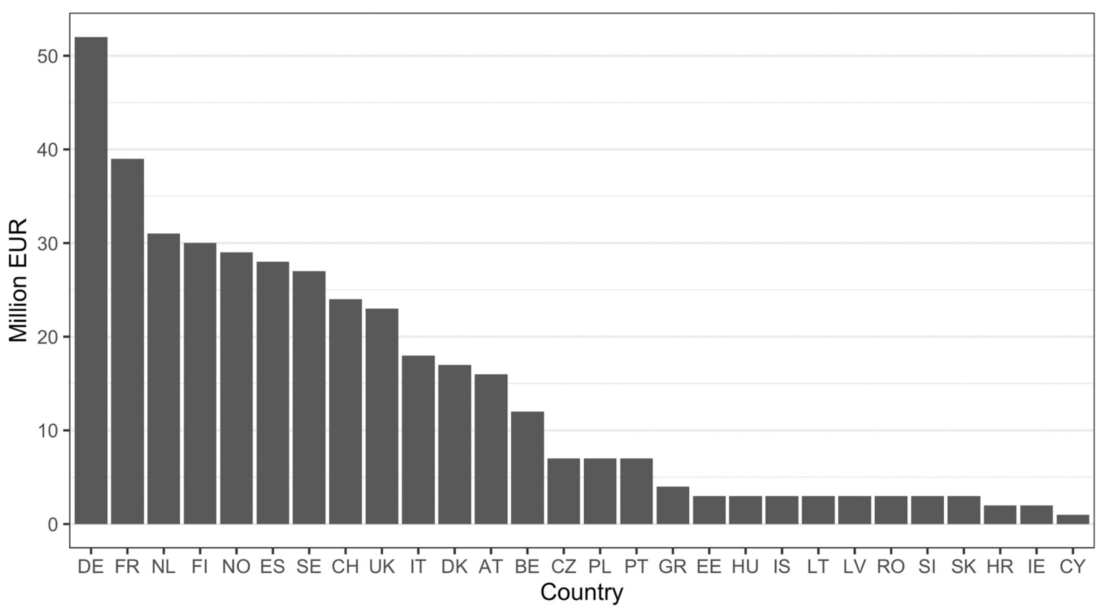

Fig. 2. National budgets.
Notes: Individual national contributions to Eurostars 1, pooled over all cutoffs and ranked by size (Makarow et al., 2014).

that the academic partners in Eurostars projects are typically directly engaged in the scientific development of the technology. In the case of SILIBACTS, for instance, academic teams were involved in the bioengineering processes necessary to adapt marine sponge genetics for industrial use – work that required experimental design, lab research, and scientific problem-solving. Such involvement is consistent with the program's requirement for co-development, and highlights that scientist' contributions often remain within the scope of their core academic competencies.

4. Data and methods

4.1. Identification

The main problem in performing causal analyses of public R&D funding programs is confounding bias (David et al., 2000). By granting only the best applications, funding agencies inflict a selection based on project quality that must be accounted for if causal effects are to be identified from the policy being studied. One way of accounting for this selection into treatment is to rely on sources of plausibly exogenous variation in the funding decisions related to projects of similar quality. We use such exogenous variation by exploiting a unique feature of budget allocation rules in European Joint Programming Initiatives.

Similar to other grant programs, Eurostars applications are evaluated based on their novelty, technological profile, and market potential. This process is organized centrally by EUREKA and is carried out by at least two independent technical experts. Their assessments are aggregated to an overall project evaluation score that ranges from 0 to 600, which is comparable across all participating countries. Fig. 3 shows the distribution of project evaluation scores for all Eurostars applications that involved academic partners.

Access to project evaluation scores would, in principle, allow the application of a regression discontinuity design (RDD), which leverages funding variations around a threshold set by the program budget. RDDs have become increasingly popular in the policy evaluation literature due to their strong internal validity (Bronzini and Iachini, 2014; Howell, 2017). However, as RDDs identify treatment effects only at a discontinuity point, their external validity remains limited. Our approach does not rely on comparisons of scientists just below and above a funding threshold, but instead exploits exogenous variation for a much wider range of project evaluation scores.[7] This results in higher external validity and greater generalizability.[8]

Key to our identification strategy is that Eurostars has no centralized program budget, despite its uniform evaluation process. To avoid cross-subsidization and the political conflicts that could arise from a centralized budget, each participating national funding agency contributes individually to the program and finances only applicants from its own country.[9] Thus, projects can be granted only when each consortium member's national budget has sufficient funds available. If one member's funds are depleted, the entire project cannot be granted, independent of its evaluation score. This funding-allocation mechanism is referred to as a *Virtual Common Pot* (VCP) in European policy circles. Compared to a situation with a centralized program budget (also known as a *Real Common Pot*, RCP), the additional national budget constraints present in a VCP create variation in funding status that is plausibly exogenous to project quality. From an econometric point of view, this variation can be used to offset selection into treatment and to recover the causal effect of the program.

To illustrate the VCP mechanism, Table 1 shows the project ranking for a hypothetical R&D subsidy program that is jointly undertaken by four countries: A, B, C, and D. Each country contributes resources to finance two project partners, with eight partners that can be funded in total. In an RCP, projects with the highest ranking would be funded until the pooled budget was exhausted. In the ranking depicted in Table 1, that implies a funding threshold at rank 3. However, in the VCP allocation, grants may not be made to the second and fourth-ranked projects if one of the countries' national budgets runs out after granting the first-ranked project (here country A), and another's runs out after granting the third (here country B). Thus, the VCP induces a variation in funding that is orthogonal to project quality. It is important to note that this variation also occurs within individual countries. In the example of Table 1, participants from country B at the second rank are not funded, while other participants from B at rank three receive funding. Thus, our empirical design does not solely rely on cross-country variation.

In a VCP, the gaps left by highly ranked but unfunded projects (partly) offset selection based on project quality. Fig. 4 shows that funding rates in our data are strictly between zero and one for project evaluation scores ranging from 400 to 520, which is the range on which our empirical analysis focuses to ensure common support (Heckman et al., 1998). The lower bound is determined by a general quality threshold, below which no project is eligible for funding; the upper bound arises from the fact that national budget constraints will always be slack for the highest-ranked projects.[10]

Hünermund and Czarnitzki (2019), analyzing the impact of the Eurostars program on firm output, investigate the risks of calculated behavior in the choice of partner. If participants were to choose partners strategically from countries with high national budgets to maximize their chances of receiving funding, and if this behavior were related to unobserved (time-variant) characteristics that affect research productivity, the estimation results could be biased. However, such calculated behavior is improbable in the case of Eurostars, as participants would need to have known the size of national budgets relative to the demand for funding, and this information was not publicly available during the runtime of the Eurostars program. Information about the workings of the VCP funding mechanism was not disseminated by EUREKA either, so it is unlikely that participants had the detailed information required to game the system in this way.[11] Furthermore, suitable project partners for highly specialized research projects are not easily substitutable, which also limits the potential for such calculated choices of partners. This corroborates evidence from a survey conducted in the course of the official evaluation of Eurostars (Makarow et al., 2014), concluding that participants selected their project partners predominantly based on either their ability to foster technology transfer or previously existing relationships (Hünermund and Czarnitzki, 2019). The authors further perform a series of robustness checks, confirming that identification remains unaffected by the potential risk of strategic behavior in a VCP.

Table A5.1 in the appendix presents regressions of pretreatment researcher characteristics (career age, publication stock, citation stock, and patent application stock) on treatment status and evaluation scores. The fact that we do not find any significant differences across the treatment and control groups for researchers in projects of similar quality strengthens our argument that the remaining variation in funding in a VCP is exogenous to research productivity. To further exploit the panel nature of our data, we employ individual fixed effects models, which subsume time-invariant controls (including project evaluation scores) and additionally account for other unobserved time-invariant characteristics such as the composition of project consortia and heterogeneities across fields.

4.2. Data sources

Our study builds on Eurostars 1's (2008–2013) administrative records, as provided by the EUREKA secretariat in Brussels. These records contain detailed information on both successful and unsuccessful project applications. After initial processing,[12] the applications include 770 scientists for whom we then collected publication and patent information. To ensure the validity of our data, we conducted this collection in

[7] Technically, the availability/depletion of national budgets acts as an instrument for Eurostars funding (Hünermund and Czarnitzki, 2019). However, since we restrict our sample to eligible projects with evaluation scores above 400, there is full compliance and the instrument and treatment thus collapse to the same variable.

[8] Additionally, an RDD would be difficult to apply in our setting because the probability of winning a grant just above the funding threshold is relatively low in Eurostars and only increases for higher evaluation scores (see Figure 4). As a consequence, the discontinuity would be extremely fuzzy, calling into question the validity of the design.

[9] Figure 2 shows each participating country's budget. The EUR 100 million that the European Commission contributed to the program was used to top up the individual national budgets (Hünermund and Czarnitzki, 2019).

[10] Appendix Figure A1.1. depicts funding rates depending on project evaluation ranks per cutoff round. The gaps in the ranking of nonfunded projects illustrate the variation introduced by a VCP funding allocation rule, which we exploit for identification.

[11] Also note that our empirical estimations consider first-time applicants, which reduces the risk of learning from repeated participation.

[12] Initial processing omitted applications from non-EUREKA countries and restricted the range of evaluation scores to ensure common support, as explained in Section 4.1.

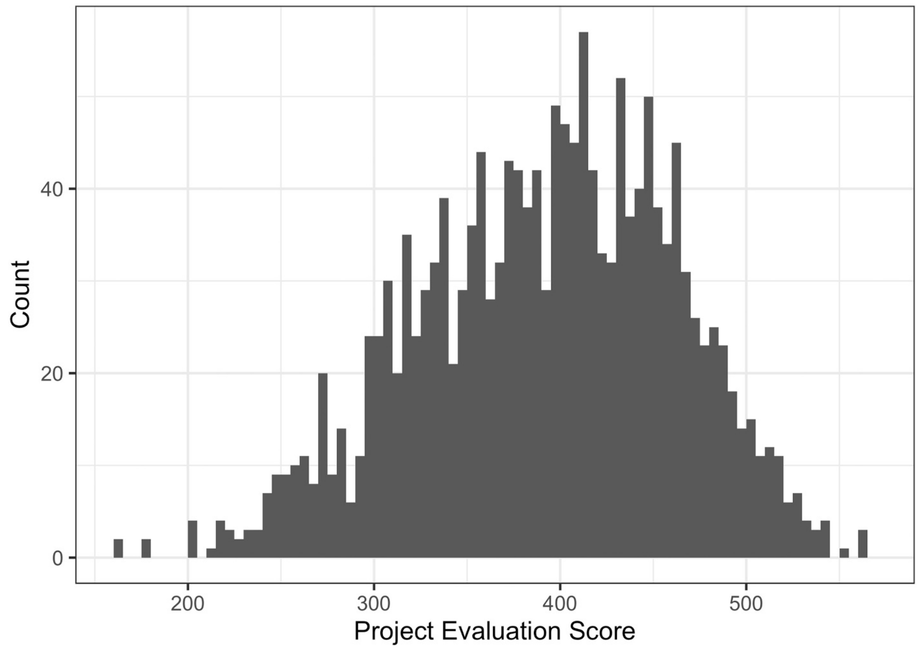

Fig. 3. Distribution of project evaluation scores.
Notes: Histogram (bin size = 5) of project evaluation scores for Eurostars applicants from academic sector.

Table 1
The working of a virtual common pot.

Rank	Project Consortium	VCP	RCP
1	2 project partners from country A, 1 project partner from country C	✓	✓
2	1 project partner from country A, 1 project partner from country B 1 project partner from country D		✓
3	1 project partner from country B, 1 project partner from country C	✓	✓
4	1 project partner from country A, 2 project partners from country B, 1 project partner from country C		
5	1 project partner from country B, 2 project partners from country D	✓	

Notes: This is a slightly adapted version of a similar example in Hünermund and Czarnitzki (2019).

several steps. First, we collected *curriculum vitae* (CV) information for each scientist, drawing on various sources, including online CVs, personal webpages, and LinkedIn. Three scientists were excluded at this stage, as their names were too common to identify them with certainty. We then conducted searches based on the scientists' last names and first initials to match each one to SCOPUS researcher ID(s), using the CV information for validation. We screened the records for credibility and removed 86 scientists from the sample for whom no plausible match in SCOPUS could be found. In most of these cases, the listed contact persons were not scientists but administrators or project managers who were not actively publishing, and thus were not in the study's target population. In a small number of cases, the listed researcher was employed in a firm rather than at a university or research center. For a few other cases, the best match was still uncertain, so the observation was removed.

After this exercise, our sample contained information on 682 principal investigators (PIs) of Eurostars project applications, of which 51.3 % obtained funding. The average grant amounted to EUR 192 thousand, although individual grants could go up to EUR 973 thousand.[13] We observed the scientists from the year in which they published their first publication. If no publications were recorded for three consecutive years, we assumed an exit from publishing activities and right-censored observations accordingly.[14] The final panel contains 13,816 individual-year observations between 1970 and 2015.[15] We observe researchers for a median of 20 years.

4.3. Outcome variables

The goal of our analysis is to characterize Eurostars' effect on scientific research. Therefore, we first examine the effect of Eurostar participation on the amount and quality of scientific publications and patenting. We consider patenting as a measure of technological output, but also as a measure of a potential shift of direction from more basic research to more applied or marketable research (e.g., Azoulay et al., 2009). We then investigate the potential mechanisms through which these effects manifest. To that end, we consider two further sets of outcome variables. The first set captures changes in scientists' research interests, and tests whether the Eurostars program's applied nature induced researchers to investigate research topics that were not part of their agendas prior to program participation. The second set captures

[13] The Eurostars grant is comparable in size to a Marie Skłodowska-Curie Individual Fellowship grant, amounting to roughly 150,000–200,000 EUR over 24 months (Federal Ministry of Education and Research, 2020), but is smaller than the average R01-equivalent grant by the National Institutes of Health, which amounted to USD 534 thousand in 2018 (Lauer, 2019). The average Eurostars project, on average, amounted to EUR 1.4 million (Copernicus, 2019), which is of the same order of magnitude as other grants with strong commercialization components. These include grants by ARPA-E (USD 500 thousand to USD 10 million, cf. ARPA-E, 2020b), the European Innovation Council's (EIC) Pathfinder Pilot (up to EUR four million), or the EIC's Accelerator Pilot (EUR 500 thousand to 2.5 million, cf. European Commission, 2020).

[14] While it is in principle possible for a scientist to take an extended leave of absence and to return to publishing in a later career stage, we did not observe this in our final sample.

[15] The cutoff was chosen to leave a citation window of at least three years between the last publication and the time of data collection.

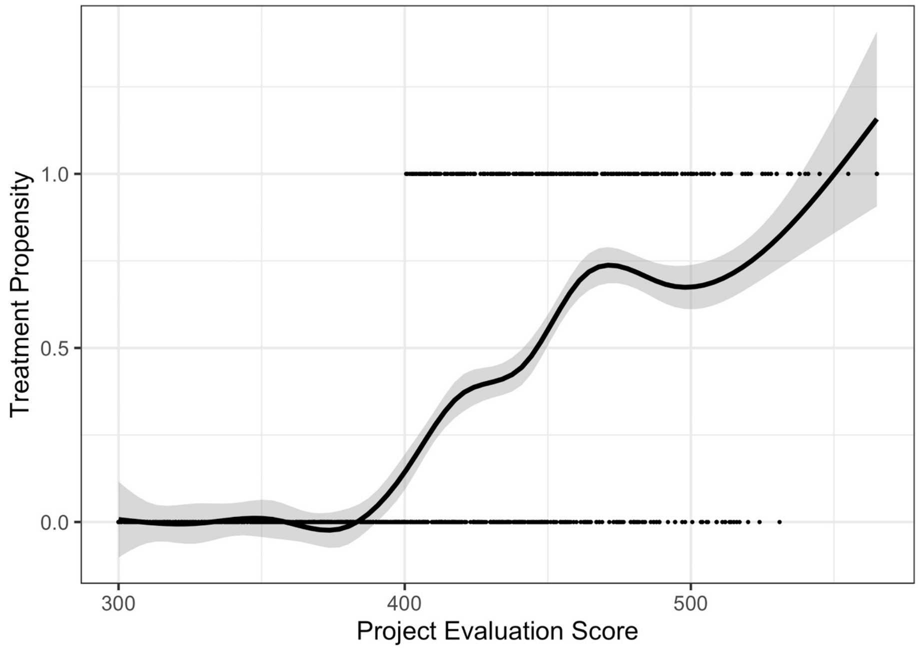

Fig. 4. Treatment propensity depending on project evaluation scores.
Notes: Solid line shows probabilities to obtain Eurostars funding for different project evaluation scores (starting from 300, using a cubic smoothing spline). Grey area corresponds to 95 % confidence bands. Dots depict individual data points. To ensure sufficient overlap, we restrict our estimation sample to project evaluation scores between 400 and 520.

whether Eurostars leads to changes in collaborative networks. The program might have induced scientists to expand their coauthor networks or collaborate more closely with industry coauthors, also in academic publishing, since their joint work may be a way to increase knowledge spillovers and therefore productivity. On the other hand, the grant may have allowed participating scientists to increase their lab capacity through hiring additional researchers, in which case the additional productivity would stem from a resource rather than a knowledge effect.

4.3.1. Publications

The bibliographic data source for our analysis was Elsevier's SCOPUS database. In line with standard bibliometric practice (Glänzel, 2003), we focused on articles, conference papers, reviews, and letters, but omitted abstracts, editorials, corrections, retractions, book reviews, and other types of documents. Records from which the year of publication or journal information was missing were dropped from the analysis (0.9 % of publications). All measures were calculated using integer counting, and all documents were weighted equally for all coauthors. To minimize the risk of false positives in assigning articles to scientists because of name ambiguity, we disambiguated retrieved records before their final inclusion in the sample by building clusters based on similarity in name and affiliation information and validating whether these clusters matched the information in the researchers' CVs.[16] This approach allowed us to link research output to the right researcher, thus minimizing the potential for measurement error (Doherr, 2017, 2018). The final sample covers 64,781 matched documents. We quantified research output using annual publication counts, which ranged from 0 to 73 in the sample and averaged 4.3 publications per year per researcher (descriptive statistics for variables in our sample are shown in Table 2). In the five years before applying to Eurostars, the average scientist obtained 25 publications (median: 14), amounting to an average H-index of 9.4 in the same period (median: 7).[17]

4.3.2. Top publications

We also measured publications in high-quality journals by counting the number of publications in journals that SCOPUS's CiteScore metric ranks in the top-10 % of all journals.[18] The average scientist in the sample published 0.38 top publications per year.

4.3.3. Patents

We gathered patent information from the PATSTAT database, focusing on European Patent Office applications. We assigned patent applications to researchers when the inventor's name matched the researcher's name and when the assignee's name coincided with her institutional affiliation. Since this approach may lead to underestimating academic patenting when intellectual property is assigned to a private actor rather than to the academic partner (Lissoni and Montobbio, 2015), we disambiguated patents in a way similar to that we used for publications, clustering patents into inventor-careers (Doherr, 2017, 2018) and matching researchers to these clusters. It follows that, as long as one patent by the scientist was owned by the university or another institution listed on the scientist's CV, the match was correct for all

[16] See Appendix 2 for more information about how we built the clusters.

[17] To further understand how Eurostars applicants compare to other groups of scientists, we benchmarked the sample to those reported in some recent studies of academic scientists. We present the screened studies and indicators in Table A3.1 in the Appendix. Eurostars scientists are, on average, more productive than the broader population of academic scientists (e.g., Ding et al., 2010; Hottenrott and Lawson, 2017; Grimpe, 2012) but less productive than elite scientists (e.g., Azoulay et al., 2017). Instead, the sample's productivity resembles that of applicants to other grants (e.g., Azoulay, 2011; Jacob and Lefgren, 2011; Ayoubi et al., 2019).

[18] The journal-level CiteScore metric is similar to Web of Science's Impact Factor. A journal's CiteScore metric for a given year is calculated as the number of citations that articles that the journal published in the preceding three years received in that year, divided by the number of citable articles published by the journal in those three years.

Table 2
Descriptive statistics.

	Mean	Std. Dev.	Min.	Max.
Publications	4.26	6.09	0	73
Top Publications	0.38	1.18	0	19
New Journals	1.46	1.91	0	19
New Keywords	38.62	50.18	0	522
Abstract Similarity	0.79	0.25	0.0003	1
Patenting	0.02	0.14	0	1
Publications with Industry	0.40	1.10	0	20
Publications without Industry	3.86	5.63	0	63
Coauthors	24.33	41.89	0	607
New Coauthors	10.29	17.68	0	504
New Institutions	4.60	8.07	0	141
Funding	0.14	0.35	0	1
Project Evaluation Score	447.38	31.48	400	520
Experience	11.64	8.70	0	45
Public Research Organization	0.41	0.49	0	1
Cutoff 1	0.11	0.32	0	1
Cutoff 2	0.09	0.28	0	1
Cutoff 3	0.10	0.30	0	1
Cutoff 4	0.09	0.29	0	1
Cutoff 5	0.08	0.28	0	1
Cutoff 6	0.11	0.31	0	1
Cutoff 7	0.12	0.32	0	1
Cutoff 8	0.09	0.28	0	1
Cutoff 9	0.09	0.28	0	1
Cutoff 10	0.13	0.33	0	1
EU6	0.52	0.50	0	1
EU15	0.29	0.45	0	1
EU28	0.08	0.26	0	1
Other	0.12	0.33	0	1

Notes: N equal to 13,816. The unit of observation is the individual per year, therefore *Funding* has a lower average value here (14.3 %) than it does at the group level (51.3 %).

patents by this researcher, even when the patents list a corporate affiliation. This corrects for any underestimation or overestimation of scientists' patenting due to the strategic allocation of patent rights to public or private actors.[19] Since the average number of patents per scientist-year is low (0.031), we used a patenting dummy in the estimation.

4.3.4. Research agenda

To quantify changes in researchers' agendas, we compared the researcher's current and past work.[20] While relatedness is typically measured through patterns in co-authorship, citations, and (key)words, recent approaches use more comprehensive metrics based on text analysis (Gentzkow et al., 2019; Lu and Wolfram, 2012). We employed several measures. First, we conducted a co-word analysis based on the logic that two documents are more similar if they share more keywords (Coulter et al., 1998; Ding et al., 2001). For every researcher-year, we counted the number of previously unused keywords that surfaced. (We used index keywords to ensure that shifts in vocabulary do not contaminate our analysis.) If becoming a Eurostars PI was associated with a high number of previously unused keywords, we concluded that the program caused a shift in the researcher's published content. Researchers in the sample specified an average of 38.62 new keywords in their articles each year.

We also use a second measure for changes in a research agenda since co-word analysis depends on a stable keyword interpretation across documents (Leydesdorff, 1997) and index terms being assigned objectively and consistently (Law and Whittaker, 1992). For every researcher-year, we counted the number of journals in which the researcher published for the first time, as publishing in a different set of journals indicates that the researcher is active in a different field, is investigating different research questions, or is addressing a different audience. On average, researchers published 1.46 articles in new journals each year.

A third measure of changes in a research agenda is based on paper abstracts. We applied a Latent Dirichlet Allocation (LDA) model to the 64,516 publications for which an abstract was available. We calculated the relatedness of a researcher's work in one year to her previous work as the cosine similarity between the average topic space vector of publications in the focal year compared to the average of the three preceding years.[21] A negative causal link between Eurostars funding and cosine similarity suggests that the researcher shifted her research focus due to the project. This analysis required several preparatory steps, including standardizing terms and removing irrelevant stop words. We describe these steps in Appendix 4. On average, the annual output by researchers in the sample had a cosine similarity of 0.79 compared to the output of the preceding three years.

4.3.5. Collaboration networks

We used the affiliation information in SCOPUS to determine how many publications listed at least one coauthor who is affiliated with a firm. This measure indicates the extent to which a researcher's work is interwoven with corporate R&D (Arora et al., 2018). We interpret an increase in collaboration with the private sector after engaging in Eurostars as a sign of a stronger orientation toward the private sector, which might extend beyond the boundaries of the funded project. The average researcher in the sample published 0.40 papers per year with at least one industry coauthor – approximately 10 % of their annual output.

Eurostars funding may also expose researchers to new potential collaborators from academia thanks to, for instance, increased travel budgets and the opportunity to hire research staff. Involvement in the project might also bring increased visibility in the scientific community (Azoulay et al., 2014; Bol et al., 2018). Therefore, part of the effects found for other outcome variables might be due to an expansion of coauthor networks instead of changes in productivity or re-orientation. To exclude this alternative explanation, we considered the number of distinct coauthors with whom each scientist worked in a year and the number of new coauthors introduced in that year. Scientists in the sample collaborated with an average of 24.3 colleagues each year, among whom 10.3 were new. As an alternative measure, we counted the number of new institutions among the scientists' list of collaborators and

[19] See Appendix 2 for additional details about the clustering algorithm. The algorithm also corrects for misattributions arising from shared names among inventors (Lissoni et al., 2010; Trajtenberg et al., 2009). Cappelli et al. (2019), applying the algorithm to analyze the mobility of Italian inventors, report that it passes the benchmark proposed by Lissoni et al. (2010) with a recall of around 91 % and a precision of almost 100 %.

[20] An alternative approach could be attempting to characterize researchers' work as more "basic" or "applied", and to test whether Eurostar nudges researchers to more "applied" work. However, this is difficult to track in the multidisciplinary context of Eurostars, as most typical measures of appliedness are journal-based (e.g., Narin et al., 1976) and suffer from issues of discipline-specificity (e.g., Boyack et al., 2014). Hence, we opt for a broader text-based approach that aims to measure changes in research agendas.

[21] Cosine similarity, a commonly used similarity measure in text-mining applications, captures the similarity of two vectors through their direction (Sighal, 2001). Focusing on direction overcomes the issue of longer documents' tending to have more words in common with other documents than shorter documents do. The cosine similarity between two vectors $\overrightarrow{a}$ and $\overrightarrow{b}$ can be calculated as $\cos(\theta) = \frac{\overrightarrow{a} \bullet \overrightarrow{b}}{\|\overrightarrow{a}\| \|\overrightarrow{b}\|} = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^2}\sqrt{\sum_{i=1}^{n} b_i^2}}$, where a_i and b_i represent elements of $\overrightarrow{a}$ and $\overrightarrow{b}$. Cosine similarity ranges from -1 to 1, where -1 means that the vectors are going in exactly opposite directions, 0 means that the vectors are perpendicular, and 1 means exactly overlapping vectors. However, the measure is bounded to [0,1] in text analysis applications, as the underlying word vectors are term frequencies, so they are non-negative. Our results are not sensitive to the specific choice of three years as baseline period.

found that each scientist in the sample collaborated with an average of 4.6 new institutions each year.[22]

4.4. Methods

We use Poisson models for count-dependent variables (Hausman et al., 1984) and linear models when dependent variables are continuous or binary. The regression equation for linear estimation is specified as:

$$y_{it} = \alpha_i + \beta D_{it} + X_{it}\gamma + \lambda_t + \varepsilon_{it}, \tag{1}$$

while in Poisson, exponentiated values of the linear index in (1) are used to model the conditional mean of the data:

$$\mu_{it} = \exp(\alpha_i + \beta D_{it} + X_{it}\gamma + \lambda_t). \tag{2}$$

D_{it} denotes the treatment indicator, which, for researchers that obtained Eurostars funding, switches to 1 in the year of application and remains so until the end of the observation period. We allow for individual-specific offsets, α_i, that account for time-invariant unobserved heterogeneity, such as gender, field of study, and unobserved differences in ability. Furthermore, all regressions include a set of time dummies, λ_t, to account for common time trends. X_{it} is a vector of time-invariant control variables.

We control for researchers' experience, which is not time-constant and might influence publication and patenting rates through life-cycle effects (Levin and Stephan, 1991). Experience is measured as the time since the researcher published her first publication. Researchers in our sample have accumulated a median of 15 years of experience at the time of their project applications. Furthermore, we add a squared term of this variable to capture additional nonlinear effects.

Although treatment timing varies over five years in our sample, the two-way fixed effects models we apply are appropriate if there is a large never-treated group and treatment effect heterogeneity over time is expected to be small (Baker and Larcker, 2022). Section V.5 explores the robustness of our main findings to alternative estimators that account for variation in treatment timing and presents tests of possible violations of the parallel trends assumption. Standard errors are clustered at the level of the individual researcher throughout the regressions.[23]

5. Empirical findings

In the following, we present estimation results for our main dependent variables on research productivity, research agendas, and collaboration patterns (Table 3). Subsequently, we show split-sample regressions to shed light on the potential heterogeneity of treatment effects along several dimensions (Table 4). Table 5 displays an analysis of the long-run effects of Eurostars funding on scientists' productivity and research career, and finally, Tables 6–8 test the validity of our results with respect to the parallel trends assumption and variation in treatment timing.

5.1. Impact on productivity and research direction

Columns 1–3 of Table 3 present regression results for the effect of Eurostars funding on the number of publications, top publications, and patents. An increase in either one of those variables could hint at *knowledge spillovers* from industry to science. Our findings suggest that the applied nature of Eurostars' grants does not generally hurt scientific productivity. Point estimates indicate that, following funding,

Table 3
Effect of Eurostars funding on research productivity, research agendas, and collaboration patterns.

	Productivity			Research Agenda			Industry Coauthors		Networks and Resources		
Dependent Variable:	Publications	Top Publications	Patenting	New Keywords	New Journals	Abstract Similarity	Publications with Industry	Publications with-out Industry	Coauthors	New Coauthors	New Institutions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Funding	0.028	−0.010	0.006	0.005	−0.034	−0.002	0.221 **	0.005	0.024	0.006	−0.018
	(0.050)	(0.093)	(0.006)	(0.045)	(0.049)	(0.011)	(0.100)	(0.053)	(0.056)	(0.064)	(0.063)
Experience	0.105 ***	0.019	0.001	0.041 *	0.050 **	0.001	0.247 ***	0.100 ***	0.148 ***	0.163 ***	0.165 ***
	(0.020)	(0.081)	(0.001)	(0.025)	(0.022)	(0.005)	(0.068)	(0.021)	(0.020)	(0.023)	(0.028)
Experience Squared	−0.002 ***	−0.002 ***	−0.000	−0.001 ***	−0.001 ***	0.000	−0.002 ***	−0.002 ***	−0.002 ***	−0.002 ***	−0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	Poisson	Poisson	OLS	Poisson	Poisson	OLS	Poisson	Poisson	Poisson	Poisson	Poisson
Observations	13,816	10,138	13,596	13,294	12,410	12,623	11,686	13,747	13,816	10,710	10,672
No. of Researchers	682	449	682	678	661	682	543	672	682	668	656

Notes: Cluster-robust standard errors in parentheses. Researchers with time-constant outcomes are dropped from Poisson FE estimations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[22] To measure when a PI collaborates with a particular coauthor for the first time, we disambiguated all the PI's coauthors in a manner similar to what we did for the PIs. We similarly disambiguated institutions based on their name and location. See Appendix 2 for more details.

[23] We also investigated block-bootstrapped standard errors, as suggested by Bertrand et al. (2004), in a robustness check and found similar results.

Table 4
Split sample analyses.

Dependent Variable:	Publications	Publications with Industry	Publications	Publications with Industry
	(1)	(2)	(3)	(4)
Panel A: Split by affiliation	University Researchers		PRO Researchers	
Funding	0.046	0.140	0.025	0.403 ***
	(0.064)	(0.139)	(0.082)	(0.133)
Observations	8063	7131	5753	4555
No. of Researchers	366	309	316	234
Panel B: split by field	ICT		Non-ICT	
Funding	0.046	0.335 **	0.020	0.171
	(0.101)	(0.170)	(0.054)	(0.124)
Observations	3326	2838	10,490	8848
No. of Researchers	182	147	500	396
Panel C: split by citation stock	Above median citations		Below median citations	
Funding	0.023	0.146	0.047	0.421 ***
	(0.055)	(0.122)	(0.099)	(0.159)
Observations	7268	6636	6548	5050
No. of Researchers	333	293	349	250
Panel D: split by experience	More than 12 years experience		Less than 12 years experience	
Funding	0.006	0.321 ***	0.212 **	−0.065
	(0.064)	(0.115)	(0.099)	(0.194)
Observations	10,863	9516	2953	2170
No. of Researchers	427	367	255	176
Panel E: split by grant size	Larger grants		Smaller grants	
Funding	0.056	0.322 **	0.023	0.162
	(0.078)	(0.145)	(0.074	(0.115)
Observations	9670	8149	10,684	9039
No. of Researchers	483	382	531	420
Individual Fixed Effects	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Method	Poisson	Poisson	Poisson	Poisson

Notes: Cluster-robust standard errors in parentheses. Researchers with time-constant outcomes are dropped from Poisson FE estimations. Regressions include controls for researcher experience and experience squared, except for panel D, where experience constitutes the split variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

researchers produce an average of 3 % more publications.[24] However, this positive effect is small and statistically insignificant ($p = 0.574$). Similarly, we find no significant effects on top publications or patenting. The latter results align with previous research showing no impact of Eurostars' funding on patenting among participating firms (Hünermund and Czarnitzki, 2019). This suggests that any increase in scientists' patenting would require them to file patents independently rather than with project partners, which appears less likely. Regarding researchers' experience, our results follow a typical academic lifecycle pattern, characterized by an inverse U-shaped relationship in publishing (Levin and Stephan, 1991), peaking approximately 25 years after an individual's first publication.

Columns 4–6 of Table 3 tackle potential changes in the research agenda of scientists by presenting estimation results related to new

Table 5
Long-run effects of Eurostars funding (2015–2024).

Dependent Variable:	Exit	Publications	Publications with Industry	Citation-weighted Publications
	(1)	(2)	(3)	(4)
Funding	−0.009	0.174	0.314 **	0.360
	(0.027)	(0.133)	(0.155)	(0.364)
Project Evaluation Score	−0.000	0.001	0.002	−0.003
	(0.000)	(0.002)	(0.002)	(0.006)
Experience	−0.003**	0.003	0.013**	0.040 **
	(0.002)	(0.006)	(0.006)	(0.017)
University Researcher	0.077 ***	−0.645 ***	−0.528 ***	−0.522 *
	(0.025)	(0.123)	(0.144)	(0.310)
EU6	−0.030	0.010	−0.110	−0.177
	(0.040)	(0.202)	(0.256)	(0.384)
EU15	0.035	−0.289	−0.296	−0.434
	(0.045)	(0.213)	(0.256)	(0.347)
EU28	−0.129 ***	−0.090	−0.920 ***	−0.729 *
	(0.043)	(0.245)	(0.338)	(0.422)
Constant	0.279	3.931 ***	1.096	8.232 ***
	(0.185)	(0.802)	(0.928)	(2.173)
Time Dummies	Yes	Yes	Yes	Yes
Method	OLS	Poisson	Poisson	Poisson

Notes: Heteroskedasticity-robust standard errors in parentheses. $N = 642$.

keywords, new journals, and the similarity of papers' abstracts compared to previous publications' abstracts. We find no evidence of an effect of Eurostars funding on research agendas and the topics on which scientists work. It thus seems unlikely that researchers shift their research efforts to more applied topics as a result of the commercialization activities Eurostars requires.

5.2. Impact on co-authorship structure and group size

To examine the impact of Eurostars grants on *collaboration and network structure*, we identify all publications that are coauthored by industrial partners. Results on the estimation of the effect of Eurostars funding on publication numbers, separately for publications with and without industry coauthors, are reported in columns 7–8 of Table 3. The results show that the number of publications with industry partners increases by 25 % after scientists receive Eurostars funding ($p = 0.026$). In contrast, publications without industry partners do not change significantly ($p = 0.920$). Since productivity gains are concentrated in co-publications with industry (without any decline in publications coauthored solely within academia) we can rule out the possibility that scientists use Eurostars funding to cross-subsidize their general research agendas. Instead, Eurostars funding seems to lead to increased engagement with industry partners. These findings suggest a compositional shift rather than a productivity trade-off.

Finally, another potential mechanism at play might be a *resource effect*, whereby Eurostars funding provides scientists with the financial resources they need to support their general research agenda, without necessarily inducing complementarity effects from the industry-science collaboration. Productivity effects could also occur because the grant allows PIs to build larger research labs, hire new post-docs and doctoral students, or expand their network in other ways, such as by increased conference travel or visibility within the scientific community (Azoulay et al., 2014; Bol et al., 2018). The positive effects we observe could then be driven by improved access to the human capital in a denser network of potential coauthors, rather than by direct industry-academia knowledge spillovers. If that is the case, we should see either that the researcher works with a larger number of coauthors after receiving Eurostars funding (and so devotes less time to each publication) or that

[24] These numbers are incidence-rate ratios, which represent the multiplicative effect on y for a unit increase in D: $E(y|D=1,X=x)/E(y|D=0,X=x)$. For example, in Table 3, the incidence rate ratio is calculated as $e^{0.028} - 1 = 2.84\%$.

Table 6
Parallel pre-treatment trends.

Dependent Variable:	Publications	Top Publications	Patenting	New Keywords	Publications with Industry	Coauthors
	(1)	(2)	(3)	(4)	(5)	(6)
Ever Treated × t-1	−0.008	−0.171	−0.013	−0.028	0.180	−0.055
	(0.077)	(0.138)	(0.010)	(0.073)	(0.149)	(0.083)
Ever Treated × t-2	−0.038	0.116	−0.007	−0.073	0.126	−0.053
	(0.074)	(0.129)	(0.010)	(0.075)	(0.160)	(0.083)
Ever Treated × t-3	0.020	0.046	−0.004	−0.018	0.240	−0.031
	(0.070)	(0.131)	(0.010)	(0.067)	(0.157)	(0.074)
Ever Treated × t-4	−0.028	−0.024	−0.007	−0.060	0.216	−0.073
	(0.065)	(0.123)	(0.009)	(0.062)	(0.149)	(0.067)
Ever Treated × t-5	0.010	−0.280	−0.010	−0.017	−0.094	−0.045
	(0.057)	(0.134)	(0.008)	(0.056)	(0.138)	(0.059)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Method	Poisson	Poisson	OLS	Poisson	Poisson	Poisson
Observations	13,816	10,138	13,596	13,294	11,686	13,816
Test on joint significance of pre-treatment dummies	$\chi^2 = 3.68$,	$\chi^2 = 7.36$,	F = 0.58,	$\chi^2 = 2.36$,	$\chi^2 = 7.33$,	$\chi^2 = 2.06$,
	$p = 0.60$	$p = 0.20$	$p = 0.71$	$p = 0.80$	p = 0.20	$p = 0.84$

Notes: Cluster-robust standard errors in parentheses. Post-treatment interactions included but omitted from the regression table. Researchers with time-constant outcomes are dropped from Poisson FE estimations. *Ever Treated* is equal to one if the researcher obtained a Eurostars grant in the future, and zero otherwise. Interactions with post-treatment period dummies and controls for researcher experience as well as experience squared are also included in the regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
Decomposition of the two-way fixed effects estimator with variation in treatment timing (Goodman-Bacon, 2021).

Dependent Variable:	Publications	Top Publications	Patenting	New Keywords	Publications with Industry	Coauthors
	(1)	(2)	(3)	(4)	(5)	(6)
Early-treated Treatment vs. Later-treated Control	0.286 [0.084]	0.015 [0.084]	0.009 [0.084]	−0.010 [0.087]	0.086 [0.084]	2.330 [0.084]
Later-treated Treatment vs. Earlier-treated Control	−0.281 [0.144]	0.188 [0.144]	0.024 [0.144]	−4.082 [0.149]	0.076 [0.144]	−0.069 [0.144]
Treatment vs. Never-treated	0.230 [0.772]	0.098 [0.772]	0.020 [0.742]	2.208 [0.764]	0.191 [0.772]	2.691 [0.772]
Overall Effect	0.161	0.104	0.020	1.076	0.165	2.262

Notes: Average difference-in-differences estimates with respective weights in square parentheses. All estimates obtained from linear two-way fixed effects models without controls using the bacondecomp Stata module (Goodman-Bacon et al., 2019). Since the decomposition requires a strongly balanced panel, the sample is restricted to observations after 2005 that have full records available until the end of the observation period.

Table 8
Callaway and Sant'Anna (2021) estimator.

Dependent Variable:	Publications	Top Publications	Patenting	New Keywords	Publications with Industry	Coauthors
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	0.325	0.116	0.020	1.242	0.155 **	3.214
	(0.325)	(0.081)	(0.017)	(3.008)	(0.078)	(2.396)

Notes: Cluster-robust standard errors in parentheses. All estimates are obtained via linear models using the csdid Stata module (Rios-Avila et al., 2021). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

they introduce additional coauthors to their network more frequently.

Results related to testing these mechanisms are reported in columns 9–11 of Table 3. We estimate the effect of Eurostars funding on the number of distinct coauthors with whom a researcher works, the number of new coauthors with whom they connect for the first time, and, as a robustness check, the number of new institutions with which they collaborate. For our analysis, we treat firms as institutions since the goal is to determine whether researchers expand their networks. Across all measures, we find no impact of Eurostars funding on network size or turnover, with effects remaining statistically insignificant at the 5 % level. Even the overall number of coauthors (as well as the number of new coauthors) does not change at a higher rate than the control group, although the number of publications with industry partners increases. Taken together, this suggests that either PIs substitute scientific coauthors with coauthors from industry or that the additional coauthored publications are done with industry partners with which scientists have already collaborated before. We cannot, however, conclude on potential research assistance the PIs might have received because of the grant, which may have helped them without being visible in terms of coauthorship on their publications.

On the whole, our findings corroborate results from the previous literature that point to complementarities between commercialization activities and research (Perkmann et al., 2013). While these complementarities are hypothesized as being driven by mechanisms such as knowledge spillovers from industry to academia (Agrawal and Henderson, 2002; Azoulay et al., 2009; Lee, 2000; Mansfield, 1995; Perkmann and Walsh, 2009), the effects we find could also be explained by other mechanisms, such as a positive effect on researchers' resource endowments, or access to critical research infrastructure and materials. However, since the cost of capital goods and other expensive equipment is not eligible for funding in R&D grant programs like Eurostars,[25] we

[25] See, for example, the eligible costs in individual participating countries here: https://eurekanetwork.org/programmes/eurostars/funding-information/ (last accessed September 5th, 2025).

rule out the possibility that our results are driven purely by capital deepening. Of course, it could be the case that the industry-science collaboration itself provides access to important research infrastructure from the collaborating firms. However, we interpret this mechanism as another form of industry-academia spillovers.

5.3. Effect heterogeneity across sub-samples

To provide additional insights into potential heterogeneities among treatment effects, we perform a set of split-sample analyses (Table 4). Since universities may benefit from external funding differently from public research organizations, we split PIs based on their affiliations. In universities, scientists might use grant money to "buy out" of teaching obligations to increase their research time (Smith and Smith, 2012), while scientists who are employed by other research institutions typically have little or no teaching obligations. By contrast, these organizations are often funded through contracted research, and grant money alleviates the burden to look for other sources of external funding.[26] The extent to which scientists engage in applied research varies depending on their institution's focus. Researchers in these organizations may already have closer ties to industry than their university counterparts, which could influence the benefits they derive from industry-science collaborations. Our findings in Panel A of Table 4 support this interpretation, showing that the positive impact on industry co-authored publications is primarily driven by scientists at public research organizations, with a 50 % increase ($p = 0.002$).

Panel B splits the sample based on the projects' technological fields. Since Eurostars projects mainly concern engineering, ICT, and bioscience, we split the sample into ICT and others to keep sample sizes sufficiently large.[27] The results indicate heterogeneous effects of funding: for ICT-related projects, funding leads to a 40 % increase in industry co-publications ($p = 0.049$). In contrast, effects in other fields remain insignificant. One explanation for this finding might be that the typical link between industry and science is less developed in ICT than it is in the biosciences and engineering (Perkmann et al., 2013), which may result in larger gains for PIs in ICT-related projects when they work with industry partners through Eurostars compared to scientists in other fields. This pattern is also in line with Cohen et al. (2020), who argue that researchers in highly applied fields face lower opportunity costs in terms of lost research when they engage in commercialization, as their field is already oriented toward concrete problem-solving. In such fields, engagement in commercialization might even lead to more knowledge discovery.

We also analyze heterogeneity in the researcher's citation count at the time of the project application (Panel C). This split allows us to account for potential differential effects based on how well a scientist is established in her community (Azoulay et al., 2014; Bol et al., 2018). We compare citations for three experience cohorts (1–10, 11–20, and 20+ years of experience) and split the sample at the median of each category. The results indicate that the positive effect on industry co-authored publications is concentrated in the lower half of the citation distribution, with an increase of 52 % ($p = 0.008$), emphasizing that less established scientists benefit the most from the complementarities that result from projects co-developed with industry.

Although citation counts generally increase with seniority, the two characteristics are not fully correlated (corr. = 0.49 in our sample). To account for this, we divide the sample at the median career seniority of 12 years (Panel D). Our results show that early-stage researchers benefit from funding by increasing their overall publication output by 24 % ($p = 0.033$), but do not produce more industry co-authored publications. In contrast, senior researchers see an increase in industry collaborations by 38 % ($p = 0.005$), but do not experience a rise in overall publication volume. This result is in line with commonly observed life-cycle patterns in science production (Levin and Stephan, 1991). Junior scientists might be more interested in using the funding to produce basic science, strengthen their reputations in the discipline, and obtain tenure at their institutions. In contrast, senior researchers might approach the funding more from the perspective of general knowledge transfer.

Finally, we split the sample based on the average grant size of EUR 192,000. Panel E of Table 4 reveals that the positive effects of Eurostars funding are primarily driven by larger grants, which increase industry co-authored publications by 38 % ($p = 0.022$), compared to just 18 % for smaller grants ($p = 0.157$). This suggests that, while some grants may have been too small to impact the principal investigator's research behavior meaningfully, larger grants have a stronger influence.[28]

5.4. Testing the long-run impact of Eurostars funding

This section examines whether the effects of Eurostars funding on scientists' research behavior persist well after the funded projects have concluded – unlike the main analysis, which focuses on how funding influences scientific output and collaboration patterns in the short-run. Specifically, we analyze researchers' publication records during the period 2015–2024, up to a decade after the Eurostars 1 program ended. As in the main analysis, we focus on articles, conference papers, and reviews, and interpret a complete absence of publications over this period as an indication that a principal investigator (PI) has exited academia or is no longer in an active research role. To perform this analysis, we employ cross-sectional regressions with a long time lag between treatment and outcome, as the treatment may affect the dependent variables' means, making fixed effects problematic due to the "bad controls" issue (Hünermund et al., 2025). This approach is feasible because our identification strategy relies on cross-sectional variation in treatment status within a VCP, as outlined in Section 4.1. To ensure unconfoundedness, we control for project evaluation scores, time dummies (i.e., competition round fixed effects), researchers' experience, institutional affiliation at the time of application (university vs. public research organization), and the scientists' country of residence.[29]

Table 5 shows that Eurostars funding has a significant impact of 37 % ($p = 0.043$) on the number of publications co-authored with industry between 2015 and 2024. While we also find positive point estimates for overall publication output and citation-weighted publications (with citations measured at the end of the observation window), these effects are not statistically significant. To assess long-term career success, we interpret the absence of any publications from a given scientist during this period as an indication that they have left academia. However, our analysis does not find a significant effect of Eurostars funding on the likelihood of exit.

In terms of control variables, it is interesting to note that project evaluation scores do not show a statistically significant effect in the regressions in Table 8, suggesting that project quality evaluated for the

[26] For example, the German Fraunhofer Society, the world's largest applied research institute, draws 70 % of its budget from contract research (as opposed to 30 % from base funding from the German federal and state governments). Contract research includes contracts with industry as well as publicly financed research projects, so researchers might substitute one for the other and still comply with funding expectations (Fraunhofer Society, 2019).

[27] Traditionally, EUREKA programs were focused on ICT, which is why we consider ICT a separate category to account for the additional experience in that sector. However, separate analyses of engineering and biosciences showed similar results for both groups.

[28] It should be noted that these split-sample analyses do not provide a formal test of whether effect sizes differ significantly across sub-samples, as such tests are not straightforward to implement in our estimation setting. They are therefore best interpreted as suggestive evidence.

[29] Sample size limitations do not allow us to consider all 33 participating countries individually in cross-sectional regressions. Instead, we group countries into four mutually exclusive groups (EU6, EU15, EU28, and Other).

consortium as a whole is not strongly associated with outcomes at the level of the individual researcher.[30] Some cutoff dummies yield significant coefficients, but no clear temporal trend emerges. Likewise, country affiliation has a limited impact, with one notable exception: researchers from the group of mostly Eastern European member states that joined the EU in 2004 (EU28) tend to produce fewer industry co-authored and citation-weighted publications but have a significantly lower probability of exiting academia.

Overall, these findings suggest that the positive effect of Eurostars funding on collaborative research with industry partners is persistent and extends well beyond the program's runtime.

5.5. Robustness test: parallel trends and variation in treatment timing

Table 6 shows the results of testing for the presence of parallel trends in the pre-treatment period. We re-estimated our two-way fixed effects (TWFE) models by including interactions of a treatment group dummy (*Ever Treated*) with pre-treatment-period time dummies, $t_{-1}, \ldots, t_{-5}$, relative to the application year (as well as post-treatment interactions and controls for researcher experience). For the sake of space, Table 6 reports results only for our main outcome variables – publications, top publications, and patenting – as well as new keywords, publications with industry, and number of coauthors, since the latter three each represent one additional dimension of outcomes in which we have interest (i.e., research agendas, co-publications with industry, and collaboration patterns). We find that all pre-treatment interactions are jointly insignificant, which strengthens our confidence in the assumption that funded and non-funded scientists' productivity would evolve similarly in the absence of treatment.

Scientists in our sample received funding at different points in time. A newer literature on difference-in-differences (DD) estimation (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Imai and Kim, 2021) discusses difficulties with interpreting TWFE estimation results if treatment timing varies. Potentially problematic in this case is that units that have already been treated can serve as a control group for units that received treatment later on (and vice versa). As Goodman-Bacon (2021) demonstrates, the coefficient of a linear TWFE estimator with variation in treatment timing is a weighted average of all possible 2×2 comparisons (treated vs. untreated, and treated earlier vs. treated later), with possibly negative weights if treatment effects are heterogeneous over time. As an analytic tool, Goodman-Bacon proposes a decomposition of the DD treatment effects into individual comparison groups, which we present in Table 7. Since the technique requires a strongly balanced panel, we restrict attention to observations after 2005, when complete records are available, until the end of the observation period. Moreover, all TWFE models are estimated by linear regression.

Table 7 shows that the purely timing-based comparisons (earlier-treated observations in the treatment group vs. later-treated observations in the control group, and later-treated observations in the treatment group vs. earlier-treated observations in the control group) receive only moderate weights. The largest share (74–77 %) of the overall effect is attributable to a comparison of treated vs. never-treated units, which can be interpreted in a way that is equivalent to the canonical DD design, with only two time periods. In terms of the decomposition of treatment effects, Table 7 shows that the timing-only comparisons are always smaller than the treated vs. never-treated comparison. In some cases, such as for publications, new keywords, and coauthors, the estimates in the timing-only comparison, which contribute around 15 % to the overall effect, even reverse in sign, suggesting that the marginal effects when estimated by TWFE are lower bounds compared to a situation with no variation in treatment timing.

Finally, in Table 8, we present robustness checks using the estimator proposed by Callaway and Sant'Anna (2021), which is designed to avoid negative weights arising from variation in treatment timing.[31] Our qualitative results remain largely unchanged. This confirms the hypothesis that TWFE models are appropriate in our case, because the sample contains a large never-treated group (i.e., applicants who did not receive Eurostars funding) and treatment effect heterogeneity was likely not that pronounced over the runtime of the program (de Chaisemartin and D'Haultfœuille, 2023).

6. Discussion and conclusions

Translational programs aiming to support the transition from academic research to new products and applications are becoming increasingly important in the science policy landscape. While the Eurostars program may not strictly qualify as a translational program – since firms can apply without an academic partner – its structure and operation align with translational objectives when scientists are involved. This makes Eurostars an ideal setting for analyzing the impact of such programs on scientific output and direction, as well as for deriving policy recommendations regarding their desirability and feasibility (e.g., Azoulay and Li, 2022). If no adverse effects on science are observed in a context where market performance is the primary criterion of success, it is reasonable to expect that less commercially oriented programs will also not generate negative impacts.

Our study reveals that the commercial nature of industry-science collaborations within Eurostars does not negatively impact scientific activity. Instead, we observe a shift in collaboration patterns: participation in the program increases the number of publications co-authored with industry, without affecting the total number of publications. Importantly, there is no evidence that participation in Eurostars affects the direction of research agendas, as measured by keyword usage, journal diversification, and abstract similarity. These findings suggest that the applied nature of the program does not necessarily divert scientists from their existing research trajectories.

We identify knowledge spillovers from industry to academia as a key mechanism behind the observed collaboration effects. Participation in Eurostars projects increases the likelihood that researchers publish with industrial partners; however, this effect is not accompanied by a wider diversification of co-author networks or institutional collaborations. This suggests that Eurostars participation primarily operates at the intensive margin, strengthening existing ties with industry rather than expanding networks at the extensive margin. Moreover, we find no evidence that funding enables researchers to scale up their laboratories or hire additional personnel to boost general scientific output, thereby making a resource-based explanation for our findings less likely. Although Eurostars' translational objectives emphasize knowledge flows from academia to industry, our evidence of persistent industry co-authorship suggests reverse flows from industry to academia as well. Given the collaborative nature of R&D, knowledge is likely to move in both directions, reinforcing one another.

We find that several factors moderate these mechanisms. First, institutional context plays a role in shaping the effects of industry-science collaborations. Our results indicate that university-based researchers do not experience a significant boost in publication output following Eurostars funding. In contrast, researchers affiliated with public research organizations are more likely to increase their industry co-authored publications. This suggests that researchers in applied research settings may be better positioned to benefit from such

[30] We explored the sensitivity of our results to different specifications (i.e., higher-order polynomials, as well as linear and cubic splines) for the project evaluation score controls and found the results to be robust.

[31] Table A5.2 in the appendix lists other possible aggregations of treatment effects, including by group and calendar period. Furthermore, based on the estimator by Callaway and Sant'Anna, we present a power analysis for detecting linear violations of the parallel trend assumption, following the recommendations by Roth (2022), in Table A5.3.

collaborations than their counterparts in more basic research environments. This stronger effect observed among researchers in public research organizations (PROs) may seem surprising, given their existing ties to industry. However, this proximity likely enhances their ability to mobilize Eurostars funding effectively. PRO scientists often face fewer institutional constraints and have more targeted organizational incentives to pursue applied work. As such, the funding may enable them to deepen or formalize collaborations that previously existed on a more informal basis. Additionally, the marginal increase in co-publications likely reflects their capacity to convert structured collaboration into scientific output more efficiently than researchers in more academically focused environments.

Second, seniority also moderates the effects of Eurostars funding. Early-career researchers tend to increase their overall publication output, while senior researchers experience a stronger increase in industry co-authored publications. This may indicate that younger scientists use the funding to establish themselves academically, whereas more senior researchers leverage it to deepen existing industry relationships. Similarly, scientists with lower prior citation counts benefit more in terms of increased industry co-authorship, while more highly cited researchers see little to no effect, suggesting that Eurostars collaborations may be more valuable for those still establishing their professional networks.

Third, when examining disciplinary differences, we find that ICT-related projects exhibit the strongest increase in industry co-publications, while no significant effects are observed in biosciences and engineering. This suggests that industry collaborations in ICT may generate larger relative benefits, possibly due to a less developed tradition of university-industry partnerships in this field compared to sectors like biotechnology and engineering (Perkmann et al., 2013). As a result, when ICT researchers engage with industry partners through Eurostars, the collaboration may yield greater relative gains than in fields where such partnerships are already well-established. This aligns with Cohen et al. (2020), who suggest that researchers in highly applied fields face lower opportunity costs when engaging in commercialization, as their research is already problem-driven. However, these discipline-specific findings should be interpreted in the light of the program's field composition: Eurostars mainly attracts domains where the modal researcher already operates close to application. In other words, the scope for significant basic-to-applied "shifts" is more limited in Eurostars than in fields with a greater distance to market-oriented research.

Fourth, grant size further conditions the impact of Eurostars funding. Larger grants are associated with a more pronounced increase in industry co-authored publications, whereas smaller grants have weaker or insignificant effects. This suggests that funding levels influence the extent to which scientists can engage meaningfully in industry collaborations, possibly due to differences in available resources, project scale, or the ability to sustain long-term partnerships.

Finally, our results indicate that Eurostars funding significantly increases industry collaboration, with a 37 % rise in co-authored publications between 2015 and 2024. This effect persists beyond the duration of the program, highlighting its lasting influence on academic–industry linkages. The stronger long-term effect compared to the short-term impact likely reflects that industry-science funding triggers durable behavioral changes: once collaborative ties with industry are established, they tend to persist and generate follow-on projects, likely reinforced by trust, reputation, and indirect network spillovers.

Our analysis yields important policy insights: despite well-founded concerns, our results indicate that competitively funded industry-science programs need not be subject to the doubts raised in previous literature on industry-science relationships. While Eurostars does not appear to increase overall scientific productivity, it does strengthen direct engagement between industry and academia. This aligns with the program's goal of fostering industry-science collaboration, without having observable negative externalities on scientific output. It raises, however, questions about whether such partnerships contribute to broader scientific advancements beyond the funded projects. In light of the absence of a significant increase in general scientific output, policymakers should consider whether additional incentives are needed to ensure that industry-science collaborations generate wider knowledge spillovers, and also impact science positively. From an industry perspective, our findings are reassuring, since they imply that translational programs do not harm public knowledge production while compensating for diminished investments in private-sector research (Arora et al., 2018). An important venue for future research would be to enhance our understanding of the exact channels through which knowledge flows between industry and science to allow for such complementarities.

At the same time, our results are not without limitations. They are derived from a context in which the majority of research funding originates from traditional, research-oriented grants. Consequently, our conclusions apply to an environment where multiple funding instruments coexist, and we are unable to isolate the effects of Eurostars funding from interactions with other grants. A more detailed analysis of cross-program effects and potential (dis)complementarities between traditional science funding and translational incentives would be required to infer whether a particular type of grant is preferred over another. Furthermore, focusing on applicants does not allow our conclusions to be generalized to the broader population of scientists, some of whom would never consider such an application. Rather, our results pertain to the "marginal" scientists who might consider applying to a translational program such as Eurostars.

Given the growing importance of programs that jointly support research and commercialization, future studies should investigate the mechanisms behind spillover effects between the scientific and industrial sectors. Specifically, further research should examine whether participation in translational programs influences researchers' co-authorship networks with industry partners outside the original consortium, and how such collaborations affect research productivity and direction. Future research could also examine whether greater collaboration with industry affects universities' educational missions, identify which industry sectors provide the strongest complementarities with academic research, and analyze the network dynamics that underpin these partnerships. While this paper does not seek to provide guidance on the administrative trade-offs between the costs and benefits of translational programs, a deeper understanding of the broader implications of cross-sectoral linkages could inform more effective policy decisions and shed light on potential second-order effects arising from intensified industry-science collaboration. Finally, future research should explore whether programs involving larger corporate partners or alternative funding structures produce stronger or qualitatively different outcomes.

CRediT authorship contribution statement

Paul Hünermund: Writing – review & editing, Methodology, Formal analysis, Data curation.

Cindy Lopes-Bento: Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization.

Maikel Pellens: Writing – review & editing, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Authors are listed alphabetically. They gratefully acknowledge the three anonymous reviewers for their invaluable feedback and constructive suggestions, and the participants at presentations at ZEW; the ifo Institute; WU Vienna; the Workshop Series on Innovation at University of Luxembourg; the 14th BRICK Workshop on the Organization, Economics and Policy of Scientific Research; the 9th ZEW/MaCCI Conference on the Economics of Innovation and Patenting, the DRUID22 conference; the Academy of Management Annual meeting; and the OIS Conference for their thoughtful comments and stimulating discussions that helped improve this paper. They thank Thorsten Doherr for help with the data collection and Lawrence Krug, Leo Latscha and Lea Reitmeier for excellent research assistance. Lopes-Bento gratefully acknowledges financial support from FNR (DYK-LSFNR1-O2030).

Online appendix

The online Appendix of this artcile can be found online at https://doi.org/10.1016/j.respol.2025.105393.

Data availability

The data that has been used is confidential.

References

Aghion, Philippe, Dewatripont, Mathias, Stein, Jeremy C., 2008. Academic freedom, private-sector focus, and the process of innovation. RAND J. Econ. 39 (3), 617–635.
Agrawal, Ajay, Henderson, Rebecca, 2002. Putting patents in context: exploring knowledge Transfer from MIT. Manag. Sci. 48 (1), 44–60.
Arora, Ashish, Belenzon, Sharon, Patacconi, Andrea, 2018. The decline of science in corporate R&D. Strateg. Manag. J. 39 (1), 3–32.
ARPA-E, 2020a. ARPA-E Budget. Accessed 2025-09-02. https://arpa-e.energy.gov/?q=arpa-e-site-page/arpa-e-budget.
ARPA-E, 2020b. FAQ. Accessed 2025-09-03. https://arpa-e.energy.gov/about/faq.
Ayoubi, Charles, Pezzoni, Michele, Visentin, Fabiana, 2019. The important thing is not to win, it is to take part: what if scientists benefit from participating in research Grant competitions? Res. Policy 48 (1), 84–97.
Azoulay, Pierre, Zivin, Joshua S. Graff, Manso, Gustavo, 2011. Incentives and creativity: evidence from the academic life sciences. RAND J. Econ. 42 (3), 527–554.
Azoulay, Pierre, Ding, Waverly, Stuart, Toby, 2009. The impact of academic patenting on the rate, quality and direction of (public) research output. J. Ind. Econ. 57 (4), 637–676.
Azoulay, Pierre**,** Erica Fuchs**,** Anna P. Goldstein **and** Michael Kearney**.** 2019b. "Funding breakthrough research: Promises and challenges of the "ARPA model."" In *Innovation Policy and the* Economy, Volume 19, edited by Josh Lerner and Scott Stern. National Bureau of Economic Research.
Azoulay, Pierre, Ganguli, Ina, Zivin, Joshua Graff, 2017. The mobility of elite life scientists: professional and personal determinants. Res. Policy 46, 573–590.
Azoulay, Pierre, Graff, Joshua S., Zivin, Danielle Li, Sampat, Bhaven N., 2019a. Public R&D Investments and private-sector patenting: evidence from NIH funding rules. Rev. Econ. Stat. 86 (1), 117–152.
Azoulay, Pierre, Li, Danielle, 2022. Scientific Grant funding. In: Goolsbee, Austan, Jones, Ben (Eds.), Innovation and Public Policy. University of Chicago Press.
Azoulay, Pierre, Stuart, Toby, Wang, Yanbo, 2014. Matthew: effect of fable? Manag. Sci. 60 (1), 92–109.
Baker, Andrew C.**,** David F. Larcker**,**a nd Charles C.Y. Wang. 2022. "How much should we trust staggered difference-in-differences estimates?" J. Financ. Econ. 144: 370–395.
Beck, Susanne**,** Tiare-Maria Brasseur**,** Marion Kristin Poetz**, and** Henry Sauermann. 2019. "What's the problem? How crowdsourcing contributes to identifying scientific research questions." In Academy of Management Proceedings (vol. 1): 15282. New York: Academy of Management.
Bertrand, Marianne, Duflo, Esther, Mullainathan, Sendhil, 2004. How much should we trust differences-in-differences estimates? Q. J. Econ. 119 (1), 249–275.
Bikard, Michaël, Vakili, Keyvan, Teodoris, Florenta, 2019. When collaboration bridges institutions: the impact of university-industry collaboration on academic productivity. Organ. Sci. 30 (2), 426–445.
Blumenthal, David, Campbell, Eric G., Anderson, Melissa S., Causino, Nancyanne, Louis, Karen Seashore, 1997. Withholding research results in academic life science: evidence from a National Survey of faculty. Jama 277 (15), 1224–1228.
Blumenthal, David, Causino, Nancyanne, Campbell, Eric, Louis, Karen Seashore, 1996. Relationships between academic institutions and industry in the life sciences—an industry survey. N. Engl. J. Med. 334 (6), 368–374.
Bol, Thijs, de Vaan, Mathijs, van de Rijt, Arnout, 2018. The Matthew effect in science funding. Proc. Natl. Acad. Sci. 115 (19), 4887–4890.
Bonvillian, William, 2006. Power play. The American Interest 2 (2), 39–49.
Boyack, Kevin W., Patek, Michael, Ungar, Lyle H., Yoon, Patrick, Klavans, Richard, 2014. Classification of individual articles from all of science by research level. J. Inf. Secur. 8 (1), 1–12.
Bronzini, Raffaello, Iachini, Eleonora, 2014. Are incentives for R&D effective? Evidence from a regression discontinuity approach. Am. Econ. J. Econ. Pol. 6 (4), 100–134.
Callaway, Brantly, Sant'Anna, Pedro H.C., 2021. Difference-in-differences with multiple time periods. J. Econ. 25 (2), 200–230.
Cappelli, Riccardo, Czarnitzki, Dirk, Doherr, Thorsten, Montobbio, Fabio, 2019. Inventor mobility and productivity in Italian regions. Reg. Stud. 53 (1), 43–54.
Cohen, Wesley M., Sauermann, Henry, Stephan, Paula, 2020. Not in the job description: the commercial activities of academic scientists and engineers. Manag. Sci. 66 (9), 4108–4117.
Copernicus. 2019. Access to Finance: Eurostars. Retrieved from https://www.copernicus.eu/sites/default/files/2019-06/Finance-Eurostars-20190405-EN-WEB.pdf.
Coulter, Neal, Monarch, Ira, Konda, Suresh, 1998. Software engineering as seen through its research literature: a study in co-word analysis. J. Am. Soc. Inf. Sci. 49 (13), 1206–1223.
Czarnitzki, Dirk, Grimpe, Christoph, Toole, Andrew A., 2015. Delay and secrecy: does industry sponsorship jeopardize disclosure of academic research? Ind. Corp. Chang. 24 (1), 251–279.
Dasgupta, Partha, David, Paul A., 1994. Towards a new economics of science. Res. Policy 23 (5), 487–521.
David, Paul A., Hall, Bronwyn H., Toole, Andrew A., 2000. Is Public R&D a complement or substitute for private R&D? A review of the econometric evidence. Res. Policy 29 (4–5), 497–529.
de Chaisemartin, Clément, D'Haultfœuille, Xavier, 2023. Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: a survey. Econ. J. 26 (3), C1–C30.
D'Este, Pablo, Perkmann, Markus, 2011. Why do academics engage with industry? The entrepreneurial university and individual motivations. J. Technol. Transf. 36 (3), 316–339.
Ding, Waverly W., Levin, Sharon G., Stephan, Paula E., Winkler, Anne E., 2010. The impact of information technology on academic scientists' productivity and collaboration patterns. Manag. Sci. 56 (9), 1439–1461.
Ding, Ying, Chowdhury, Gobinda G., Foo, Schubert, 2001. Bibliometric cartography of information retrieval research by using co-word analysis. Inf. Process. Manag. 37 (6), 817–842.
Doherr, Thorsten**.** 2017. "Inventor mobility index: a method to disambiguate inventor careers." ZEW-Centre for European Economic Research Discussion Paper 17–018.
Doherr, Thorsten, 2018. "Disambiguation by namesake risk assessment". In *Disambiguation of Researcher Careers: Shifting the Perspective from Documents to Authors.* Dissertation PhD-FDEF-2018-07, p. 7–40. University of Luxembourg, Luxembourg.
European Commission, 2008. "Towards Joint Programming in Research: Working Together to Tackle Common Challenges More effectively." COM(2008) 468 final. https://ec.europa.eu/research/press/2008/pdf/com_2008_468_en.pdf.
European Commission, 2020. "Enhanced EIC Pilot: Funding." Accessed 2020-09-03.. https://ec.europa.eu/research/eic/index.cfm?pg=funding.
Eurostars, 2014. Project: Encapsulation of bacteria with biosilica for fabrication of bacterial bioreactors and biosensors. Accessed 2025-09-06. https://www.era-learn.eu/network-information/networks/eurostars/eurostars-cut-off-1/encapsulation-of-bacteria-with-biosilica-for-fabrication-of-bacterial-bioreactors-and-biosensors.
Evans, James A., 2010a. Industry collaboration, scientific sharing, and the dissemination of knowledge. Soc. Stud. Sci. 40 (5), 757–791.
Evans, James A., 2010b. Industry induces academic science to know less about more. Am. J. Sociol. 116 (2), 389–452.
Federal Ministry of Education and Research, 2020. Marie Skłodowska-Curie European Fellowships. Accessed 2025-09-06. https://www.research-in-germany.org/en/research-funding/funding-programmes/eu–marie-sklodowska-curie.html.
Fleming, Lee, Mingo, Santiago, Chen, David, 2007. Collaborative brokerage, generative creativity, and creative success. Adm. Sci. Q. 52 (3), 443–475.
Fleming, Lee, Sorenson, Olaf, 2004. Science as a map in technological search. Strateg. Manag. J. 25 (8–9), 909–928.
Fraunhofer Society, 2019. Annual Report 2018: 70 Years of Fraunhofer – 70 Years of Future. Fraunhofer Society E.V., Munich.
Gentzkow, Matthew, Kelly, Bryan, Taddy, Matt, 2019. Text as data. J. Econ. Lit. 57 (3), 535–574.
Glänzel, Wolfgang, 2003. *Bibliometrics as a Research Field: a Course on Theory and Application of Bibliometric Indicators.* Course Script. Katholieke Universiteit Leuven, Leuven.
Goldfarb, Brent, 2008. The effect of government contracting on academic research: does the source of funding affect scientific output? Res. Policy 37 (1), 41–58.
Goodman-Bacon, Andrew, 2021. Differences-in-differences with variation in treatment timing. J. Econ. 225 (2), 254–277.
Goodman-Bacon, Andrew, Goldring, Thomas, Nichols, Austin, 2019. "Bacondecomp: Stata module for decomposing difference-in-differences estimation with variation in treatment timing." *Statistical Software Components* S458676, Boston College Department of Economics.
Grimpe, Christoph, 2012. Extramural research Grants and scientists' funding strategies: beggars cannot be choosers? Res. Policy 41, 1448–1460.
Gulbrandsen, Magnus, Smeby, Jens-Christian, 2005. Industry funding and university professors' research performance. Res. Policy 34 (6), 932–950.
Hausman, Jerry A., Hall, Bronwyn H., Griliches, Zvi, 1984. Econometric models for count data with an application to the Patents-R&D Relationship. Econometrica 52 (4), 909–938.
Heckman, James J., Ichimura, Hidehiko, Todd, Petra, 1998. Matching as an econometric evaluation estimator. Rev. Econ. Stud. 65 (2), 261–294.
Hottenrott, Hanna, Lawson, Cornelia, 2017. Fishing for complementarities: research Grants and research productivity. Int. J. Ind. Organ. 51, 1–38.

Hottenrott, Hanna, Lopes-Bento, Cindy, 2014. (international) R&D collaboration and SMEs: the effectiveness of Targeted Public R&D Support Schemes. Res. Policy 43 (6), 1055–1066.
Howell, Sabrina T., 2017. Financing innovation: evidence from R&D Grants. Am. Econ. Rev. 107 (4), 1136–1164.
Hünermund, Paul, Beyers, Louw, Rönkkö, Mikko, 2025. The choice of control variables in empirical management research: how causal diagrams can inform the decision. Leadersh. Q. 36 (2), 101845.
Hünermund, Paul, Czarnitzki, Dirk, 2019. Estimating the causal effect of R&D subsidies in a Pan-European program. Res. Policy 48 (1), 115–124.
Hünermund, Paul, Licht, Georg, Rammer, Christian, 2016. Evaluierung der nationalen Förderung im Förderprogramm Eurostars 1 (2008–2013). Bundesministerium für Bildung und Forschung, Mannheim. Accessed 2021-01-15. https://www.zew.de/en/publications/evaluierung-der-nationalen-foerderung-im-foerderprogramm-eurostars-1-2008-2013-1.
Imai, Kosuke, Kim, In Song, 2021. On the use of two-way fixed effects regression models for causal inference with panel data. Polit. Anal. 29 (3), 405–415.
Jacob, Brian A., Lefgren, Lars, 2011. The impact of research Grant funding on scientific productivity. J. Public Econ. 95 (9–10), 1168–1177.
Lauer, Mike, 2019. NIH annual snapshot: FY 2018 by the numbers. Extramural Nexus. Accessed 2020-09-03. https://web.archive.org/web/20250422193342/https://nexus.od.nih.gov/all/2019/03/13/nih-annual-snapshot-fy-2018-by-the-numbers/.
Law, John, Whittaker, John, 1992. Mapping acidification research: a test of the co-word method. Scientometrics 23 (3), 417–461.
Lee, Yong S., 2000. The sustainability of university–industry research collaboration: an empirical assessment. J. Technol. Transf. 25 (2), 111–133.
Levin, Sharon G., Stephan, Paula E., 1991. Research productivity over the life cycle: evidence for academic scientists. Am. Econ. Rev. 81 (1), 114–132.
Leydesdorff, Loet, 1997. Why words and co-words cannot map the development of the sciences. J. Am. Soc. Inf. Sci. 48 (5), 418–427.
Li, Danielle, Azoulay, Pierre, Sampat, Bhaven N., 2017. The applied value of public Investments in Biomedical Research. Science 356 (6333), 78–81.
Lissoni, Francesco, Coffano, Monica, Maurino, Andrea, Pezzoni, Michele, Tarasconi, Giancarlo, 2010. "APE-INV'S "Name Game" Algorithm Challenge: A Guideline for Benchmark Data Analysis and Reporting." *Technical Report*, Academic Patenting in Europe-APE-INV.
Lissoni, Francesco, Montobbio, Fabio, 2015. The ownership of academic patents and their impact: evidence from five European countries. Revue Économique 66 (1), 143–171.
Louis, Karen Seashore, Jones, Lisa M., Anderson, Melissa S., Blumenthal, David, Campbell, Eric G., 2001. Entrepreneurship, secrecy, and productivity: a comparison of clinical and non-clinical life sciences faculty. J. Technol. Transf. 26 (3), 233–245.
Lu, Kun, Wolfram, Dietmar, 2012. Measuring author research relatedness: a comparison of word-based, topic-based, and author Cocitation approaches. J. Am. Soc. Inf. Sci. Technol. 63 (10), 1973–1986.
Makarow, Marja, Licht, Georg, Caetano, Isabel, Czarnitzki, Dirk, Elçi, Sirin, 2014. *Final Evaluation of Eurostars Joint Programme.* Final Report, European Commission. Ref. Ares(2014)3906990–24/11/2014.
Mansfield, Edwin, 1995. Academic research underlying industrial innovations: sources, characteristics, and financing. Rev. Econ. Stat. 77 (1), 55–65.
Mokyr, Joel, 2002. The Gifts of Athena: Historical Origins of the Knowledge Economy. Princeton University Press, Princeton.
Mowery, David C., Nelson, Richard R., Sampat, Bhaven N., Ziedonis, Arvids A., 2001. The growth of patenting and licensing by US universities: an assessment of the effects of the Bayh–Dole act of 1980. Res. Policy 30 (1), 99–119.
Narin, Francis, Pinski, Gabriel, Gee, Helen Hofer, 1976. Structure of the biomedical literature. J. Am. Soc. Inf. Sci. 27 (1), 25–45.
National Academies of Science, Engineering, and Medicine, 2017. An Assessment of ARPA-E. The National Academies Press, Washington, DC.
Perkmann, Markus, Tartari, Valentina, McKelvey, Maureen, Autio, Erkko, Broström, Anders, D'Este, Pablo, Fini, Riccardo, et al., 2013. Academic engagement and commercialisation: a review of the literature on university-industry relations. Res. Policy 42 (2), 423–442.
Perkmann, Markus**, and** Kathryn Walsh**.** 2009. "The two faces of collaboration: impacts of University–Industry relations on public research." Ind. Corp. Chang. 18 (6): 1033–1065, Ind. Corp. Chang..
Reagans, Ray, Zuckerman, Ezra, McEvily, Bill, 2004. How to make the team: social networks vs. demography as criteria for designing effective teams. Adm. Sci. Q. 49, 101–133.
Rios-Avila, Fernando, Pedro, H.C., Sant'Anna, and Brantly Callaway., 2021. CSDID: Stata module for the estimation of difference-in-difference models with multiple time periods. In: *Statistical Software Components* S458976. Boston College Department of Economics.
Rivest, Ronald L., Shamir, Adi, Adleman, Leonard, 1978. A method for obtaining digital signatures and public-key cryptosystems. Commun. ACM 21 (2), 120–126.
Roach, Michael, 2017. Encouraging entrepreneurship in university labs: research activities, research outputs, and early doctorate careers. PLoS One 12 (2), e0170444.
Roach, Michael, Sauermann, Henry, 2010. A taste for science? PhD scientists' academic orientation and self-selection into research careers in industry. Res. Policy 39 (3), 422–434.
Rosenberg, Nathan, 1974. Science, invention and economic growth. Econ. J. 84 (333), 90–108.
Roth, Jonathan, 2022. Pretest with caution: event-study estimates after testing for parallel trends. American Economic Review: Insights 4 (3), 305–322.
Shibayama, Sotaro, Walsh, John P., Baba, Yasunori, 2012. Academic entrepreneurship and exchange of scientific resources: material transfer in life and materials sciences in Japanese universities. Am. Sociol. Rev. 77 (5), 804–830.
Siegel, Donald S., Waldman, David, Link, Albert, 2003. Assessing the impact of organizational practices on the relative productivity of university technology transfer offices: an exploratory study. Res. Policy 32 (1), 27–48.
Smith, Erica, Smith, Andrew, 2012. Buying-out teaching for research: the views of academics and their managers. High. Educ. 63 (4), 455–472.
Stephan, Paula E., 1996. The economics of science. J. Econ. Lit. 34 (3), 1199–1235.
Tartari, Valentina, Breschi, Stefano, 2012. Set them free: scientists' evaluations of the benefits and costs of university–industry research collaboration. Ind. Corp. Chang. 21 (5), 1117–1147.
Teodoridis, Florenta, 2017. Understanding team knowledge production: the interrelated roles of technology and expertise. Manag. Sci. 64 (8), 3469–3970.
Thursby, Jerry G., Jensen, Richard, Thursby, Marie C., 2001. Objectives, characteristics and outcomes of university licensing: a survey of major US universities. J. Technol. Transf. 26 (1–2), 59–72.
Toole, Andrew A., Czarnitzki, Dirk, 2010. Commercializing science: is there a university brain drain from academic entrepreneurship? Manag. Sci. 56 (9), 1599–1614.
Trajtenberg, Manuel, Shiff, Gil, Melamed, Ran, 2009. The "names game": harnessing inventors' patent data for economic research. Ann. Econ. Stat. 93-94, 79–108.
Uzzi, Brian, Spiro, Jarrett, 2005. Collaboration and creativity: the small world problem. Am. J. Sociol. 111 (2), 447–504.
Van Atta, Richard H., 2007. Testimony before the Hearing on "Establishing the Advanced Research Projects Agency-Energy (ARPA-E)," Subcommittee on Energy and Environment, Committee on Science and Technology, *United States House of Representatives*, Washington DC.