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ERC science and invention: Does ERC break free from the EU Paradox?☆

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ABSTRACT

We explore the relationship between government-supported science and its translation into inventive activities, focusing on the European Research Council (ERC), the principal funding mechanism for top-quality research in Europe. We show that, compared to similar European research, ERC science accrues a greater number of patent citations. Moreover, patents that draw upon ERC research are of superior quality, measured by forward citations. Compared to similar European research, inventive activities arising from ERC science are more likely to be housed within universities and public research organizations. In absolute terms, however, US organizations, especially US companies, still lead in deriving the greatest benefits from ERC science. The significant disparity in corporate sector patenting linked to ERC science in the US and EU is fueled by inventions undertaken by startups, highlighting the crucial role of a dynamic startup landscape in driving inventions at the frontier of science. Overall, our findings suggest that ERC science continues to face challenges associated with the so-called European Paradox.

1. Introduction

Science has played a central role in many of humanity's greatest advances over the past century, ranging from instantaneous global communications to vaccines, medical devices to artificial intelligence, and industrial robots to new materials (Jones, 2021). Numerous day-to-day products now incorporate components developed through scientific advances years earlier. Examples include microchips or light-emitting plastics in smartphones, as well as graphene in top-performance skis or bicycles. The relationship between technical change and scientific advances has become increasingly interlinked in recent decades. Arora et al. (2023b) report that since the 1980s, the percentage of utility patents citing science has increased five-fold, while the overall number of citations to research articles in patents has exploded.

Governments play a leading role in supporting scientific endeavors, either by creating funding agencies such as the National Science Foundation (NSF) and the National Institutes of Health (NIH) in the United States or by directly funding universities and research institutions (Babina et al., 2023). Thus, understanding the extent to which government-supported science translates into technical advances that eventually leads to new products and services is of first-order importance.

In this paper, we focus on a flagship funding program for science, the European Research Council (ERC). The ERC was established by the European Commission in 2007, with the goal to support "investigator-driven frontier research across all fields, based on scientific excellence". Over the years, the ERC has become the primary funding vehicle for top-quality research in Europe. It has awarded over 10,000 grants to researchers, who have collectively published more than 200,000 articles in scientific journals. Among the ERC grantees are 12 Nobel Prize winners, 6 Fields Medalists, and 11 Wolf Prize laureates. By focusing on the ERC, we thus capture unequivocally top-notch science.

While the ERC has contributed to raising European science to the frontier, transforming the results of research into inventions that might be commercialized into new products and services is challenging.

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Our knowledge of the spillover impact of ERC science[1] on inventive activities remains limited.[2] This impact extends beyond ERC grant holders and involves all inventors who may be influenced by published science.

The difficulties in transitioning from science to invention and then commercialization have often been framed through the lens of the so-called European Paradox. This conjecture suggests that while EU scientific performance is on par with that of its main international competitors, Europe lags behind in converting research results into innovations and gaining competitive advantage (Argyropoulou et al., 2019). Despite being highly popular among policymakers (European Commission, 1995), whether this conjecture is ultimately founded has been subject to academic debate (see, for instance, Dosi et al. (2006a) and Rodríguez-Navarro and Narin (2018)). Focusing on ERC science allows us to address and potentially mitigate one of the primary concerns that have perplexed scholars debating the existence of a European Paradox, namely, whether the Paradox does not exist because European science is not cutting-edge to start with.

Our objective in this study is to assess whether science sponsored by the ERC, relative to comparable scientific research, generates more or fewer knowledge spillovers that manifest in subsequent patenting activities. In addition, we investigate the types of organizations (universities, public research organizations, companies, startups) that more frequently draw upon ERC science in their inventive activities and explore whether these inventions are more likely to occur in Europe or elsewhere.

To address our research questions, we gathered comprehensive data on all ERC-funded projects from the program's inception in 2007 until April 2022. After excluding projects not yet terminated, our final sample consists of 4,753 closed projects with 116,538 publications. To examine the publication output of these projects, we linked them to the Microsoft Academic Graph (MAG) database, a large-scale scholarly database that provides information about academic publications, authors, institutions, conferences, and more. This yielded a sample of 91,365 scientific publications published in journals in the period 2007–2018 from 4,567 closed projects. To identify the patents citing those publications and their patent holders we used the Reliance on Science (RoS) data set (Marx and Fuegi, 2020). Overall, we were able to identify a total of 32,021 unique patents that cited 11,457 unique ERC articles. Finally, to interpret the extent of the spillover effect and assess the quality of subsequent inventions against an appropriate benchmark, we developed a control sample of comparable European science that has not been funded by the ERC.

Using this dataset, we present evidence that ERC science has a similar likelihood of yielding spillover inventions to that of comparable European science, as measured by the probability of ERC publications receiving patent citations. However, conditional on being cited in patents, it receives a greater number of patent citations per publication. This suggests that when ERC science has applied value (i.e., it is cited in patents) it serves as the foundation for a greater number of inventions than comparable European science. Most importantly, inventions based on ERC science are, on average, of superior value. Our data shows that patents based on ERC science receive 21.7% more forward citations for USPTO patents and 9.21% more for EPO patents than a control group of patents. These findings indicate that ERC science is more likely to have a spillover effect on high-quality inventions compared to similar European scientific research.

Next, we examine the type and geographical location of the organizations that build upon ERC science. Our findings show that universities and public research organizations are more likely to be found as applicants of patents citing ERC science than patents citing European science of comparable quality. In other words, universities and public research organizations enjoy a comparative advantage in the exploitation of this cutting-edge science. In absolute terms, however, the corporate sector, especially US companies, still leads in converting these research findings into valuable inventions. The difference in corporate patenting between the US and EU is primarily driven by startup patents, with the US taking the lead. This underscores the dynamic innovation environment fostered by startups in the US, which spearheads invention activities at the forefront of science. Thus, although we document a robust spillover effect of ERC science on inventive activities, European industry still lags behind in fully capitalizing on the benefits derived from such a spillover. Consequently, ERC science continues to face challenges associated with the European Paradox.

The rest of the paper is organized as follows. The next section provides a brief overview of the related literature on which we build our research questions. Section 3 describes the data collection process and the methodology employed. Section 4 presents and discusses the results derived from the study. Finally, Section 5 concludes the paper by summarizing the findings' key policy takeaways and implications.

2. Related literature and research questions

In this section, we position our contribution within the existing literature on the role of science in the inventive process, the importance of government funding in facilitating scientific research, the European Paradox, the ERC program, and its impact on inventive activities. Against this backdrop, we introduce our research questions, which aim to shed light on the relationship between ERC science and inventive activity.

2.1. Science and invention

Existing research has shown the significant role of science in the invention process. In fact, many inventions would not have been possible without the underlying scientific knowledge (Narin et al., 1997; Rosenberg, 1990). Science serves as a direct input into the inventive process, narrowing the scope of the search, facilitating more targeted experimentation, decreasing search costs, and focusing inventive activities (Fabrizio, 2009; Rosenberg, 1974; Nelson, 1962; Evenson and Kislev, 1976; Kline and Rosenberg, 1986). Moreover, scientific research generates important non-findings and explanatory mechanisms (David et al., 1992) that alter inventors' search processes and lead them to use new knowledge combinations thus eliminating fruitless paths and shortening invention time (Fleming and Sorenson, 2004).

Carpenter and Narin (1983) pioneered the studies of science and innovation linkages by using the citations in the patent documents to scientific articles, which are part of the so-called Non-Patent Literature (NPL), to examine the "science dependence" of technology. In a validation exercise using survey data, Roach and Cohen (2013) found that NPL citations are informative in measuring the intellectual influence of public sector research. However, there exist widespread structural differences in the citation patterns among the different patent authorities. Citations to NPL literature have increased more rapidly for USPTO compared to EPO documents (Narin and Olivastro, 1998; Marx and Fuegi, 2020).

Building on this measure, existing studies found that prior scientific inquiries play a crucial role in the invention process. Arora et al. (2023b) report that both extensive and intensive NPL citations in patent

[1] The term 'ERC science' refers to all scientific publications that have been produced as a result of funding from the ERC and acknowledge ERC grants, including Starting Grants, Consolidator Grants, Advanced Grants, Proof of Concept Grants, and Synergy Grants. One data limitation is that there are instances where a publication may acknowledge funding from multiple sources. Attributing the specific scientific output to only one source of grant or funding mechanism is not possible in such instances.

[2] An exception is Munari and Toschi (2021) who looked at the invention activities by the ERC grant holders using 446 survey responses from scientists who applied to the Proof of Concept (PoC) scheme. They showed that receiving a follow-on PoC grant was effective in fostering the early commercialization of scientific discoveries.

documents have increased substantially since the 1980s. Patents with NPL citations receive more forward citations and are more likely to be renewed (Ahmadpoor and Jones, 2017; Sorenson and Fleming, 2004). Krieger et al. (2022) show that patents closer to science are better, more novel, and more likely to be in the tails of value distribution (greater risk and greater reward) than patents disconnected from science. The invention quality also depends on the quality of the science it is based upon. Poege et al. (2019) found a very strong positive relationship between the quality of the scientific contributions referenced in patents and the value of the inventions (monetary and non-monetary measures of patent value).

Finally, the role played by basic science in fueling invention is not uniform across scientific fields. Notably, patents within the life sciences sector tend to have a substantially higher number of non-patent literature (NPL) citations, highlighting the unique and critical role that scientific research plays in driving advancements in this field (Branstetter and Ogura, 2005).

We contribute to this literature by focusing on the inventive activities stemming from ERC science. For a meaningful comparison, we carefully control for the quality of science underpinning patents. On the one hand, as we detail in Section 3.2.1, we built a control group of publications matching ERC scientific articles by citation ranking, which helps interpreting our findings. On the other hand, our regressions include the number of article citations to account for the scientific impact of publications.

2.2. Government funding of basic science

Arora et al. (2018) document a decline in US firms' focus on scientific research, although there has been no change in the production of technical knowledge (as measured by patents). This highlights the crucial role that government-funded research programs play in innovation activities, particularly in fields neglected by private investors. Furthermore, government funding of public research is becoming increasingly crucial as new and novel ideas become harder to find. Bloom et al. (2020) show evidence, using data from various industries, products, and firms, that research effort is rising substantially while research productivity is declining sharply.

Studies have shown that public funding of research plays a significant role in generating breakthrough inventions. Corredoira et al. (2018) use data on federally funded patents to show the importance of public funding in stimulating technical progress. They find that government-funded patents are inputs into a broader range of technologies. Recent studies have also used patent-to-article citations to trace the influence of public knowledge in spurring inventions. Azoulay et al. (2019) find that public-sector funding spurs the development of corporate-sector patents. A \$10 million boost in U.S. National Institutes of Health (NIH) funding leads to a net increase of 2.3 patents. Our study is closely linked to Li et al. (2017), which used the output of research grants awarded by the NIH and found that only 10% of NIH grants generate a patent directly, but 30% generate articles that are subsequently cited by patents. The bulk of the effect of NIH research on patenting is indirect, while often policymakers focus on direct patenting by academic scientists. We will also adopt this broader view in our analysis below.

2.3. The European Paradox

While the literature has shown that both science and government-funded research are associated with greater inventive activity, the European context can be unique. There is a widespread belief among European policymakers and the research community that although European research organizations play a leading role in top-level scientific output, they lag behind in converting it into successful and profitable innovations, commonly known as European Paradox (European Commission, 1995; Argyropoulou et al., 2019). Empirical evidence provided by Tijssen and Van Wijk (1999) confirms the existence of a European Paradox in different ICT domains such as computers, data processing, and telecommunications. Radicic and Pugh (2017) examined the effectiveness of national and European Union (EU) R&D programs in promoting input and output additionality for small and medium-sized enterprises in twenty-eight European countries. The authors contend that the European Paradox, where R&D inputs are being promoted but commercialization efforts remain lackluster, still exists. In their study on the discovery of giant magnetoresistance (GMR) by French and German scientists and its commercialization by IBM, Dedrick and Kraemer (2015) argue that while the labs of the scientists received only small licensing fees and the Nobel Prize, IBM captured significant profits from selling hard disk drives and magnetic heads using GMR.

However, the existence of a European Paradox has been questioned by other scholars. Among the first to raise questions on the sheer existence of any paradox were Dosi et al. (2006a,b), who argued that Europe has weaknesses at both ends, with a scientific research system that lags behind the US in some areas and a relatively weak industry. Bonaccorsi (2007) also suggests that the weak performance of European science in fast-moving and new fields is a better explanation for the current difficulties in high-technology industries and trade than the European Paradox, which is offered as a less plausible explanation. Europe lagged significantly behind the USA in producing important and highly cited research (Rodríguez-Navarro and Narin, 2018; Herranz and Ruiz-Castillo, 2013; Bauwens et al., 2011), a weakness that was indeed addressed with the creation of the ERC.

We contribute to this debate by showing that ERC science is more conducive to better quality inventions than comparable science. However, in absolute terms, US organizations, particularly US companies, and even more so US startups, still lead in deriving the greatest benefits from ERC science.

2.4. ERC funding and inventive activity

The ERC was set up in 2007 under the EU's Seventh Framework Programme for Research, extended under Horizon 2020 (2014–2020) and continues under Horizon Europe (2021–2027). The budget allocated to ERC projects has been increasing over time: from €7.5 billion in the period 2007–2013 to €13.3 billion in the period 2014–2020. Currently, the ERC budget from 2021 to 2027 amounts to more than €16 billion, around 17% the overall Horizon Europe budget. There are three main categories of ERC grants — Starting Grants, Consolidator Grants, and Advanced Grants -given to early career researchers, experienced researchers, and established researchers, respectively. Principal Investigators from anywhere in the world can apply for an ERC grant. The host institution must be established in an EU Member State or Associated Country. As per the ERC Annual Work Program 2022 Document, "the fundamental activity of the ERC, via its main frontier research grants, is to provide attractive, long-term funding to support excellent investigators and their research teams to pursue ground-breaking, high-gain/high-risk research".[3]

There is not much evidence available on the impact of the ERC funding scheme on innovation, and the few existing studies are based

[3] While the ERC is designed to fund groundbreaking research, some studies suggest that its selection committee may limit truly innovative proposals by evaluating them based on existing knowledge boundaries (Luukkonen, 2012). Applicants with a history of high-risk research are less likely to be selected for funding, and receiving an ERC grant does not significantly increase risk-taking behavior (Veugelers et al., 2022). Ghirelli et al. (2023) study the effect of ERC grants on the research productivity and quality of the winning applicants. They find no statistical effect in a regression discontinuity design, while positive long-term effects in a difference-in-differences analysis.

on data coming from the PoC program.[4] For example, Munari and Toschi (2021), using 446 survey responses from scientists who applied to the ERC PoC scheme, found that the program effectively promoted the commercialization of research, academic engagement outcomes, as well as access to follow-on funding. The authors also discovered that the scientist's academic seniority had a negative moderating effect on the relationship between receiving PoC funding and engaging in valorization outcomes.

Between 2007 and 2016, the UK, Germany, France, and Switzerland received three times more ERC grants than Mediterranean countries like Italy, Israel, Greece, and Spain.[5] However, they received only one and a half times more PoC grants between 2010 and 2017. This difference may be due to countries with a strong tradition of applied research and academic entrepreneurship having funding opportunities for translational research from other sources, while countries with fewer opportunities rely on the PoC program (Seeber et al., 2022). Overall, the existing evidence suggests that the ERC PoC program is somewhat successful in addressing the European Paradox by supporting the translation of cutting-edge research into real-world applications, especially in countries with fewer alternative sources of funding. However, the broader impact of ERC science on inventive activities that go beyond the inventions directly developed by grant holders has not been studied. This is the focus of the current paper.

2.5. Research questions

As we have reviewed above, there is substantial evidence that science is a crucial component of technical change and that government-funded research is conducive to inventions. However, the impact of the ERC program on European inventions is *a priori* unclear. First, we do not know if the science developed in ERC projects is suitable for commercial applications, for which patented inventions are a prerequisite. Second, if the answer to the first question is positive, we still do not know whether European inventors are the best placed to benefit from it.

Concerning how much ERC science can spill over inventive activities, there are two counteracting forces. On the one hand, the ERC program is designed to support only excellent research that pushes the frontier of knowledge. The ERC provides generous multi-annual grants that come without strings attached and enable grantees to dedicate full time to their research projects. Considerable financial resources are available for research assistants, teaching buyouts, and other research-related benefits. On the other hand, the type of research funded by the ERC may be far from commercial applications, potentially isolating researchers from reality and market forces. The financial independence to pursue excellent research might distance it from the needs of both companies and the economy at large. While ERC-funded research may advance the frontier of knowledge, it is unclear whether it will also be able to spill over to inventive activities.

Therefore, our first research question is:

RQ1: Does ERC-funded science, compared to similar scientific endeavors in Europe, generate more or fewer knowledge spillovers that subsequently drive inventive activity?

Even if ERC science is particularly suitable to spill over inventive activities, it remains unclear which organizations are best placed for such endeavors. The concept of "scientific" absorptive capacity suggests that organizations must possess the capability to effectively absorb and utilize scientific knowledge (Arora and Gambardella, 1994). Consequently, universities, given their proximity to scientific advancements, can be in a favorable position to transform scientific breakthroughs into tangible inventions. However, universities might face challenges in recognizing the commercial potential associated with these inventions.

Additionally, the successful transformation of frontier science into commercially valuable innovations necessitates the existence of a supportive ecosystem (Stam and de Ven, 2021). Factors such as tech transfer funds and deep tech venture capital contribute to the development of this ecosystem (Nanda, 2020). Although science itself is not geographically bound, the presence or absence of such an ecosystem can significantly influence the inventive activity derived from frontier science.

Therefore, our second research question is:

RQ2: Which types of organizations are more likely to develop inventions based on ERC science, and in which geographical areas do these organizations tend to be located?

3. Data

3.1. Data sources

For this study, we combined several sources of data. Fig. 1 provides a stylized description of the workflow. In the following subsections, we describe in detail each step we followed to build our data set.

3.1.1. ERC publication data

ERC Research Information System (ERIS) is a primary source of data for the research output (e.g., working papers, journal articles, patents, etc.) of the ERC-funded research projects.[6] ERIS, developed by the European Research Council Executive Agency, presents and manages detailed information on the ERC funding activities, outcomes, and achievements. The ERIS integrates ERC data with external data related to the ERC projects. For each publication of an ERC-funded research project, the Scopus IDs and Microsoft Academic Graph IDs are available, which makes it easy to create links with other data sets.

There are 12,387 research projects funded by the ERC, as of April 2022, which include 4,909 projects in Physical Sciences and Engineering, 3,643 in Life Sciences, 2,409 in Social Sciences and Humanities, and 1,426 other projects (see Tables A1-A3 in Appendix A). Out of 12,387 projects, 5,404 are closed projects, 23 are early terminated projects, 13 are suspended projects due to various reasons, and 6,644 are ongoing research projects (see Table A4 in Appendix A).

As far as the research output of ERC projects is concerned, the ERIS database provides publication data for 4,278 projects, of which 4,180 were closed projects, 5 were early terminated projects, and 93 were ongoing projects (see Fig. 1). For these projects, ERIS reports a total of 141,091 scientific publications.[7] While ERIS is a valuable and reliable source of information regarding the results of ERC projects, it is not without its limitations and challenges. First, a significant issue is the presence of duplicates within the database; a single publication might be listed multiple times. This redundancy can occur when researchers submit the same article multiple times with slight variations in details, or when an article is disseminated in multiple formats, such as a conference paper and a subsequent journal publication. Table A5 in Appendix A provides an example. To ensure accuracy and prevent duplications, we utilized the Microsoft Academic Graph (MAG) ID, which serves as a

[4] The ERC PoC scheme provides up to €150,000 of additional funding to ERC grant holders to bridge the gap between their research and the early stages of commercialization. The scheme enables researchers to test the feasibility of their ideas, explore business opportunities, and establish intellectual property rights, among other things.

[5] The distribution of research funds among European countries is unequal, with some countries like the UK receiving a greater share of funding due to the concentration of research in prestigious universities and centers. In contrast, countries like Italy receive less support from the ERC and often experience a brain drain of researchers who are awarded ERC grants (Zecchina and Anfossi, 2015).

[6] https://erc.europa.eu/projects-figures/erc-research-information-system

[7] As of April 2022.

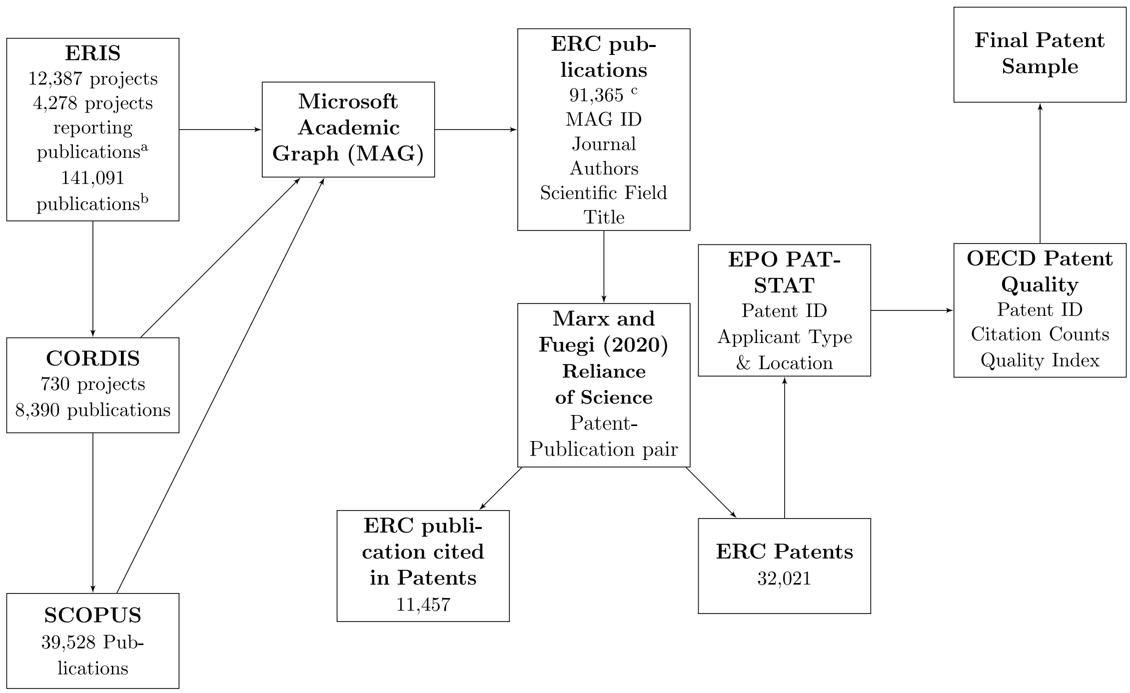

Fig. 1. Workflow description.
Notes:[a] Downloaded in April 2022. ERIS provides publication data for 4,278 projects, of which 4,180 were closed, 5 were terminated early, and 93 were ongoing projects. 1,224 closed projects do not report any publications in the ERIS database. [b] The ERIS database may contain multiple versions of the same paper. [c] We retrieved the MAG ID using the publication's DOI and title, yielding 116,538 publications from 4,753 projects across journals and conferences. After excluding entries with missing data for scientific field, publication year, and authors' affiliation, we retained 91,365 scientific journal publications from 2007 to 2018 stemming from 4,567 ERC projects published solely in journals.

unique identifier for publications, regardless of their various versions.[8] In that respect, a second related problem is that the MAG ID is available only for 96,922 publications out of 141,091 publications contained in ERIS. For the remaining 44,169 publications, we retrieved the MAG ID by matching them using the article's DOI (when available), title, and year of publication. Overall, we identified 109,332 unique publications (i.e., unique MAG ID), which were reported as the output of 4,161 closed projects in the ERIS database.

A third significant limitation of the ERIS database is the absence of reported research output for 1,224 closed ERC projects. This omission represents a substantial gap in the database's coverage of project outcomes. To address this issue, we sourced data on publications from the Community Research and Development Information Service (CORDIS).[9] The CORDIS is a database of results from projects funded by the European Union. A total of 8,390 publications were downloaded from the CORDIS database, encompassing 730 out of 1,224 projects for which ERIS does not report scientific output. We successfully matched these publications with 7,026 unique entries in the MAG database using DOI, title, and year of publication as the output of 592 closed projects. On the other hand, there remain 494 closed projects for which we have no output data in either ERIS or CORDIS databases. For this subset of projects, we have attempted to use Scopus as explained next.

Scopus is a comprehensive abstract and citation database of peer-reviewed literature, which was launched by Elsevier in 2004. To retrieve data on projects with missing publications from ERIS and CORDIS, we exploited the `funding` search field. In particular, we filtered articles published before 2018 where the funding acronym was *ERC* or the funding acknowledgment contained *European Research Council*.[10] This methodology enabled us to identify 39,528 unique Scopus publications that met our criteria. However, the approach is not without its limitations. Primarily, the *ERC* acronym is not exclusive to the European Research Council and is also used by other entities, such as the Engineering Research Center in Korea and the NSF's Engineering Research Center in the USA, leading to a significant risk of false positives. Moreover, the absence of ERC project names and funding numbers in the Scopus data complicates the task of linking publications to their originating projects and to the institutions that received the ERC grants. Given that the selection of a control sample of publications hinges on the availability of grantee institution information (refer to Section 3.2.1), this limitation hindered the use of this additional data in the initial phase of our analysis, where we evaluated the likelihood of publications receiving citations in patent documents. In the second part of our analysis, which focused on identifying patents citing ERC scientific outputs, we conducted a meticulous manual review of the acknowledgment text for all Scopus-extracted publications that conformed to the aforementioned criteria.

To summarize, our data set comprises 116,358 distinct publications (each identified by a unique Microsoft Academic ID) associated with the ERC from 4,753 closed projects, with 109,332 sourced from ERIS

[8] The MAG is an open-source database compiled by Microsoft Corporation, which provides information on authors, affiliations, citations, year of publication, DOI, title, publication venue (journal or conference name), scientific field, and other information. The extent of MAG's coverage is similar to that of Scopus and Web of Science. A study by Hug and Brändle (2017), which utilized 91,215 validated, multidisciplinary publications from the University of Zurich's Open Archive and Repository, found that MAG had the highest coverage (52.5%), followed by Scopus (52%), and Web of Science (47.2%). However, the MAG database is no longer active and maintained. The last update was done on December 31, 2021. For details, see https://www.microsoft.com/en-us/research/project/microsoft-academic-graph/. OpenAlex is an open-source alternative to MAG that builds on the last open dataset that Microsoft published by integrating other data to further develop its platform.

[9] https://cordis.europa.eu/

[10] To this purpose, we used the `AbstractRetrieval` function of the Python package `pybliometrics`. This function retrieves comprehensive bibliographic information for any given publication, including the fields `funding` and `funding_text`.

and 7,026 derived from CORDIS. From this sample, we retained only articles published in journals. We further dropped publications with missing information in the MAG database for the scientific field, year of publication, and affiliation of the authors. We keep only publications published in the years 2007–2018 in our final sample (see Tables A6-A8 in Appendix A). Our final sample comprises 91,365 scientific journal publications, originating from 4,567 ERC projects in the period 2007–2018. It encompasses 53,001 publications from Physical Sciences and Engineering projects, 27,755 for Life Sciences projects, 9,482 from Social Sciences and Humanities projects, and 1,127 from other projects.

3.1.2. Patents citing ERC science

Our measure of knowledge spillovers from science to inventive activities is whether a given scientific article is cited in patent documents. Using patent citations to NPL, we can trace inventions that build upon prior scientific knowledge (Roach and Cohen, 2013).

Specifically, we used the Marx and Fuegi (2020)'s Reliance on Science (RoS) dataset to identify the ERC publications that are cited in patent documents.[11] The RoS database provides the link between the academic research articles from the MAG database and the patent publication identifiers. Marx and Fuegi (2020) argue that their algorithm can capture up to 93% of patent citations to science with an accuracy rate of 99% or higher. The RoS dataset contains 22 million patent citations to science covering both citations on the front page and those in the body of the document. In the final sample, we have 32,021 unique patents that cite ERC articles and 11,457 unique ERC articles that receive at least one citation in patent documents.[12] It is noteworthy that, among the 32,021 patents citing ERC science, 55.83% were filed with the USPTO, followed by 23.56% as WO-PCT applications, and 9.48% with the EPO. Tables B1, B2, B4, and B5 in Appendix B report, respectively, the distribution of citing patents by patent authority, the distribution of patent-to-science citations by position within the patent document, NPL reference type, and patent technical fields.

It is also worth noting that our results are robust to different levels of confidence scores regarding the patent-to-science citation linkage. Marx and Fuegi (2020) assigned a confidence score to each patent-to-paper citation linkage. The score evaluates the extent to which the linkage corresponds to a true citation. In a robustness check, we replicated all the results for a confidence score no less than 4, which corresponds, according to Marx and Fuegi (2020), to a 99.47% precision and a 92.81% recall rate. Table B3 in Appendix B shows the distribution of the level of confidence score of ERC publication and patent linkages in our data set. Around 95.15% of ERC publication-patent linkages have a confidence score of 4 or more.

We merged the patents citing ERC science with the EPO PATSTAT database and we extracted information on the patent filing date, the International Patent Classification (IPC) classes, patent applicants, and patent inventors. We used instead the OECD patent quality indicators database (Squicciarini et al., 2013) to retrieve information on the forward citations received by a patent, the number of claims, and the family size.

Next, we identified patents owned by startups. To do so, we relied on PitchBook[13], which includes startups headquartered in North America, Europe, and Asia. We followed established best practices for performing the matching (see, for instance, Menon and Tarasconi (2017) for the matching of Crunchbase with PATSTAT, and Contigiani (2023) for the matching of Crunchbase with PatEx). In order to standardize the names of patent assignees and startups, we initially eliminated duplicate spaces, hyphens, and legal designations like LTD, CO, GMBH, and so on. Our name-matching process was based on the following criteria: exact match, alphanumeric match, Jaro–Winkler similarity, and Levenshtein distance. After obtaining candidate pairs through this matching process, we applied two filtering conditions. The first condition required that the patent's priority year be at least equal to the startup's founding year minus two. This ensured that the selected startup was operational around the time the patent was filed. The second condition involved assessing how closely aligned the patent's technology class was[14] with the startup's primary industry type. We limit our startup sample to those founded after 2007, which corresponds with the initiation of the ERC funding program.

3.2. Methodology

A primary challenge in assessing the impact of ERC-funded research on inventive activities is the lack of a counterfactual scenario. A way to address this challenge might involve examining ERC project proposals that narrowly missed funding due to scores just below the qualifying threshold, in a regression discontinuity design framework. For instance, a recent study assessing the influence of ERC grants on the research productivity and quality of awardees contrasted the grant recipients with applicants ranked marginally below the funding cutoff (Ghirelli et al., 2023). Unfortunately, implementing such a methodology is not viable in our context since information on unsuccessful applications remains confidential. Furthermore, even if details on near-miss projects were accessible, correlating them with specific research outcomes would be challenging. Indeed, there is no certainty that researchers who did not secure funding would continue their intended line of inquiry or would not secure funding from alternative sources.

Our goal remains thus confined to providing correlational evidence. However, to interpret our findings, we still need to compare them with suitable benchmarks. To do so, we utilized a matched sample methodology to construct two control groups, each corresponding to one of our research questions. The first control sample is composed of scientific research closely resembling ERC-funded science in various key aspects, but not financed by the ERC, offering a benchmark for assessing the impact of ERC publications on subsequent inventive activities. The second control sample includes patents that are comparable to those citing ERC publications but do not actually cite them, providing a benchmark against which we can compare the characteristics of the inventions that build upon ERC science.

3.2.1. Construction of a control sample of publications

To identify a control sample of publications, we proceeded as follows. For each ERC publication, we randomly selected from the universe of articles that do not belong to the sample of ERC-funded publications a control publication satisfying the following conditions. First, at least one of the authors must be from the institution that received the ERC grant. Second, the article must be published in the same journal and belong to the same scientific field (among the 251 Web of Science fields) as the ERC publication.[15] Third, the article must belong to the same citation group as the ERC publication. To this purpose, we grouped all articles published in a given year and

[11] https://zenodo.org/records/8278104

[12] To identify articles cited in patents, we utilized publications from ERIS and CORDIS, as well as those extracted from Scopus (refer to Section 3.1.1).

[13] According to Retterath and Braun (2020), PitchBook is one of the best commercial data providers for startups due to its coverage and accuracy across key dimensions such as general company data, founders, and funding information.

[14] We utilized the International Patent Classification (IPC) classes, which are categorized into 35 subgroups as defined by WIPO (World Intellectual Property Organization).

[15] To check the robustness of our findings and mitigate any potential influence stemming from variations in scientific content between ERC-funded and control publications, we constructed a control sample based on the textual components of the publications. This was achieved through the concept classification of OpenAlex, which categorizes works based on multiple concepts derived from their title and abstract. Examples and additional details can be found in Appendix E. Our baseline results remain consistent.

Table 1
Summary statistics: ERC and Control publications.

	ERC publications		Control publications		Difference
	Mean	SD	Mean	SD	
Number of authors	6.901	6.767	6.186	5.650	0.715***
Number of article citations (log)	3.331	1.308	3.195	1.252	0.136***
US co-author dummy (0/1)	0.237	0.425	0.256	0.436	−0.019***
Patent citation (0/1)	0.100	0.300	0.091	0.288	0.009***
USPTO citation (0/1)	0.063	0.242	0.055	0.229	0.007***
EPO citation (0/1)	0.021	0.145	0.018	0.133	0.004***
Number of patent citations	0.296	2.182	0.250	2.270	0.046***

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. There are $N = 57,948$ ERC publications and an equal number of Control publications. *Number of authors* is the total number of authors in a publication. *Number of article citations* is the (log) value of scientific citations received by a publication. *US co-author dummy* is a binary variable equal to one if the publication has at least one co-author affiliated with a US organization. *Patent citation* is a binary variable that is one if a publication is cited in any patent document at any patent office, and zero otherwise. *USPTO citation* and *EPO citation* are binary variables equal to one if a publication is cited, respectively, in a USPTO or EPO patent, and zero otherwise. Finally, *Number of patent citations* represents the cumulative count of patent citations received by the publication, considering only one patent per family.

scientific field into five quintiles based on the total number of citations received.[16] We dropped all ERC publications for which we could not find a suitable control. The final sample comprises 57,948 ERC publications and their respective control publications. In our baseline sample, we retain only one control publication for each ERC publication. In a robustness check. we carried out further analysis by including up to five control publications, whenever they meet the above specified conditions. Our findings remain consistent regardless of the number of control publications considered, as shown in Appendix D.

Table 1 reports descriptive statistics for the sample of ERC and control publications. Notably, approximately 10% of the ERC publications receive citations from patents. Moreover, these publications demonstrate a higher likelihood of being cited by patents from the USPTO, with a citation incidence of 6.3%, as opposed to a 2.1% citation rate from patents issued by the EPO. It is important to highlight that despite the fact that the control publications are sourced from identical journals, scientific fields, and citation distribution quintiles as their ERC counterparts, the latter exhibit a marginally higher number of scientific citations (publication-to-publication citations), as shown in Table 1. To account for this discrepancy, we will include this variable as a control in our regression analyses where relevant. Furthermore, our analysis indicates that ERC publications tend to have a slightly larger authorship team and are less likely to include a co-author based in the United States compared to the control publications. Again, we include these variables in our estimation models.

3.2.2. Construction of a control sample of patents

To investigate our second research question – identifying the organization type and geographical region most inclined to capitalize on ERC science – we utilized a methodology akin to that employed in the prior section, which is based on the seminal study of Jaffe et al. (1993).

For each of the 32,094 unique patents citing ERC articles, we randomly selected a control patent that matched several key criteria. The rationale behind this selection criteria is to ensure that counterfactual patents build upon science that is qualitatively comparable to the science used by ERC-based patents. First, the control patent needed to be classified under the same International Patent Classification (IPC) code at the 4-digit level and share the same application year as the ERC-citing patent. Second, the control patent must be filed at the same patent office as the ERC-citing patent.[17] Third, the control patent must have cited at least one scientific publication from the same journal as the ERC-cited article and co-authored by a scientist affiliated with a European institution. Finally, we dropped ERC-based patents for which we could not find a suitable control.

Overall, our final sample comprises 1,363 EPO patents that cited ERC publications, and an equal number of control patents; and 7,981 USPTO patents citing ERC publications, and an equal number of control patents.[18] Table 2 reports summary statistics.

Several notable trends emerge from our analysis. First, ERC-based patents consistently cite a greater number of NPL references compared to their control counterparts, a pattern observable in both EPO and USPTO data. Second, ERC-based patents attract a notably higher volume of forward citations, indicative of their greater impact. This trend is especially pronounced at the USPTO, where the average number of forward citations over a five-year span after publication for ERC patents is nearly double that of the controls. For EPO patents, the factor is 1.5 times higher in favor of ERC-based patents.

There is also a marked trend in the provenance of ERC-based patent applications, with academic institutions taking the lead. Specifically, 30% of USPTO ERC-based patents list a US university as the applicant, in contrast to 24% in the control group. A similar pattern is observed in the EPO data, where 32% of ERC-based patents have an EU university as the applicant, compared to 21% for the control group. This underscores the significant role of universities in driving inventions that build upon ERC science. More generally, compared to the control group, the use of ERC science seems to be particularly pronounced among top research organizations. Finally, it is worth noting that startups account for quite a large fraction of the ERC-based patents, highlighting the crucial role of a dynamic startup landscape in driving inventions at the frontier of science. This is especially the case for the USPTO, where startups are responsible for 16% of all patents citing ERC publications, a fraction that is significantly larger than the one found for the control group.

4. Results

4.1. Is ERC science spilling over inventions?

To assess whether ERC publications have a greater likelihood of receiving a patent citation, and therefore have a greater impact on inventive activities than other European publications of comparable quality (**RQ1**), we estimated, separately for the EPO and the USPTO, the following equation through a Linear Probability Model:

$$P_{it} = \beta_0 + \beta_1 (ERC\ Publication_{it}) + \eta X_{it} + \sum_f \beta_f \, \mathrm{SF}_{fi} \times \mathrm{J}_{fi} \times \mathrm{CG}_{fi} + \nu_t + \epsilon_i \quad (1)$$

[16] A few examples of ERC publications and their corresponding control publications are provided in Table B7 in Appendix B.

[17] To verify the robustness of our findings and mitigate any potential influence stemming from variations in scientific content between ERC-funded and control publications cited by the patent, we also constructed a sample of control patents using the similarity of publications based on the OpenAlex concept, as described in Appendix E. Our baseline results remain consistent.

[18] It should be noted that from the initial data set, we were forced to drop 1,674 EPO and 9,895 USPTO ERC-based patents due to the absence of suitable control patents (see Table B1).

Table 2
Summary statistics: ERC-based and Control patents.

	ERC-based patents		Control patents		Difference
	Mean	SD	Mean	SD	
Panel A: EPO					
Number of inventors	3.853	2.393	3.969	2.528	−0.116
Number of NPL citations	25.660	44.980	20.188	28.158	5.472***
Forward citations (5 years)	1.183	4.317	0.857	3.374	0.326*
Family size	5.971	5.831	6.345	5.904	−0.373
Number of claims	14.386	5.865	14.395	6.384	−0.010
Patent applicant is a:					
EU University	0.319	0.466	0.210	0.407	0.109***
EU Company	0.227	0.419	0.241	0.428	−0.013
Top research organization	0.279	0.449	0.191	0.393	0.088***
Top US research organization	0.082	0.275	0.062	0.242	0.020*
Top EU research organization	0.147	0.355	0.090	0.287	0.057***
Startup	0.098	0.298	0.103	0.305	−0.005
Startup: EU	0.040	0.195	0.028	0.165	0.012
Panel B: USPTO					
Number of inventors	3.864	2.635	3.705	2.482	0.159***
Number of NPL citations	109.918	173.883	57.714	79.082	52.204***
Forward citations (5 years)	17.441	38.196	9.605	22.839	7.835***
Family size	6.141	6.781	5.820	6.736	0.321**
Number of claims	18.589	10.899	17.524	10.454	1.065***
Patent applicant is a:					
US University	0.308	0.462	0.247	0.431	0.061***
US Company	0.369	0.482	0.382	0.486	−0.014
Top research organization	0.285	0.452	0.197	0.398	0.089***
Top US research organization	0.217	0.412	0.150	0.357	0.067***
Top EU research organization	0.035	0.185	0.024	0.153	0.011***
Startup	0.163	0.370	0.136	0.342	0.028***
Startup: US	0.130	0.337	0.107	0.310	0.023***

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. There are $N = 1,363$ EPO patents that cited an ERC publication, and an equal number of Control patents. There are $N = 7,981$ USPTO patents that cited an ERC publication, and an equal number of Control patents. *Number of inventors* is the count of inventors reported in the patent document. *Number of NPL citations* is the overall count of NPL citations in a patent document. *Forward citations* is the number of patent citations garnered within five years after the patent publication. *Family size* and *Number of claims* are, respectively, the number of patents in the patent family and the number of claims in the patent document. *US (EU) University* and *US (EU) Company* are dummy variables taking a value of one if the patent applicant is, respectively, a US (EU) university or a US (EU) company. The dummy variable *Top research organization* takes a value of one if the patent applicant is included among the top 200 public research institutions and universities, as classified by the rankings list published by the SCImago Research Group. The *Startup* dummy variable takes a value of one if the patent applicant is a startup founded after 2006. The startup data is sourced from Pitchbook. The *Startup: EU(US)* dummy equals one if the patent applicant startup's headquarters are in the EU(US).

In our model, P_{it} is a binary variable that equals 1 if publication i published in year t receives at least one citation from EPO (USPTO) patent documents, and 0 otherwise. The variable $ERC\ Publication_{it}$ indicates the source of funding for the publication: it is set to 1 if the publication originated from an ERC-funded project and 0 for publications in the control group. The matrix X_{it} encompasses a set of control variables. Specifically, following, for instance, Wuchty et al. (2007) and Bikard and Marx (2020), we include controls for the quality of publications by incorporating the logarithm of the number of scientific citations received (*Number of article citations*), the total number of authors (*Number of authors*), and the presence of a US co-author in the authorship team (*US co-author dummy*). Furthermore, $\sum_f \beta_f \, \mathrm{SF}_{fi} \times \mathrm{J}_{fi} \times \mathrm{CG}_{fi}$ represents a vector of fixed effects based on the unique combination of Scientific Field (SF), Journal (J), and Citation Group (CG), while v_t is a vector of year-fixed effects, allowing us to control for unobserved heterogeneity over time.

Table 3 reports regression results. The probability that at least one invention is built upon a given ERC publication is not different from the probability that at least one invention is built upon a control group publication, after controlling for the quality of publications.[19] Across all models, publications with higher citation and author counts show an increased probability of receiving patent citations. Notably, publications featuring a US co-author are more likely to garner citations from patents filed with the USPTO rather than the EPO.

Next, we estimated Negative Binomial regressions, where the dependent variable is the total number of patent citations received by any given publication (and not whether the publication has been cited or not in a patent). Results are reported in Table 4. Column (1) indicates that an ERC-funded publication receives, on average, 4.31% more patent citations compared to a publication from the control group.[20] In Column (2), which specifically focuses on Life Science publications, there are no statistically significant differences in citation numbers. However, when examining other sciences (physical science) excluding Life Science and Social Science and Humanities, ERC publications receive 6.59% more citations compared to the control group.[21]

[19] Results of Logit estimates are shown in Table C2 in the Appendix. Except for EPO citations, all results are similar to those from linear probability estimations. It is worth noting, however, that the number of observations significantly decreases due to the existence of clusters of $\mathrm{SF}_{fi} \times \mathrm{J}_{fi} \times \mathrm{CG}_{fi}$ within which we have no variation in the outcome, that is, all publications in the cluster either did not receive any citation or they were all cited. This is an issue known as *complete separation* in econometrics. It occurs in non-linear models, such as logistic, when there is a combination of regressors whose value perfectly predicts the outcome. This leads to issues where the logistic regression coefficients become infinitely large or undefined, as the model attempts to fit a probability of 0 or 1 exactly. As a result, maximum likelihood estimation cannot converge to a finite solution, leading to dropped observations or failed model convergence. This problem does not affect linear probability models, which use ordinary least squares and thus do not encounter issues of non-convergence under complete separation.

[20] $(e^{0.0422} - 1) \times 100 = 4.31$.

[21] Note that, when running NB regressions, the number of observations drops substantially. This is due to the existence of clusters of $\mathrm{SF}_{fi} \times \mathrm{J}_{fi} \times \mathrm{CG}_{fi}$ within which we have no variation in the outcome. In other words, within the given

Table 3
Publications: Likelihood of receiving a patent citation (Linear Probability Model).

	(1) Any Patent	(2) EPO	(3) USPTO	(4) Any Patent	(5) EPO	(6) USPTO
ERC Publication	−0.0021	0.0001	−0.0007	−0.0026	−0.0000	−0.0007
	(0.0017)	(0.0008)	(0.0013)	(0.0017)	(0.0008)	(0.0013)
Number of article citations (log)	0.0799***	0.0251***	0.0602***	0.0792***	0.0251***	0.0599***
	(0.0061)	(0.0022)	(0.0047)	(0.0059)	(0.0022)	(0.0046)
US co-author dummy (0/1)				−0.0011	−0.0025**	0.0042**
				(0.0022)	(0.0012)	(0.0019)
Number of authors				0.0007***	0.0001	0.0001
				(0.0003)	(0.0001)	(0.0002)
Constant	−0.0033	0.0514	0.0959	−0.0047	0.0510	0.0960
	(0.1049)	(0.0727)	(0.1223)	(0.1051)	(0.0726)	(0.1226)
Observations	115,896	115,896	115,896	115,896	115,896	115,896
R-squared	0.0568	0.0205	0.0556	0.0570	0.0206	0.0556
Scientific field × Journal × Citation Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Publication year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors clustered by Scientific Field × Journal × Citation Group in parentheses. This table presents results from a linear probability model evaluating the probability of ERC and control group publications being cited in patents, whether on the front page or within the document body. There are $N = 57,948$ ERC publications and an equal number of Control publications. In columns (1) and (4), a value of 1 for the outcome variable indicates a citation in any patent document, otherwise 0. In columns (2) and (5), the outcome variable is 1 if the publication is cited in an EPO patent, and 0 otherwise. In columns (3) and (6), the dependent variable is 1 for citations in a USPTO patent, and 0 otherwise. The variable *ERC Publication* is set to 1 for publications based on ERC-funded research, and 0 otherwise. The regression controls for publication quality through the total number of scientific citations the publication has received (*Number of article citations*) and the number of authors (*Number of authors*). Moreover, the regressions also control for the presence of authors affiliated with US organizations (*US co-author dummy*). All columns in the table feature fixed effects (FE) based on the unique combination of Scientific Field, Journal, and Citation Group, in addition to fixed effects pertaining to the year of publication.

Table 4
Publications: Number of citations received in patents (Negative Binomial Regression).

	(1) All	(2) Life Science	(3) Other Science
ERC Publication	0.0422**	0.0347	0.0638**
	(0.0185)	(0.0246)	(0.0285)
Number of article citations (log)	0.705***	0.718***	0.705***
	(0.0115)	(0.0158)	(0.0171)
US co-author dummy (0/1)	−0.00528	0.0400	−0.0797**
	(0.0237)	(0.0297)	(0.0406)
Number of authors	0.00594***	0.00919***	−0.00342
	(0.00146)	(0.00164)	(0.00324)
Constant	−3.426***	−3.571***	−3.227***
	(0.405)	(0.446)	(0.997)
Observations	59,044	26,188	32,438
Sci. field × Journal × Citation Group FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses. The table reports results from count models evaluating the patent citations received by both ERC and control group publications. The dependent variable is the aggregate count of patent citations for each publication. To account for the quality of the publication, the regression model incorporates the total number of scientific citations a paper has garnered (*Number of article citations*), and the count of contributing authors (*Number of authors*). Further, the model controls for the presence of authors having affiliations with US organizations (*US co-author dummy*). All columns in the table feature fixed effects (FE) based on the unique combination of Scientific Field, Journal, and Citation Group, in addition to fixed effects pertaining to the year of publication. The life science field includes publications in Biological Sciences, Medical Engineering, Environmental Biotechnology, Medical and Health Sciences, and Agricultural Sciences. Meanwhile, the other sciences encompass publications in all other fields excluding life sciences, social science, and humanities.

In summary, while the propensity of ERC-funded science to exhibit inventive potential is on par with other European scientific research, it is noteworthy that when ERC-funded work does demonstrate applied potential (i.e., it is cited in patents), it tends to contribute to a greater number of inventions compared to other research.

4.2. Are ERC-based patents more valuable?

In addition to assessing the propensity for ERC science to be transformed into inventions, we also evaluated whether patents that reference ERC publications are associated with inventions of higher impact. To that purpose, we performed separate regressions for the EPO and the USPTO, employing the following model:

$$Y_{it} = \beta_0 + \beta_1(ERC{-}based\ patent_{it}) + \eta X_{it} + \sum_f \beta_f\, \mathrm{IPC}_{fi} \times \mathrm{J}_{fi} + \nu_t + \epsilon_i \quad (2)$$

In this equation, Y_{it} represents the logarithm of the number of forward citations received by patent i within the five years following its publication year t. Forward citations are a widespread proxy for the value of inventions since the seminal work of Trajtenberg (1990).

ERC-based patent$_{it}$ is a binary variable that takes the value of 1 if the patent cites ERC-funded research, and 0 otherwise. This distinction allows us to contrast the impact of patents derived from ERC-funded science with those emerging from European science of similar quality, scientific discipline, and publication outlet. The term X_{it} represents a matrix of control variables that are likely to correlate with the value of inventions (see, for instance, Poege et al. (2019) and Harhoff et al. (2003)).

combinations of scientific field, journal, and citation group, all observations exhibit the same outcome variable, either all zero, or 1, 2, and so on. This raises issues of complete separation, whose effects are similar to the ones discussed in footnote 19.

Table 5
Patents: Number of citations received in the first five years after publication.

	EPO	EPO	EPO	USPTO	USPTO	USPTO
ERC-based patent	0.0923***	0.0925***	0.0888***	0.3427***	0.3422***	0.1972***
	(0.0300)	(0.0299)	(0.0297)	(0.0294)	(0.0294)	(0.0264)
Number of inventors	0.0167***	0.0162***	0.0031	0.0625***	0.0625***	0.0272***
	(0.0055)	(0.0055)	(0.0061)	(0.0050)	(0.0050)	(0.0047)
Number of article citations (log)		0.0525*	0.0403		0.0488*	0.0525**
		(0.0296)	(0.0280)		(0.0274)	(0.0240)
Number of NPL citations			0.0045***			0.0023***
			(0.0008)			(0.0003)
Family size			0.0273***			0.0476***
			(0.0034)			(0.0024)
Number of claims			0.0060*			0.0151***
			(0.0034)			(0.0011)
Constant	0.4968**	0.3796*	−0.0179	2.7089***	2.5925***	1.7333***
	(0.2051)	(0.2117)	(0.1494)	(0.1640)	(0.1738)	(0.1659)
Observations	2,670	2,670	2,670	15,949	15,949	15,949
R-squared	0.0917	0.0934	0.2253	0.1560	0.1564	0.2935
Technological field × Journal FE	Yes	Yes	Yes	Yes	Yes	Yes
Patent filing year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors clustered by Technological Field × Journal in parentheses. The table presents results from a linear regression model. The dependent variable is the logarithm of the number of citations received by a patent in the five years following its publication. The variable *ERC-based patent* is set to 1 for patents citing ERC-funded publications, and 0 otherwise. The regressions control for publication quality through the total number of scientific citations the publication cited in the patent has received (*Number of article citations*) and for the number of inventors in the patent (*Number of inventors*). Moreover, the regressions also control for the total number of NPL citations made by the patent (*Number of NPL citations*), the size of the patent family (*Family size*) and the number of claims of the patent (*Number of claims*). All columns include fixed effects (FE) for the combination of Technological Field (IPC 4-digit) and Journal, and for the application year of the patent.

Specifically, we account for the total number of inventors associated with the patent (*Number of inventors*), the cited publication's scientific impact (*Number of article citations*), the total number of NPL citations made by the patent (*Number of NPL citations*), the family size (*Family size*), and number of claims contained in the patent (*Number of claims*). Regressions also include a vector of fixed effects ($\sum_f \beta_f \, \mathrm{IPC}_{fi} \times \mathrm{J}_{fi}$) for the unique combination of IPC class (4-digit) × Journal, and patent application year (v_t).

Table 5 reports the regression results for Eq. (2). EPO patents citing ERC science receive on average 9.2% more forward citations than control patents.[22] The effect is larger when looking at the USPTO: ERC-based patents receive 21.7% more forward citations than control patents.[23]

The finding suggests that the inventions based upon ERC science are, on average, of greater impact and possibly value than the inventions built upon comparable European science.

4.3. Who builds upon ERC science?

We now turn our attention to the type of organizations and regions, which are more likely to exploit ERC science in patented inventions (**RQ2**). The heterogeneity in the ability of organizations to assimilate the spillover benefits of publicly funded science is an area that has attracted little attention in the literature. Transforming cutting-edge science into inventions requires substantial absorptive capacity, as highlighted by several scholars (Cohen and Levinthal, 1989; Arora and Gambardella, 1994; Sheer, 2022). It is thus reasonable to hypothesize that the output of ERC science is more likely to be converted into inventions within entities that possess enhanced levels of absorptive capacity. In this section, we provide empirical evidence of differences in the geographical location and the organizational type of patent applicants, comparing instances involving ERC science with those of a control group.

Specifically, we estimated the following equation:

$$P_{it}^{sm} = \beta_0 + \beta_1(ERC\text{−}based\ patent_{it}) + \eta X_{it} + \sum_f \beta_f \, \mathrm{IPC}_{fi} \times \mathrm{J}_{fi} + v_t + \epsilon_{it} \quad (3)$$

In this equation, P_{it}^{sm} denotes a binary indicator variable that is set to 1 if the applicant of patent i, filed in year t, belongs to organizational type s and is located in the region m; the variable is assigned a value of 0 in all other cases. As far as organizational types s are concerned, we distinguished three types: (a) Universities and public research organizations, (b) Companies, and (c) Top universities and public research organizations. For the third category, we have identified the top 200 public research institutions and universities based on the rankings published by the SCImago Research Group.[24] With respect to regions m, we focus on organizations located in (i) USA and (ii) Europe.

ERC-based patent$_{it}$ in Eq. (3) is, as before, a binary variable that takes the value of 1 if the patent cites ERC-funded research, and 0 otherwise. Regressions control for a number of factors (X_{it}): the total number of inventors associated with the patent (*Number of inventors*), the cited publication's scientific impact (*Number of article citations*), the total number of NPL citations made by the patent (*Number of NPL citations*), the family size (*Family size*), and number of claims contained in the patent (*Number of claims*). Regressions also include fixed effects for the unique combination of IPC class (4-digit) × Journal ($\sum_f \beta_f \, \mathrm{IPC}_{fi} * \mathrm{J}_{fi}$), and patent application year (v_t).

Fig. 2 illustrates the estimated value and the 95% confidence interval for the coefficient β_1, which is linked to our variable of interest, *ERC-based patent*$_{it}$. Full regression estimates are reported in Tables C5 and C6 in Appendix C. Results show that, besides an obvious "home advantage" effect, Universities and top public research organizations lead in the exploitation of ERC science. For example, the probability that an EPO (USPTO) patent citing ERC science belongs to a university is 11.79 (5.72) percentage points higher than a control patent. Similarly, an ERC-based patent is between 6 and 8 percentage points more likely to be applied by a top 200 research organization than a control patent.

22 $(e^{0.0888} - 1) \times 100 = 9.21$.

23 We also tested the robustness of results by using as dependent variable the patent quality index developed by Squicciarini et al. (2013). Results are reported in Table C3 in Appendix C and are qualitatively similar.

24 SCImago is a Spain-based research group from the Consejo Superior de Investigaciones Científicas (CSIC), University of Granada, Extremadura, Carlos III (Madrid) and Alcalá de Henares.

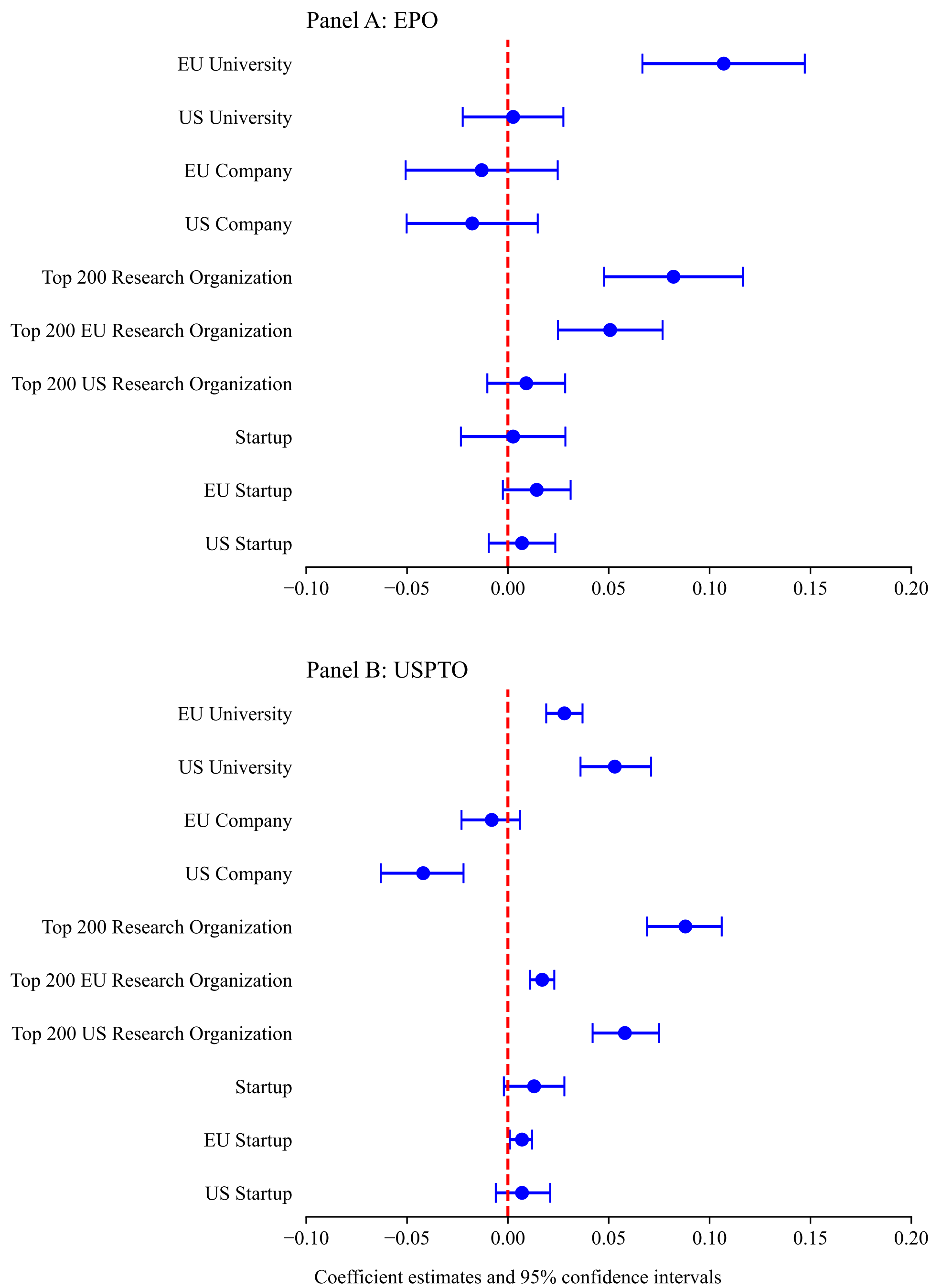

Fig. 2. Probability that the patent assignee is a university, company, top Research Organization or startup for an ERC-based patent.

Having established that ERC science is exploited chiefly by universities and public research organizations, to what extent do these spillover effects remain within Europe? As noted above (see Section 3.1.2), around 55% of all citations to ERC science come from USPTO patents, whereas citations from EPO patents account for just 9.48%, which is slightly larger than the percentage of citations from SIPO patents (8.09%).[25] In and of itself, this does not necessarily mean that Europe lags behind its competitors in exploiting the benefits of the science it funds and generates. European organizations can and do protect their inventions in other jurisdictions via direct patent filing or via the WIPO-PCT patent system. To address this issue, we focused our attention on patent families that include patent filings at both the EPO and USPTO. These are arguably the patents with greater economic value. We found 9,608 such patent families, each with at least one patent referencing ERC science.

Fig. 3 reports the distribution of those patents by organization type and location. The evidence reveals that while universities and public research entities may have a comparative edge in harnessing ERC science, as inferred from the preceding analysis (see Fig. 2), it is the corporate sector that leads in absolute terms in translating this science into valuable inventions. Corporations are responsible for approximately 54% of all patent families that cite ERC publications, with U.S. firms being particularly prominent, accounting for about 26% of all such citations. Moreover, the aggregate share of US companies and universities stands at around 41.4%, slightly eclipsing the 32.7%

[25] Table B1 in Appendix B.

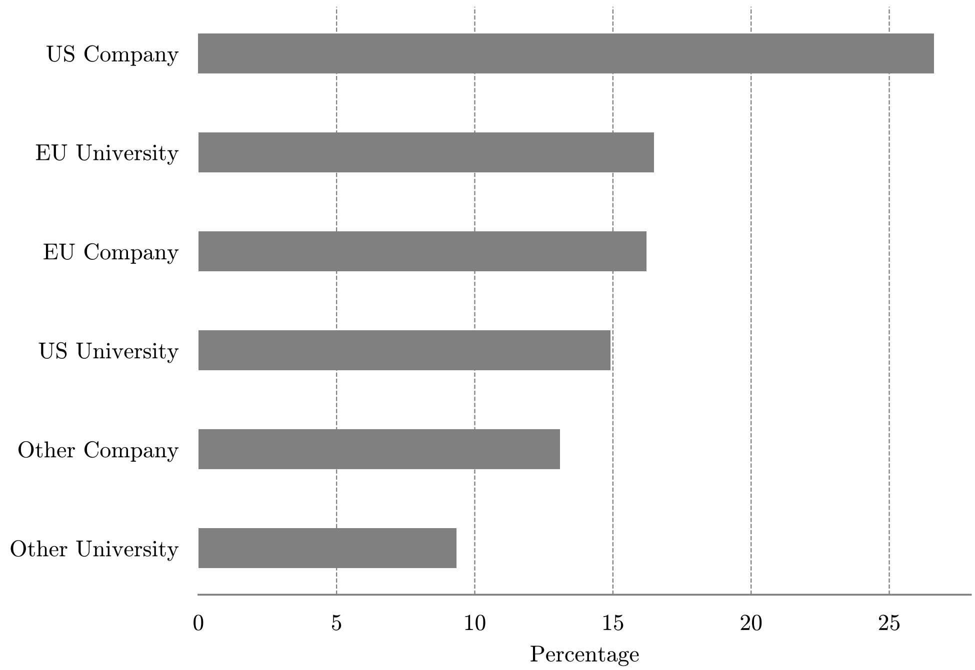

Fig. 3. Patent families citing ERC publications
The figure reports the percentage distribution of ERC-based patent families by type and location of patent assignee. Data includes only families with patent filings at both the EPO and USPTO.

associated with European organizations. This indicates the substantial absorptive capacity present within the U.S. innovation ecosystem.[26]

Next, we examined the share of startups in the company's patents. Startups[27] account for 37.1% of the company's patents in the US and 21% in the EU, as shown in Fig. 4. The high share of startups' inventive activities is partially driving the gap between corporate patenting in the US and the EU. One-third of corporate patent applications in the US have startups as patent applicants, highlighting the role of the vibrant innovation ecosystem led by startups in the US in absorbing and leading inventive activities at the frontier of science. In contrast, the EU lags behind due to the absence of a startup ecosystem and regulatory environments that throttle new ventures. This hinders the full capitalization of the excellent and frontier science in the EU.

5. Conclusion and discussion

The purpose of this paper was to present some *facts* regarding the impact of science funded by the ERC on technological progress. The emerging portrait of the European research system is one of mixed outcomes. On the bright side, although ERC science demonstrates the same potential of inspiring inventive activities as comparable European research does, it serves as the foundation for a greater volume of inventions when it possesses applied value. Even more importantly, inventions based upon ERC science are, on average, of greater impact than the inventions built upon comparable European science.

On the dark side, ERC science does not directly *filter* through to the corporate sector. Universities appear to have a comparative edge in patenting inventions derived from ERC science relative to those based on similar European research. This could suggest either a heightened absorptive capacity within academia or a broader gap between ERC science and commercial applications compared to non-ERC science. Moreover, in absolute terms, US organizations, and particularly US companies, including US startups, appear to lead in the exploitation of scientific outputs from ERC-funded projects.

Our findings reveal that the potential of ERC science to foster inventions is not a concern. However, the so-called "European Paradox" becomes apparent when attempting to capture the spillover effects and transform excellent science into inventive activities. Our research also emphasizes the importance of startups and new ventures in stimulating inventive activities, particularly at the forefront of the scientific frontier. This highlights the paramount importance of cultivating an ecosystem conducive to bridging this divide. For instance, initiatives like the European Innovation Council (EIC) Accelerator or other targeted policies and investments, align with the objective of strengthening an European innovation ecosystem able to capitalize on scientific advancements.

In addition, our findings call for a deeper understanding of the role of university patenting as a bridge in transferring technical knowledge, especially at the frontier of science. For instance, in a recent paper, Arora et al. (2023a) challenge the notion that public science is a nonrival public good that contributes to corporate R&D through knowledge spillovers and argue that *"public inventions compete with corporate inventions more than they act as inputs into corporate innovation"*. Further research that triangulates data from patents and startup foundation could investigate if those startups based on ERC science compete or cooperate with large incumbents.

Finally, we have chosen to benchmark ERC science with comparable European science. A fruitful avenue of future inquiry could compare the ERC with a US program meant to support top-notch science and explore whether they systematically diverge in terms of knowledge spillovers that manifest in subsequent patenting activities.

This study presents several limitations. First, the impact of ERC-funded science was assessed using patent data, which, while commonly employed in empirical literature as a measure of innovation output,

[26] Universities and public research organizations represent approximately 40% of all patent families that cite publications funded by the ERC. In contrast, these institutions account for only 14.5% of all patent families that cite any scientific publication, and just 6.9% of all patent families filed at both the EPO and the USPTO. This disparity highlights the preferential access that universities have to the fundamental science emerging from ERC-funded projects.

[27] Startups are the new ventures founded after 2006 sourced from PitchBook, as described in Section 3.1.2.

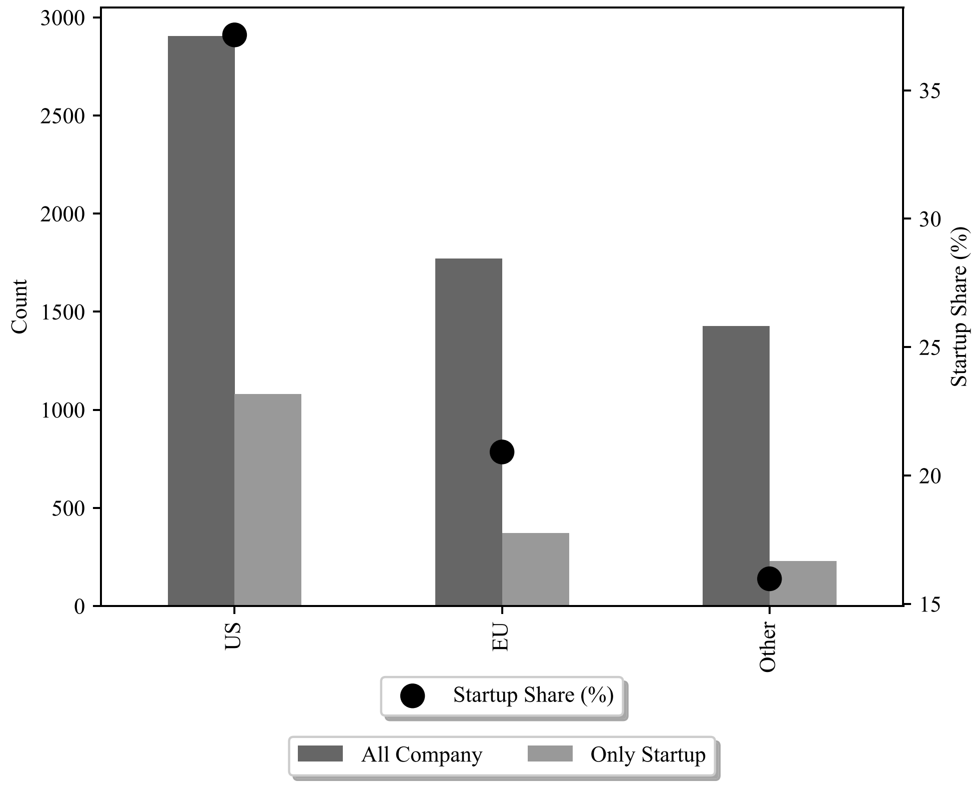

Fig. 4. Patent families citing ERC publications: All companies and startups
The figure reports the number of ERC-based patent families with corporate and startup assignees. The right axis shows the percentage share of startup patents in all corporate patents. Data includes only families with patent filings at both the EPO and USPTO.

serves as an imperfect proxy. The economic value of patents varies considerably; many patents do not transition to commercial products and thus hold no commercial value. Additionally, the propensity to patent inventions varies widely across firms, industries, and countries. The effectiveness of patents as a mechanism for appropriating intellectual property also differs across jurisdictions, influencing firms' preferences for utilizing patents over other methods, such as trade secrets.

A second major limitation concerns the identification of counterfactuals and the chosen unit of analysis. Ideally, we would have examined the impact of researchers who secured ERC funding in comparison to those who applied but were not selected, due to marginally lower scores. However, data on unsuccessful applicants is confidential and unavailable for analysis. Consequently, as a second-best approach, our study compared the publications of ERC awardees with those of comparable quality from non-ERC grantees. For these reasons, it is crucial to note that our findings should not be interpreted as establishing a causal link between receiving ERC grants and the production of commercially impactful publications.

Despite these limitations, we hope that the findings will stimulate further research into the broader effects of this pivotal European program supporting basic research.

CRediT authorship contribution statement

Jay Prakash Nagar: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Stefano Breschi:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Writing – original draft, Writing – review & editing. **Andrea Fosfuri:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.respol.2024.105038.

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