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

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ABSTRACT:

We quantify the impact of publicly co-funded industry-science collaborations on science output. Such "duo programs" encourage scientists to co-develop innovation projects with firms, combining the attributes of competitive research funding with those of science commercialization programs. Their focus on commercialization leads them to require more time and effort from scientists than traditional science funding programs and might also lead applicants to adopt projects with higher commercial potential. The question thus arises whether such programs, which are becoming increasingly popular, impose a cost in terms of scientific productivity or the direction of science. We investigate the effect of participation in one such program, a European Joint Programming Initiative that encourages cross-border research collaboration to commercial ends. To ensure causality, we use plausibly exogenous variation in funding decisions that results from restrictions in the program's budget-allocation rules. We find no evidence that co-funded industry-science collaborations negatively impact science. On the contrary, our results indicate that they increase the number of top publications by participating scientists, in particular jointly with coauthors from industry, while the direction of scientists' research agendas remains unaffected.

Keywords: *Innovation; Academic engagement; R&D policy, Joint Programming Initiative*

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I. Introduction

Scientific findings' potential for contributing to welfare-enhancing innovations has long been understood (Azoulay and Li, 2020; Dasgupta and David, 1994; Mokyr, 2002; Rosenberg, 1974). Roughly 40 percent 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 value derived for academic research and training (Azoulay et al., 2019a; Azoulay and Li, 2020; 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, 2020; Rivest et al., 1978). The social importance of (basic) science, combined with the private sector's need to collaborate with science to yield higher research and development (R&D) productivity (Bikard et al., 2019; Cockburn and Henderson, 1998; Lacetera, 2009; Owen-Smith and Powell, 2004; Zucker et al., 2002a,b), has led policy-makers and research funders to increase their investments in such collaborations.[1] In the context of industry's recent tendency to decrease their basic research investments (Arora et al., 2018), efficient collaboration between industry and science seems vital for the economy overall.

The literature has established the positive effect of industry-science collaboration for industry (Mansfield, 1995; Zucker et al. 1998), but the effect on science continues to be debated (see, e.g., Perkman et al., 2013; 2020). Among other concerns are those that pertain to corporate secrecy and firms' competitive behavior's limiting effect on scientific collaboration, teaching, contribution to open science, and more generally, the dissemination of findings (Bikard et al., 2019; Czarnitzki et al., 2015; Evans, 2010a; Lee, 2000; Murray, 2010; Shibayama et al., 2012; Toole and Czarnitzki, 2010; Thursby and Thursby, 2001). While these concerns are well

[1] The US NIH has developed several funding programs that encourage collaboration between academia and industry initiatives. One initiative, Discovering New Therapeutic Uses for Existing Molecules, earmarked $575 million for the National Center for Advancing Translational Sciences to test previously developed compounds from industry partners for therapeutic effectiveness. The program also developed template agreements with the purpose of shortening negotiations between industrial and scientific partners. For more information, please see http://www.nih.gov/news-events/news-releases/nih-fund-collaborations-industry-identify-new-uses-existing-compounds or http://www.nih.gov/news-events/news-releases/nih-launches-collaborative-program-industry-researchers-spur-therapeutic-development. In Europe, several initiatives in the Horizon 2020 Framework Programme encourage intersectoral collaboration, as does the Joint Programming Initiative Eurostars, where collaboration between SMEs and science is highly encouraged. For more information, please see https://www.eurostars-eureka.eu/ or https://ec.europa.eu/programmes/horizon2020/en/h2020-section/fet-flagships.

documented, science is also likely to benefit from such collaborations, as they may lead to new insights likely to inspire future research (Azoulay et al., 2009; Agrawal and Henderson, 2002; Lee, 2000; Mansfield, 1995; Perkmann and Walsh, 2009), and provide access to the high-end infrastructure that is often unavailable to financially constrained scientists (D'Este and Perkmann, 2011; Tartari and Breschi, 2012). Industry-science partnerships also bring opportunities for specialization by allowing each of the partners to focus on what they do best and on what their respective institutions reward most (Aghion et al., 2008; Sauermann and Stephan, 2013), resulting in efficiency and productivity gains for both partners, potentially leading to greater scientific output (Bikard et al., 2019).

Such effects of collaborations between industry and science may be accentuated if partnerships stem from a *publicly co-funded industry-science collaboration* grant system, namely "duo programs" combining characteristics of the traditional competitive research grant and of academic commercialization. When scientists collaborate with industry in duo programs, they have to fulfill all of competitive research grants' traditional criteria (i.e., grants based on research proposals evaluated and ranked by a public body) *and* the criteria to translate their findings into a marketable product (i.e., academic commercialization). Fulfilling such conditions requires considerable time and effort from scientists when they apply for the grant, when the application is funded for the research part of the proposal, and after the technology has been developed to ensure successful end-user utility and commercialization. Therefore, the commercial nature of the program, combined with the preceding research, is more resource demanding than other grants and may impact the scientists' research agenda, exacerbating concerns about negative impacts on science. Yet, close collaboration with industry from the start of a research proposal can promote steeper knowledge spillovers and specialization effects from industry to science than the ones that are created if an inter-sectoral collaboration starts only after a technology is developed to look for promising commercialization venues.

To date, no empirical evidence is available to corroborate which of these mechanisms prevails for such programs. Due to the financial incentives for both partners in publicly co-funded industry-science projects, we suggest that the complementarities between industry and science are greater than the costs. In other words, access to new ideas, insights, and approaches, combined with group diversity, increased visibility, and access to R&D staff, (high-end) industry equipment, and experts to take care of commercialization, increase scientific productivity. Therefore, given the potential gains for both industry and science, combined with recent evidence that firms are turning away from basic research (Arora et al., 2018), fostering effective industry-science technology transfers has become a priority. Azoulay and Li (2020) highlight the need to evaluate the potential and feasibility of such "translational incentives", since many existing programs address follow-on economic activities only in a passive way, such as by removing obstacles to commercialization (i.e., unclear or limited intellectual property rights). However, left to their own devices, scientists are unlikely to take the necessary steps to translate results from science to industry (Barham et al., 2020; Cohen et al., 2020). Therefore, an increasing trend in recent programs is to make commercialization an integral part of their objectives. A primary example of this is the ARPA (Advanced Research Projects Agency) research funding in the US, oriented towards commercialization and societal impact. In particular, participants in the ARPA-E program are required to develop a technology-to-market (T2M) plan describing the project's commercialization strategy (National Academies of Sciences, Engineering, and Medicine, 2017). Despite these programs' high profiles (Bonvillian, 2006; Van Atta, 2007), empirical evaluations remain scarce, along with conclusive findings on the impact of commercialization incentives on science (Azoulay et al., 2019b; Azoulay and Li, 2020).[2]

To help clarify the impact of such translation incentive programs and to adhere to current state-of-the-art standards in program evaluation, we present a large-sample causal evaluation of the type of grant that combines competitive research and commercial output in one call. We construct a panel of the population of scientists involved in a EU flagship Joint Programming Initiative (JPI), and study how participation affects their scientific output. To ensure causality, we make use of a unique budget-allocation rule specific to JPIs which creates plausible exogenous variation in funding between applicants with projects of similar quality. This program shares many design features with similar grant schemes that aim to combine state-of-the-art research with successful commercialization. The findings are therefore relevant to other "duo programs" following the same objectives in and outside of the EU.

We first investigate whether participation in the program affects scientists' productivity and technological output and find no evidence that translational incentive programs negatively impact either one of those dimensions. On the contrary, we find that participating scientists increase the number of top publications. We then explore potential mechanisms behind these

[2] 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 with respect to prospective funding, commercialization, and development pathways" (National Academies of Sciences, Engineering, and Medicine, 2017, p. 3-33).

effects and treatment effect heterogeneity. We first analyze whether program participation redirects participating scientists' agendas towards previously unexplored research areas, such as topics that may be more promising for commercialization. We then investigate whether participation allows researchers to expand their co-author network, e.g., by hiring more graduate students or post-docs through the additional resources provided by the grant, or by co-publishing increasingly with industry partners due to increased knowledge spillover effects. Our analysis provides no evidence that participating scientists switch their research agenda because of the program, nor do we find that the additional top publications of grant holders were driven by increased lab capacity as measured by the number of co-authors. By contrast, we find that the additional top publications stem from co-publications with co-authors from industry, emphasizing the complementarity effects realized by the collaboration. Finally, our results indicate that scientists who are less well established in terms of their citations or years of experience benefit more from publicly co-funded industry-science collaborations.

II. Conceptual background

A. A brief look into the policy: The Eurostars Joint Programming Initiative

Eurostars, one of the EU's flagship programs, promotes R&D and innovation in small and medium-sized enterprises (SMEs). It 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 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.[3] (See Figure 1 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 (the so-called "cutoffs").

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

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.[4] The key criterion was that an SME was the main project applicant. Once these requirements were met, universities and research institutes (as well as larger companies) were allowed to join a project.[5] The consortia consisted of an average of 3.3 partners from 2.5 countries. About 21 percent of program co-applicants were from academia. 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 bio-active 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 exceeded $4 billion in 2015 (Eurostars, 2014).[6]

B. Literature Review

Industry-science collaboration and scientific productivity

Historically, universities have fulfilled the role of producing and disseminating knowledge by autonomous researchers, such that researchers freely selected their projects, methods, and modes of dissemination (Aghion et al., 2008). With increased collaboration between industry and science, scholars have expressed concerns about, for example, 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;

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[4] 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).

[5] In personal communications, several Eurostars applicants opined that having a science-based partner on the project increased their chances of obtaining funding.

[6] Other Eurostars success stories can be reviewed at https://www.eurostars-eureka.eu/eurostars-success-stories

Czarnitzki et al., 2015; Evans, 2010a; Lee, 2000; Louis et al., 2001; Shibayama et al., 2012; Stephan, 1996; Thursby and Thursby, 2001); and a shift from general to more direct forms of knowledge exchange (Shibayama et al., 2012). For instance, Toole and Czarnitzki (2010) conclude that combining academic research with commercialization requires an important trade-off, as active involvement in for-profit activities by NIH-supported life scientists is costly for universities in terms of the volume and quality of journal publications, awards, and patents. Goldfarb (2008) finds similar results for engineers who are sponsored by industry, and Czarnitzki et al. (2015) find that industry sponsorship increases the probability of publication delays from 14 percent to 33 percent, and the probability that findings have to be kept secret (eliminating publication) from 11.2 percent to 35 percent. This effect is amplified by the fact that it is typically the most successful scientists who participate in commercialization (Bekkers and Bodas Freitas, 2008; Gulbrandsen and Smeby, 2005; Haeussler and Colyvas, 2011; Perkman et al., 2013; Zucker and Darby, 1996; Zucker et al., 1998; 2002a; 2002b).[7] However, other authors find no such trade-offs. For instance, Gulbrandsen and Smeby (2005) conclude that faculty who have industrial involvement publish at least as many scientific articles as their peers who do not have such ties, although their articles tend to be of a more applied nature. Perkman et al. (2013) corroborate these findings, showing in their literature review that academic engagement and commercialization are complementary to academic research. Such complementarities can emerge when industry contacts become sources of new ideas, thus creating knowledge spillovers from industry to academia (Agrawal and Henderson, 2002; Azoulay et al., 2009; Lee, 2000; Mansfield, 1995; Perkmann and Walsh, 2009). Likewise, Bikard et al. (2019) find synergies between industry and scientific research insofar that scientists who have industry collaborators produce more follow-on publications than do academic scientists who have no industry collaborators. This effect is particularly noticeable for research that has high commercial potential and is done with an established industry partner. Apart from knowledge spillovers, the additional funds received from industry may lead to resource spillovers in which involved university departments 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).

[7] On top of the potential impacts on scientific output (publications) of leading scholars' engagement in for-profit activities, an impact on (graduate/post-graduate) students in terms of education and supervision may also be felt if the best scientists engage in (too much) commercialization (Bianchini et al., 2016). Relatedly, since industrial funding is often given to the most prestigious institutions, there is a risk of a funding distortion. For example, in the UK, 33 percent of the total university income from industry was given to only 6 percent of the institutions (Geuna, 2001).

Competitively co-funded scientific research funding and scientific productivity

Scientific research funding from competitively evaluated grant applications has a positive impact on scientists' careers and productivity that is driven by access to additional resources, the signaling effect of such grants, and by the well-known Matthew effect (Azoulay et al., 2014; Bol et al., 2018). The competitive nature and low acceptance rate of competitive research grants provide the grantee with a quality stamp, which often leads to a virtuous circle for future grants and opportunities for career advancement (Lanahan and Armanios, 2018).[8] Examining the impact of federal funding on university-level research output, Payne and Siow (2003) find that $1 million in federal research funding is associated with ten more publications and 0.2 more patents. Jacob and Lefgren (2011) find a similar estimate for NIH grants, with $1.7 million in funding's being associated with one additional publication over the next five years, a 7 percent increase. Other studies that address the impact of individual grants also find positive effects on scientific outcomes (Arora and Gambardella, 2005; Averch, 1987; 1989; Azoulay and Li, 2020; Hottenrott and Lawson, 2017).

Competitively co-funded industry-science collaboration and scientific productivity

In studying the effects of industry-science collaboration and external research funding on scientific productivity, scholars typically view the two separately.[9] In doing so, the literature misses the effect of *competitively funded* industry-science collaborations on scientific productivity. In other words, we lack insights into the effect of programs that combine characteristics from both activities and so are likely to impact scientific output in ways other than each activity would separately.

When scientists engage in a publicly co-funded industry-science program, the funding program provides them with the finances they need to perform cutting-edge research and then to bring those research results to the market through commercialization. This approach has several peculiarities. On one hand, the scientists' academic freedom to choose their projects, research methods, and how to disseminate results is obstructed. Since commercialization is an integral part of the project, research may need to be realigned to projects with commercial

[8] Success rates across countries, funding agencies, institutions and programs vary but strongly suggest that the competition is fierce, independent of the specific program. As a case in point, the ERC starting grant financed by the European Commission had a success rate of 12.7 percent in 2018.

[9] While some studies analyze whether industry collaborations open the doors for future funding (Thursby and Thursby, 2011) or whether private funding impacts the effect of public funding (Hottenrott and Lawson, 2017), no causal analyses have been performed on the impact of competitive industry-science grants on scientific productivity.

potential, which are often less risky and less basic. Moreover, the private-sector competition that is linked to these projects may impede scientists from freely engaging in knowledge exchange with their peers (Blumenthal et al., 1996; Mindruta, 2013; Stuart and Ding, 2006; Toole and Czarnitzki, 2010; Zucker and Darby, 1996). In addition, writing an industry-science proposal that contains cutting-edge science and is also marketable may require more time from the scientist since she is involved in both parts of the proposal—the science and the market potential—independent of the outcome of the project. In other words, a project's potential to bring a technology to the market has to be assessed before the potential for the developed technology's success can be assessed. Compared to conventional competitive research grants, these grants require more time and offer less space for academic freedom. While the above aspects may be less prevalent for scientists that are already involved in—or oriented towards—more applied work, the increasing trend of funding programs that combine state-of-the-art research with commercialization in one call, combined with the high pressure that scientists face to acquire third party funding, also pushes less applied scientists to embark on this road and puts additional pressure on already applied scientists to become less selective in the projects they pursue.

On the other hand, the co-development of a competitively funded project between industry and science obliges both partners to work together closely, even when they are developing the proposal, before the project starts. 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 have greater complementarities than those of non-competitively or non-publicly co-funded industry-science projects, since a proposal requires tight collaboration and knowledge- and idea 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 avoid intellectual lock-in and to embark on explorations (Beck et al., 2019; Fleming et al., 2007; Reagans et al., 2004; Teodoridis, 2017; Uzzi and Spiro, 2005).

No empirical evidence is available to corroborate which of these mechanisms prevails for such programs. Because, in a publicly co-funded industry-science project, both partners have a financial incentive (compared to financial gains that are directed mainly toward science in non-publicly co-funded projects), our view is that the complementarities in industry-science relationships that benefit science are greater in the context of publicly co-funded projects. Therefore, we suggest that access to new ideas, insights, and approaches, combined with group diversity, increased visibility, and access to R&D staff, (high-end) industry equipment, and experts to take care of commercialization, increase scientific productivity. In what follows, we present a causal analysis to guide policy-makers in future program developments by means of a unique investigation of the EU Eurostars program, the leading program on publicly co-funded industry-science collaborations in the EU and several non-EU OECD countries.

III. Data and Methods

A. Identification

The main problem in performing causal analyses for R&D policy evaluation 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 recoverable from the policy being reviewed. 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 JPIs.

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.[10,11]

[10] Figure 2 shows the distribution of Eurostars' project evaluation scores of all the applications that involved academic partners.

[11] Access to scores would allow us to apply a regression discontinuity design (RDD), which relies on exogenous variation around the funding threshold and has gained in popularity in the recent literature because of its high internal validity (Bronzini and Iachini, 2014; Howell, 2017). However, as RDDs identify treatment effects only at the discontinuity point, their external validity remains limited. In comparison, our approach allows us to identify causal effects along a wide range of project evaluation scores, which results in higher external validity and greater generalizability.

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 it may cause, each participating national funding agency contributes individually to the program and finances only applicants from its own country.[12] Thus, projects can be granted only when each consortium member's national budget has sufficient funds available, so 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 in European policy circles as a *Virtual Common Pot* (VCP). Compared to a situation with a centralized program budget (also known as a *Real Common Pot*, RCP), the additional national budget constraints in a VCP create variation in funding status that is independent of 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, so eight partners 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 cutoff 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 budget 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 independent of project quality. This variation also occurs in countries where funding constraints are not yet binding: participants from country B at the second rank in Table 1 are not funded, while those at rank three are.

In a VCP, the gaps left by highly ranked but unfunded projects (partly) offset selection based on project quality. Figure 3 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.

Hünermund and Czarnitzki (2019b), analyzing the impact of the Eurostars program on firm output, investigate the risks of calculated behavior in the choice of partner. If participants were

[12] Figure 1 shows each participating country's budget. The EUR 100 million that the European Commission contributed to the program were used to top up the individual national budgets (Hünermund and Czarnitzki, 2019a).

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 have 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.[13] Furthermore, suitable project partners for highly specialized research projects are not easily substitutable, which also limits the potential for such calculated choices of partners. Hünermund and Czarnitzki (2019b) present evidence from a survey conducted in the course of the official evaluation of Eurostars (Makarow et al., 2014), which shows that participants selected their project partners predominantly based on either their ability to foster technology transfer or previously existing relationships. Furthermore, Hünermund and Czarnitzki conduct a series of robustness checks that indicate that partner identification is not compromised by the risk of calculated behavior in a VCP.

In our analysis, as a baseline, we estimate pooled regression models controlling for project evaluation ranks, cutoff dummies, as well as countries of residence[14], because they determine treatment status in a VCP. Table A3.1 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 group for researchers in projects of similar quality strengthens our argument that the remaining variation in funding in a VCP is exogenous to research productivity. We then move over to fixed effects models, which subsume the time-invariant controls of the pooled regressions and additionally account for other unobserved time-invariant characteristics such as the composition of the project consortium and heterogeneities across fields.

[13] Also note that our empirical estimations consider first-time applicants, which reduces the risk of learning from repeated participation.
[14] 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). However, variations at the individual country level is absorbed in models with individual fixed effects.

B. Data Sources

Our study builds on Eurostars' administrative records, as provided by the EUREKA secretariat in Brussels. These records contain detailed information on project applications that received grants, as well as those that did not. After initial processing,[15] 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 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 so 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, and 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 percent obtained funding. The average grant amounted to EUR 192 thousand, although individual grants could go up to EUR 973 thousand.[16] We observed the scientists from the year in which they published their first publication, and when no publications were recorded for three consecutive years, we assumed an exit from academia and right-censored observations accordingly. The final panel contains 13,816 individual-year observations between 1970 and 2015.[17] We observed researchers for a median of 20 years.

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[15] Initial processing omitted applications from non-EUREKA countries and restricted the range of evaluation scores to ensure common support, as explained in Section 3.A.

[16] 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). EUREKA reports that the average Eurostars project on average amounted to EUR 1.4 million (EUREKA, 2020), 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).

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

C. Variables

The first 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 program participation. The second set captures 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.

Main outcome variables

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.[18] 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). We also measured publications in high-

[18] See Appendix 1 for more information about how we built the clusters.

quality journals by counting the number of publications in journals that SCOPUS's CiteScore metric ranks in the top 10 percent of all journals.[19] The average scientist in the sample published 0.94 top publications per year. We used a citation-weighted publication count as the quality indicator in a robustness check.[20]

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)[21] 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 patents by this researcher, even when the patents list a corporate affiliation. Since the average number of patents per scientist-year is low (0.031), we used a patenting dummy in the estimation.

Additional outcome variables

Research agenda. To quantify changes in a researcher's research agendas, we compared the researcher's current and past work. 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 our analysis is not contaminated by shifts in vocabulary.) 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.

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[19] 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.

[20] A drawback of using citation-weighted publications as quality indicators is that the Eurostars 1 program ran until 2013, and sufficient time must be allowed to let publications accumulate citations. As the publication data was collected over the course of 2017, we restrict our sample to observations up to 2015 when we count citations. Therefore, we prefer journal-based quality metrics over document-level indicators in this particular setup, even though the relationship between the former and the latter can be weak (Rehn et al., 2014).

[21] See appendix 1 for additional details about the clustering algorithm.

We also used a second measure for changes in a research agenda since co-word analysis depends on a stable keyword interpretation across documents (Leydesdorff, 1997) and on index terms' being assigned objectively and consistently (Law & Whittaker, 1992). For every researcher-year, we counted the number of journals that 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, and 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.[22] A negative causal link between Eurostars funding and cosine similarity indicates that the researcher changed her research focus because of the project. This analysis required several preparatory steps, including standardizing terms and removing irrelevant stopwords. We describe these steps in Appendix 2. 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.

Collaboration networks We used the affiliation information in SCOPUS to determine how many publications listed at least one co-author who is affiliated with a firm. This measure indicates the extent to which a researcher's work is interwoven with corporate R&D (Arora, 2018). We took researchers' collaborating more with the private sector after engaging in Eurostars than before as a sign of 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 percent of their annual output. Moreover, they published in an average of 0.11 top publications with industry coauthors, which reflects a similar ratio.

Eurostars funding may also cause researchers to be exposed to new potential collaborators from academia because of (for instance) increased travel budgets and the opportunity to hire

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[22] 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 $\vec{a}$ and $\vec{b}$ can be calculated as $\cos(\theta) = \frac{\vec{a}\cdot\vec{b}}{\|\vec{a}\|\|\vec{b}\|} = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^2}\sqrt{\sum_{i=1}^{n} b_i^2}}$, where a_i and b_i represent elements of $\vec{a}$ and $\vec{b}$. 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.

research staff. Involvement in the project might also bring 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, among which 10.3 were new. As an alternative measure, we counted the number of new institutions among the scientist's list of collaborators and found that each scientist in the sample collaborated with an average of 4.6 institutions new institutions each year.[23]

Control variables

As explained in more detail in Section 3.A, we controlled for the project evaluation scores that Eurostars application received. Combined with the VCP setup and jointly with cutoff dummies and controls for country affiliation, this approach ensured an unconfounded treatment status. We also controlled for researchers' experience, which is not time-constant and might influence publication and patenting rates through life-cycle effects (Levin and Stephan, 1991). We captured experience as the time since the researcher published her first publication. Researchers in our sample had accumulated a median of 15 years of experience at the time of their project applications. We added a squared term of this variable to capture additional nonlinear effects. We also controlled for shared trends using a set of time dummies and introduced researcher fixed effects to absorb individual-level heterogeneity, accounting for factors like gender, field of study, and unobserved differences in ability.

D. Methods

Our main identification argument (as laid out in Section III.A) is built on cross-sectional variation in funding status in a VCP. Consequently, we started out with pooled regressions, which we then complemented with fixed effects regressions to exploit the panel dimension of our data fully. We used Poisson models for count-dependent variables (Hausman et al., 1984) and linear models when dependent variables were continuous or binary. The regression equation for pooled linear estimation is specified as:

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

[23] To measure when a PI collaborates with a particular co-author for the first time, we disambiguated all the PIs' coauthors in a manner similar to what we did for the PIs. We similarly disambiguate institutions based on their name and location. See Appendix 1 for more details.

where 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; and X_{it} is a vector of control variables containing project evaluation scores, cutoff and country group dummies, researcher experience, and experience squared. Furthermore, all regressions include a set of time dummies, λ_t. For Poisson, exponentiated values of the linear index in (1) are used to model the conditional mean of the data:

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

In the fixed effects models, we also allow for individual-specific offsets, α_i, that account for time-invariant unobserved heterogeneity. As a result, all time-constant control variables were dropped from the regressions. Section IV.D discusses the findings from testing the presence of parallel trends in the pre-treatment period once individual fixed effects have been incorporated. Standard errors are clustered at the level of the individual researcher throughout the regressions.[24]

IV. Empirical Findings

Here we present the results of cross-sectional and fixed effects estimations for our main dependent variables related to scientific productivity (Table 3). Then we turn our attention to additional outcome measures to clarify the mechanisms through which productivity gains might be realized (Table 4). Subsequently, we present split sample analyses to shed light on the potential heterogeneity of treatment effects along several dimensions, including affiliation, field, citation stock, and experience (Table 5). Finally, we test the validity of our results with respect to parallel pre-treatment trends and variation in treatment timing (Tables 6 and 7).

A. Main results

Table 3 shows pooled regression results for the number of publications, top publications, and patents. We find a positive effect on productivity of Eurostars' grants, as after receiving funding, researchers produce an average of 21 percent more publications (p=0.013) and 33 percent more top publications (p=0.005) per year.[25] In contrast, grants have no significant effect on patenting, although one might expect consortium members to patent their inventions from a

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

[25] 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 $e^{0.192} - 1 = 0.21$.

Eurostars project to protect them from imitation. However, Hünermund and Czarnitzki (2019b) find no effect on patenting in a study of Eurostars' impact on participating firms, suggesting that an increase in patenting by scientists would require them to file more patents independently, without their project partners, which seems less likely.

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 columns 1–3, suggesting that project quality evaluated for the consortium as a whole is not strongly associated with outcomes at the level of the individual researcher. Some cutoff dummies show significant coefficients, but there appears to be no particular temporal trend. Similarly, the effect of country affiliation appears to be modest, except for the group of mostly Eastern European member states that joined the EU in 2004 (EU28), as researchers from these countries have fewer top publications and less propensity to patent. With respect to experience, we find the typical academic lifecycle pattern of an inverse-U relationship in publishing (Levin and Stephan, 1991), with a peak at around 25 years after the first publication.

Table 3 also presents fixed effects regressions, which largely confirm our pooled estimation results, although with some important differences. First, a positive impact of Eurostars funding on scientists' general publication is not confirmed by the fixed effects estimations, as the marginal effect turns insignificant and drops from 21 percent in the pooled model to 3 percent in the fixed effects Poisson model. This discrepancy suggests that the broad country groups we formed to account for a limited number of Eurostars applications in some jurisdictions cannot absorb all of the unobserved heterogeneity that the individual-level fixed effects can pick up. Second, the estimated effect on top publications declines but remains statistically significant ($p<0.038$) and quantitatively meaningful (17%). In other words, once individual-level heterogeneities are accounted for, Eurostars grants are not associated with a larger general scientific output, but they do increase the number of high-quality publications. In contrast, the effect on patenting remains small and insignificant.

On the whole, our findings corroborate results from the previous literature that points to complementarities between commercialization activities and research (Perkman et al., 2013). While these complementarities are hypothesized as being driven by 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 mechanisms like a positive effect on researchers' resource endowments, expansion of their coauthor networks, or improved access to research infrastructure as a result of winning a Eurostars grant. At the same time, the traditional productivity measures we investigated do not allow us to assess whether the applied nature of Eurostars projects incentivizes scientists to change their research trajectories and explore new research topics. We address both of these questions in the next section.

B. Additional outcome measures

Table 4 presents estimation results related to new keywords, new journals, and the similarity of papers' abstracts with respect to previous publications' abstracts. For none of these three measures do we find evidence of an effect of Eurostars funding on research agendas and the topics on which scientists work. Given that academics do not frequently change fields, this finding suggests that the additional top publications we infer from our previous estimations are likely to be in the scientists' main fields of expertise. Our findings also make it appear unlikely that researchers shift their research agendas to more applied topics as a result of the commercialization activities Eurostars requires.

If researchers do not change the types of research they pursue, then, another explanation for the effects we find might be that 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. To investigate this mechanism, we identify all publications that are co-authored by industrial partners and estimate the effect of Eurostars funding on publication numbers separately for publications with and without industry coauthors. If productivity effects are explained purely by the financial resources from the grant, we should see the number of publications increase, independent of industry collaboration. Regression results reported in Table 4 show that the number of publications with industry partners increases substantially after scientists receive Eurostars funding (25%; p=0.026). In contrast, publications without industry partners do not increase significantly (1%; p=0.920), but they also do not decrease, which would imply a substitution effect. We observe a similar pattern for top publications; where the relative increase is much stronger among top publications with industrial partners (59%; p=0.002) than without (13%, p=0.124). Therefore, as most of the benefits of grants seem to occur when the scientists who receive them publish with industry (and there is no decrease in publications without an industry coauthor), it appears unlikely that scientists realize productivity gains simply by subsidizing their general research agendas with the help of Eurostars funding.

Another explanation for our findings could be that productivity gains are realized via scientists' acquisition of critical research infrastructure that was otherwise unaffordable. However, in most European countries, the cost of capital goods and other expensive equipment are not eligible for funding in R&D grant programs like Eurostars.[26] Therefore we rule out the possibility that our results are driven purely by capital deepening. Of course, it might be the case that the industry-science collaboration itself provides access to important research infrastructure from the collaborating firms, but we interpret this mechanism as another form of industry-academia spillovers.

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 she introduces additional coauthors to her network more frequently.

The results of testing this hypothesis are in Table 4. 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 she connects for the first time, and, as a robustness check, the number of new institutions with which she collaborates. For the purpose of 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. Hence, we exclude the possibility that the observed productivity effects can be explained by the expansion of collaboration networks or better access to human capital. Even the overall number of co-authors (as well as the number of new co-authors) does not change, although the number of publications with industry partners increases (Table 4). This result suggests that either PIs substitute scientific co-authors with co-authors from industry or that the additional co-authored publications are done with industry partners with which a scientist has already collaborated.

C. Split sample analyses

Before concluding, we perform a set of split sample analyses that provide additional insights into potential heterogeneities among treatment effects along several policy-relevant

[26] See, for example, the eligible costs in Germany at https://www.eurostars-eureka.eu/countries/germany, and those for the UK at https://www.eurostars-eureka.eu/sites/default/files/UK%20Eligible%20Project%20Costs%20for%20EUREKA%20Eurostars%20Prgrammes._0.pdf

dimensions (Table 5).[27] Since universities may benefit from external funding differently than public research organizations do, 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, 2011), while scientists who are employed by other research institutions typically have little or no teaching obligations. These organizations are often funded through contracted research, and grant money alleviates the burden to look for other sources of external funding.[28] Depending on the institutes' focus, scientists in these organizations may engage more intensely in applied work, so they are already closer to industry than the typical university scientist, and the complementarity that they derive from an industry-science collaboration may differ. Our results support this interpretation: Whereas funding leads to more top publications by university scientists (19%; p=0.037), it results in more overall publications with industry by scientists at public research organizations (50%; p=0.002), with no significant impact on top publications.[29] These results highlight the importance of the institutional context for the scientific partner.

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.[30] The results show that the funding has heterogeneous effects: With ICT-related projects, funding generates more publications with industry (40%; p=0.049) and more top publications (28%; p=0.037), whereas with the other fields effects 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

[27] In these analyses, we focus on industry publications and top publications because the results in the full sample are strongest for these outcomes. For overall publication output, we generally find no differences except for less experienced scientists who benefit more from receiving a grant.
[28] For example, the German Fraunhofer Society, the world's largest applied research institute, draws 70 percent of its budgets 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,).
[29] We caution against interpreting non-significant results as precise zero effects, however, since limited sample sizes per group and the resulting reduced statistical power render it difficult to detect smaller effect sizes in these split sample analyses.
[30] Traditionally, EUREKA programs were focused on ICT, so 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.

in commercialization, as their field is already oriented towards concrete problem-solving. In such fields, engagement in commercialization might even lead to more knowledge discovery.

We also analyze heterogeneity in the number of citations at the time of the project application. 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 effects are concentrated at the bottom half of the citation distribution, emphasizing that less established scientists benefit the most from the complementarities that result from projects co-developed with industry.

While the number of citations usually increases with seniority, the two characteristics do not fully correlate (corr. = 0.49 in our sample), which is why we split the sample at the median of career seniority (12 years). Early-stage researchers benefit from funding by generating more top publications (55%; p=0.001) but do not co-produce more publications with industry. Senior researchers publish more with industry (38%; p=0.005) but do not generate more top publications. 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 top-level science, strengthen their reputations in the discipline, and obtain tenure at their institutions, whereas senior researchers might approach the funding more from the perspective of general knowledge transfer.

D. 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, $t_{-1}, \dots, t_{-5}$, 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, 2018; Goodman-Bacon, 2018; Imai and Kim, 2020) 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 (2018) demonstrates, the coefficient of a linear TWFE estimator with variation in treatment timing is a weighted average of all possible 2×2 comparisons (treated versus untreated, and treated earlier versus 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 full 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 percent to the overall effect, even reverse in sign, suggesting that the marginal effects estimated by a TWFE estimator are lower compared to a situation that has no variation in treatment timing. Thus, while not fully conclusive, a decomposition of DD treatment effects according to Goodman-Bacon (2018) suggests that our results should be interpreted as lower bounds for the general effect of Eurostars funding on the production of scientific knowledge.

V. Discussion and Conclusions

Programs that combine basic research and commercialization activities play an increasingly important role for funders and policy-makers. This paper addresses a recent call for improving evaluations of the desirability and feasibility of publicly co-funded industry-science collaborations (Azoulay and Li, 2020). Specifically, we investigate the impact of industry-science collaborations on science in a setting in which such relationships are an integral part of competitive research grants. Widespread concerns about these relationships pertain to the potential for corruption of academic norms, obstruction of educational tasks, secrecy of research findings, or shifts in research agendas. Such concerns are accentuated if the collaboration starts at a project's proposal stage—so it embarks on a much longer and more tenuous road than the typical joint commercialization endeavor does—and when it is paid for by taxpayers' money. If academic standards and knowledge production suffer because of such grants, it would be prudent to rethink this type of policy and to redirect public funding. However, our study raises no such concerns, as our main results reveal that programs that have commercial ends do not negatively impact science, and that scientists who collaborate with industry produce significantly more top publications, without shifting patterns of co-authorship or research agendas. We also find that scientists who are less well-established, as measured by the number of citations or the years of experience, benefit more from industry collaborations. In other words, participation in such programs could present an opportunity for early-stage career scientists who are typically bound by their tenure criteria to earn third-party funding and to participate in science valorization activities for their institutions, both of which are positively impacted by participation in the program. We therefore believe prior literature only provides a partial picture of the impact of cross-sectoral collaborations, as it conceptualizes science in industry and academia as pursuing different goals (Perkmann and Walsh 2009, Evans 2010a, Toole and Czarnitzki 2010). Our results show that this need not be the case, and that both sectors can collaborate in mutually beneficial ways. For the projects in our analysis, we find crossing institutional boundaries to be a source through which different skills and objectives open doors for increased scientific productivity.

Our study also pushes current econometric standards for R&D policy evaluation in the field. We use advanced disambiguation techniques to identify author and inventor identities and employ state-of-the-art text analysis tools to measure changes in scientists' research agendas. We also address the well-known problem of selection into treatment that is present in most policy evaluation studies by taking advantage of a unique administrative feature that provides us with plausibly exogenous variation in funding for project applications of similar quality. This analysis permits us to assess the causal impact of one of the EU's most important JPIs and overall of translational funding programs that are gaining in importance internationally.

For policy makers, a first take away is that the different approaches to science in academia and industry do not have to lead to conflicting results. While there is a risk that practices such as secrecy and patenting could hurt basic research (Arrow 1962, Aghion et al. 2008, Murray and Stern 2007, Evans 2010b, Murray 2010, Shibayama et al. 2012), one should note that basic research and commercialization are not necessarily two ends of the same continuum and that commercial potential does not necessarily harm scientific productivity (Bikard et al, 2019; Stokes, 1997). Our results show that competitively funded industry-science programs are not subject to the concerns raised by previous literature on industry-science relationships. To the contrary, we show that industry and academia are complements rather than substitutes, and that co-funded industry-science collaborations positively impact science productivity without altering research agendas or compromising scientific networks. Those findings are reassuring since they allow to advance science while compensating for diminished investments in research by the private sector (Arora et al., 2018) and firms' increasing tendencies to outsource basic research to external partners (Rafols et al., 2014). Our results contribute to understanding the ramifications of the rising demand for industry collaborations for scientific partners, highlighting that such collaborations can present significant opportunities.

Despite the supportive results, these findings should not instill over-confidence, and they do not mean that co-funded industry science collaborations should replace traditional science funding programs. Since traditional competitive research grants are still in place and are still heavily used by scientists, we cannot conclude that the existing funding landscape should be substituted by translational programs. While the evidence presented here reassures funding agencies and university administrations that academic knowledge will not suffer from close collaboration with industry, they are evaluated in a context in which such funding co-exists with the traditional research funding. One should also not interpret these results as an indication that scientists should be pushed in the direction of translational programs, since the collaboration between science and industry may not be equally fruitful to the two parties for all kinds of projects and across all disciplines. A more detailed analysis of cross-program effects and potential (dis)complementarities between traditional science funding and translational incentives would be required before conclusions about an optimal policy mix can be drawn. In light of the likely increase in importance of programs that fund research and its commercialization in one call, future research should seek to identify the mechanisms of the spillovers between the two sectors. Future research should also determine whether universities' educational responsibilities suffer under increased collaboration with industry. Finally, while it is beyond the scope of this paper to advise on the (administrative) balance between the cost and benefits of translational programs, more information on this issue would help to increase the efficiency of decision-making related to policy.

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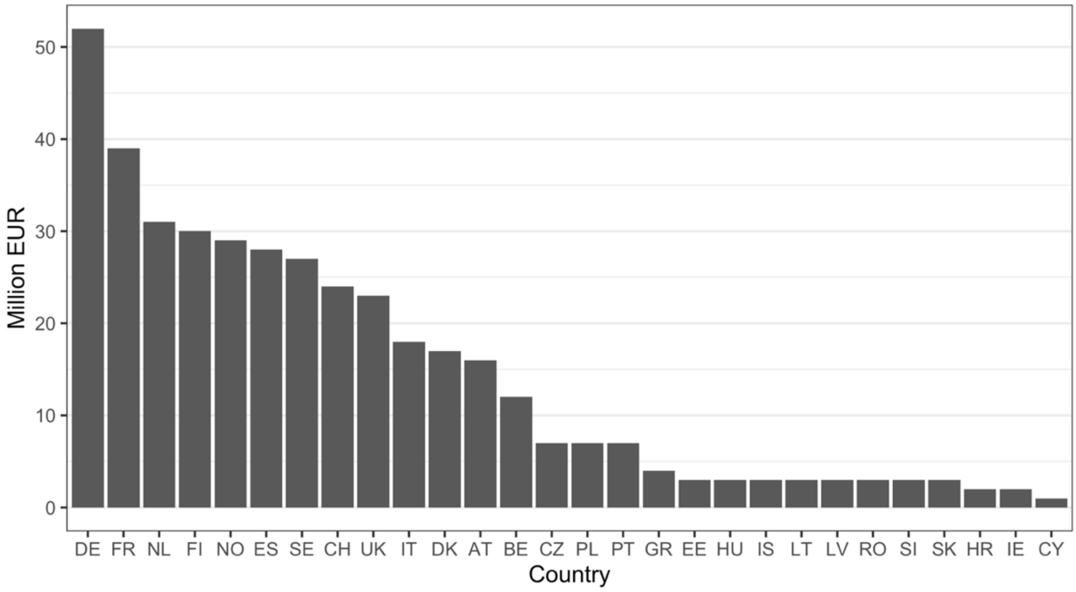
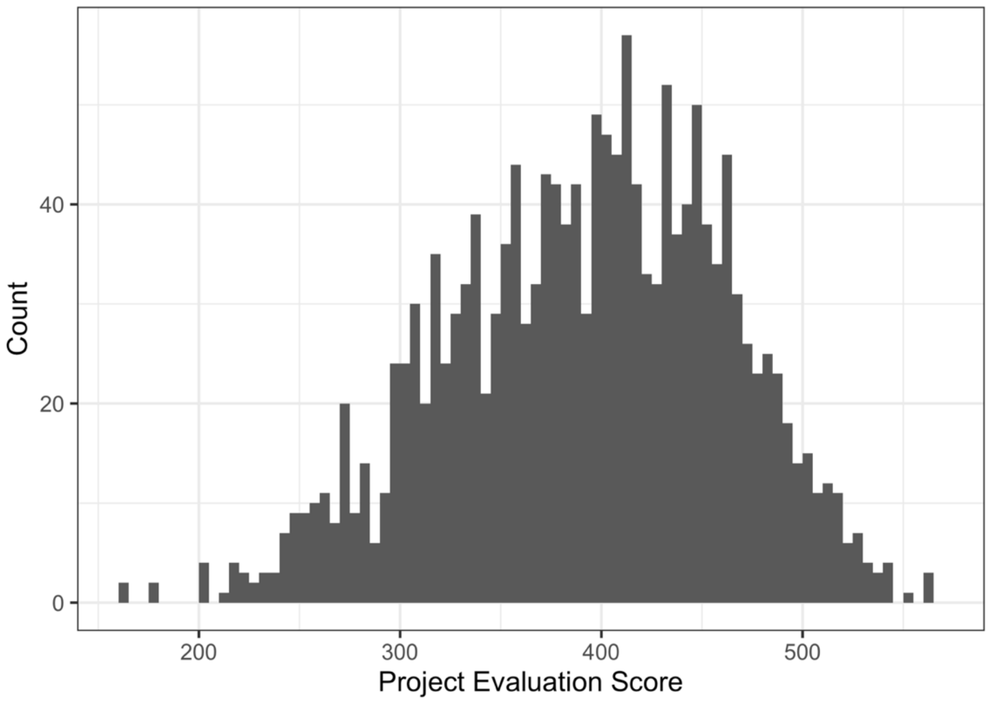
VII. Tables and Figures

Figure 1 – National budgets



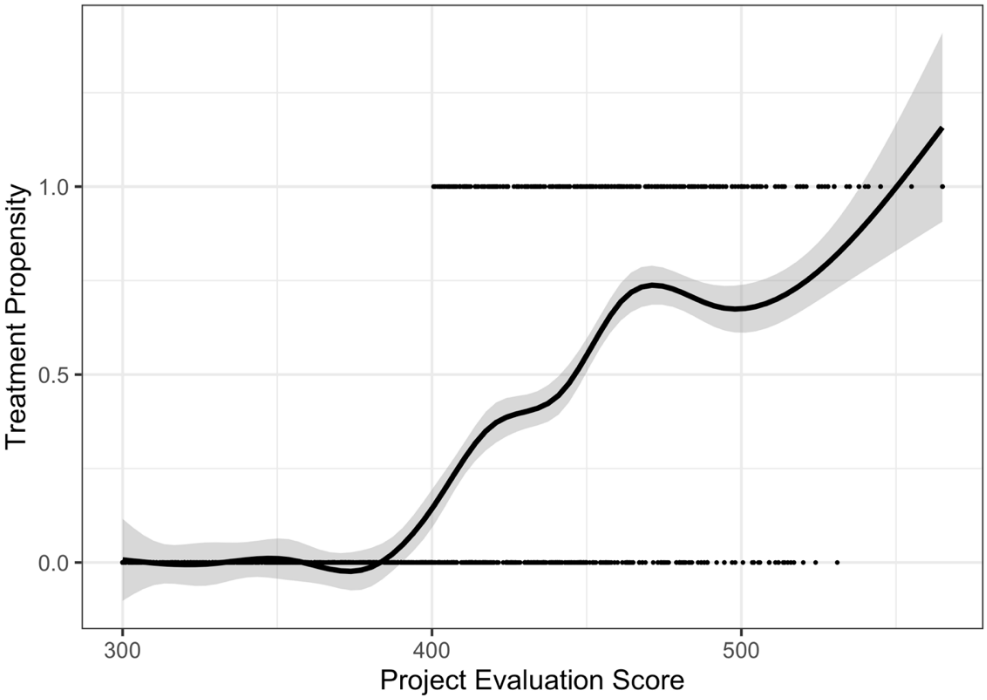
Notes: Individual national contributions to Eurostars 1, pooled over all cutoffs and ranked by size (Makarow et al., 2014).

Figure 2 – Distribution of project evaluation scores



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

Figure 3 – 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. In order to ensure sufficient overlap, we restrict our estimation sample to project evaluation scores between 400 and 520.

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 partners 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 (2019a).

Table 2 – Descriptive statistics

	Mean	Std. Dev.	Min.	Max.
Publications	4.26	6.09	0	73
Top Publications	0.94	2.22	0	35
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
Top Publications with Industry	0.11	0.47	0	9
Top Publications without Industry	0.84	2.00	0	32
Citation-weighted Publications	113.31	298.78	0	6285
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
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-year, therefore *Funding* has a lower average value here (14.3%) than at it does at the group level (51.3%).

Table 3 – Main results related to researcher productivity and commercialization

	Pooled models			Fixed effects models		
Dependent Variable:	Publications	Top Publications	Patenting	Publications	Top Publications	Patenting
	(1)	(2)	(3)	(4)	(5)	(6)
Funding	0.192	0.282	0.004	0.028	0.155	0.006
	(0.078)	(0.100)	(0.007)	(0.050)	(0.075)	(0.006)
Experience	0.106	0.100	0.000	0.105	-0.029	0.001
	(0.008)	(0.014)	(0.001)	(0.020)	(0.060)	(0.001)
Experience Squared	-0.002	-0.002	-0.000	-0.002	-0.002	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Project Evaluation Score	0.001	-0.001	0.000			
	(0.001)	(0.002)	(0.000)			
Cutoff 2	-0.186	0.081	-0.020			
	(0.186)	(0.270)	(0.017)			
Cutoff 3	-0.368	-0.383	-0.013			
	(0.181)	(0.213)	(0.016)			
Cutoff 4	-0.265	0.070	-0.027			
	(0.172)	(0.213)	(0.016)			
Cutoff 5	0.075	-0.029	-0.019			
	(0.164)	(0.233)	(0.015)			
Cutoff 6	-0.168	-0.116	-0.024			
	(0.168)	(0.220)	(0.015)			
Cutoff 7	0.036	0.216	-0.030			
	(0.159)	(0.224)	(0.015)			
Cutoff 8	-0.220	-0.001	-0.020			
	(0.165)	(0.219)	(0.017)			
Cutoff 9	0.022	0.044	-0.023			
	(0.211)	(0.290)	(0.016)			
Cutoff 10	0.062	0.363	-0.013			
	(0.153)	(0.221)	(0.016)			
EU6	-0.018	-0.054	-0.003			
	(0.115)	(0.188)	(0.009)			
EU15	-0.193	-0.341	-0.015			
	(0.124)	(0.196)	(0.009)			
EU28	-0.119	-0.485	-0.027			
	(0.167)	(0.228)	(0.010)			
Constant	-0.103	-2.280	0.010			
	(0.532)	(0.901)	(0.039)			
Individual Fixed Effects	No	No	No	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Method	Poisson	Poisson	OLS	Poisson	Poisson	OLS
Observations	13816	13816	13596	13816	12887	13596
No. of Researchers	682	682	682	682	620	682

Notes: Cluster-robust standard errors in parentheses. Researchers with time-constant outcomes are dropped from Poisson FE estimations.

Table 4 – Additional results related to pursued research agendas, co-publications with industry and collaboration patterns

	Research Agenda			Publications with Industry Coauthors				Collaborations		
Dependent Variable:	New Keywords	New Journals	Abstract Similarity	Publications with Industry	Publications without Industry	Top Publications with Industry	Top Publications without Industry	Coauthors	New Coauthors	New Institutions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Funding	0.005	-0.034	-0.002	0.221	0.005	0.463	0.118	0.024	0.006	-0.018
	(0.045)	(0.049)	(0.011)	(0.100)	(0.053)	(0.149)	(0.077)	(0.056)	(0.064)	(0.063)
Experience	0.041	0.050	0.001	0.247	0.100	-0.036	-0.028	0.148	0.163	0.165
	(0.025)	(0.022)	(0.005)	(0.068)	(0.021)	(0.160)	(0.062)	(0.020)	(0.023)	(0.028)
Experience Squared	-0.001	-0.001	0.000	-0.002	-0.002	-0.000	-0.002	-0.002	-0.002	-0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	Poisson	Poisson	OLS	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Observations	13294	12410	12623	11686	13747	7610	12414	13816	10710	10672
No. of Researchers	678	661	682	543	672	352	589	682	668	656

Notes: Cluster-robust standard errors in parentheses. Researchers with time-constant outcomes are dropped from Poisson FE estimations.

Table 5 – Split sample analyses

Dependent Variable:	Publications with Industry	Top Publications	Publications with Industry	Top Publications
	(1)	(2)	(3)	(4)
Panel A: Split by affiliation	University Researchers		PRO Researchers	
Funding	0.140	0.171	0.403	0.175
	(0.139)	(0.082)	(0.133)	(0.155)
Observations	7131	7686	4555	5201
No. of Researchers	309	343	234	277
Panel B: split by field	ICT		Non-ICT	
Funding	0.335	0.247	0.171	0.046
	(0.170)	(0.119)	(0.124)	(0.086)
Observations	2838	3216	8848	9671
No. of Researchers	147	171	396	449
Panel C: split by citation stock	Above median citations		Below median citations	
Funding	0.146	0.112	0.421	0.221
	(0.122)	(0.096)	(0.159)	(0.104)
Observations	6636	7080	5050	5807
No. of Researchers	293	319	250	301
Panel D: split by experience	More than 12 years experience		Less than 12 years experience	
Funding	0.321	0.106	-0.065	0.436
	(0.115)	(0.085)	(0.194)	(0.130)
Observations	9516	10277	2170	2610
No. of Researchers	367	400	176	220
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 last set of regressions, where experience constitutes the split variable.

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	0.004	-0.013	-0.028	0.180	-0.055
	(0.077)	(0.108)	(0.010)	(0.073)	(0.149)	(0.083)
Ever Treated × t-2	-0.038	0.136	-0.007	-0.073	0.126	-0.053
	(0.074)	(0.099)	(0.010)	(0.075)	(0.160)	(0.083)
Ever Treated × t-3	0.020	0.066	-0.004	-0.018	0.240	-0.031
	(0.070)	(0.097)	(0.010)	(0.067)	(0.157)	(0.074)
Ever Treated × t-4	-0.028	0.080	-0.007	-0.060	0.216	-0.073
	(0.065)	(0.102)	(0.009)	(0.062)	(0.149)	(0.067)
Ever Treated × t-5	0.010	0.054	-0.010	-0.017	-0.094	-0.045
	(0.057)	(0.095)	(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	13816	12887	13596	13294	11686	13816
Test on joint significance of pre-treatment dummies	$\chi^2 = 3.68$, $p = 0.60$	$\chi^2 = 4.88$, $p = 0.43$	$F = 0.58$, $p = 0.71$	$\chi^2 = 2.36$, $p = 0.80$	$\chi^2 = 7.33$, $p = 0.20$	$\chi^2 = 2.06$, $p = 0.84$

Notes: Cluster-robust standard errors in parentheses. 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.

Table 7 – Decomposition of two-way fixed effects estimator with variation in treatment timing (Goodman-Bacon, 2018)

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]	0.063 [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]	0.040 [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]	0.229 [0.772]	0.020 [0.742]	2.208 [0.764]	0.191 [0.772]	2.691 [0.772]
Overall Effect	0.161	0.188	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.

APPENDICES

Appendix 1: Scientist career disambiguation

Studies on individual's research production suffer from the "who is who" and "John Smith" problems (Trajtenberg et al. 2006). The "who is who" problem means that differences in spelling might lead research outputs to not be attributed to the correct scientist, while the "John Smith" problem means that shared names among scientists, namesakes, can lead to misattributions. Past Initiatives have called on researchers to come up with algorithmic solutions (Lissoni et al. 2010).

In this paper, we make use of recently developed algorithms (Doherr 2017, 2018) to minimize the risk of name-related problems in our analyses.[31] Doherr (2017) proposes a method for solving name-related issues and applies this to inventor data. The algorithm clusters patents into inventor-careers, which are determined by constructing and combining relationship networks of patents based on meta-characteristics, such as the inventor's name and home address, the name and address of the applicant, co-inventors, direct and indirect patent citations, and technology classes. These networks heuristically receive different weights, and are transformed into clusters by traversal, a method from graph theory. The algorithm traverses each constructed network recursively and combines all touched patents into clusters. Each potential addition to a cluster is evaluated in terms of the similarity and uniqueness of the traits under consideration. When clusters grow too large, the algorithm returns to the starting point and repeats the traversal stage at a higher quality requirement. The algorithm considers each network, and therefore characteristic, separately and hierarchically, starting with the names and addresses of inventors. Once clusters of inventors with similar names and similar home addresses have been created, it does the same for assignee names and addresses, then co-inventors, and so on. The resulting structure, which combines clusters in a layered, onion-like, manner represents inventor careers, spanning the patent output of an inventor across multiple assignees. This approach has the advantage that it eliminates the common issue with academic patenting that many patents by academic inventors are not owned by the university (Lissoni 2012): one university-owned patent document is sufficient to retrieve all - university owned and other - patent applications by the inventor. Cappelli et al. (2019), applying the algorithm to analyze the mobility of Italian inventor, report that it passes the benchmark proposed by Lissoni et al. (2010) with recall around 91% and precision of almost 100%.

For the purposes of our study, we matched each Eurostars PI to the universe of inventor careers among EPO patent documents. We matched each PI by inventor name and assignee name and address, using the same similarity measures as for the original disambiguation. The name match is further refined by incorporating the namesake risk assessment described in Doherr (2018). This algorithm reduces the probability of wrongly assigning inventor-careers to Eurostars PIs by incorporating the probability of another person with the same name into the calculation of similarity scores. This is achieved by comparing the PI's last and first name to a calibrated population. This population consists of business owners, managers, and major shareholders in Germany over 15 years as represented in the "Creditreform" stakeholder database of the German Credit rating agency. This database contains 6.7 million such names, and covers nearly all firms in Germany. Whereas these data are not representative of the full population (for instance, Doherr (2018) reports that only 27% of stakeholders are female), the data does represent a range of ethnic groups, especially through the inclusion of a large proportion of micro-sized firms. These data are used to create a predictive model of the number of namesakes for a given combination of first and last names, which is then used to weigh

[31] See Doherr (2017, 2018) for full descriptions of the methods, including pre-cleaning steps like pre-cleaning and handling of misspellings and technical details. Thanks to Thorsten Doherr for help with the disambiguation.

potential matches between Eurostar PIs and inventor careers by the inverse of the relative frequency of the combination.

We applied a comparable methodology for refining the publication data correction. Although each Eurostars PI has been associated with a set of Scopus IDs based on CV information, it might still be the case that individual documents in the set of Scopus IDs are misallocated. Therefore, we applied the same disambiguation algorithms described above, taking the scientist's name (in this case, a combination of the last name and the first initial was employed) and affiliation as parameters to disambiguate the data. Each identified cluster was then verified manually and benchmarked to CV information before inclusion in the final dataset. In the same vein, we further disambiguated identified clusters by institution and co-author, in order to quantify the number of (new) coauthors and institutions that the PI worked with in each year.

Appendix 2: Latent Dirichlet Allocation (LDA) analysis

Generally speaking, the goal of many text analysis methods is to find similarities across a set of documents as indicators of relatedness. One approach to quantifying similarity is to represent a document (in our application, an abstract) as a vector, where every word is a dimension (Salton & McGill 1983). In the Vector Space Model, document relatedness can be established through e.g. cosine similarity or Euclidian distance. The output of a researcher throughout one year can then be characterized through the average vector of the individual document vectors (Lu and Wolfram, 2012). The Vector Space Model, however, assumes that the words in the documents are independent from one another. This assumption is likely to be violated, as terms associate to one another semantically. Therefore, several improvements have been made over the Vector Space Model over recent years. A first improvement has been done with so-called Topic Models. Topic Models relieve the assumption of independence among words by modeling groups of co-occurring terms as latent topics. A further improvement has been proposed by the widely used Latent Dirichilet Allocation (LDA) (Blei et al. 2003), on which we reply in our analysis. LDA is an unsupervised machine learning method, which relies on a sparse Dirichilet prior in the topic distribution. This improves over co-existing methods such as Probabilistic Latent Semantic Analysis (pLSA) by incorporating the intuition that documents typically concern a small number of topics, and that topics use only a small set of words frequently (Girolami & Kaban 2003). The LDA model thus achieves two goals: it relieves the assumption of word independence, and it reduces the document space to a lower-dimensional topic space. We conducted the LDA analysis on the 64,516 publication records for which abstracts were available (99.6%). LDA requires significant data preparation.[32] First, we tokenized the abstract texts and built bigrams and trigrams for common word combinations. Tokens were lemmatized using pretrained Spacy entity recognition models. Second, we removed tokens in the NLTK (Natural Languages Toolkit) dictionary of stop words. To further remove uninformative tokens, we filtered out tokens with low weights in a Term Frequency – Inverse Document Frequency (TF-IDF) model. The LDA model was trained in MALLET. We compared solutions for 200, 400, 800, 1200, 1600, and 4000 topics. All solutions yielded extremely similar results in terms of scientist-year cosine similarities. For computational efficiency, we preferred to use the sparse 400-topic solution.

[32] The LDA analysis is carried out in Python, and the data preparation relies on the Natural Languages Toolkit (NLTK) (Bird et al. 2009), Gensim (Rehurek and Sojka 2010), and spaCy libraries (Honnibal and Monani 2017). The LDA model was estimated using the Machine Learning for Language Toolkit (MALLET) (McCallum 2002) and further processed with Gensim.

Appendix 3: Supplemental Analyses

Table A3.1 – Correlation of treatment status with pretreatment characteristics

Dependent Variable:	Career Age	Publication Stock	Citation Stock	Patent Application Stock
	(1)	(2)	(3)	(4)
Ever Treated	-0.093	1.584	-37.326	-0.217
	(0.719)	(6.520)	(333.709)	(0.144)
Project Evaluation Score	0.011	0.106	7.566	0.002
	(0.012)	(0.105)	(5.377)	(0.002)
Constant	10.257	12.115	-1378.848	-0.207
	(5.080)	(46.086)	(2358.761)	(1.020)
Individual Fixed Effects	No	No	No	No
Time Dummies	No	No	No	No
Method	OLS	OLS	OLS	OLS
Observations	682	682	682	682

Notes: Heteroskedasticity-robust standard errors in parentheses. Regression of pretreatment characteristics (measured at the time of application) on treatment status (*Ever Treated*) controlling for Eurostars project evaluation scores. Unit of analysis is the individual researcher in our sample. *Publication Stock*, *Citation Stock*, and *Patent Application Stock* refer to the cumulative sum of the respective variables counted from the year of first publication. *Career Age* corresponds to the number of years that have been passed since the first publication, again measured in the year when a researcher applies for Eurostars funding.