Research Policy 55 (2026) 105528

Contents lists available at ScienceDirect

Research Policy

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

Where do ideas go? A spatial analysis of the patenting impact of publicly funded basic science

Laura Toschi [a], Federico Munari [a,*], Maurizio Sobrero [b], Hérica Morais Righi [a], Sebastiano Leonelli [a]

[a] Department of Management, University of Bologna, Italy
[b] Emirates Center for Entrepreneurship Research, United Arab Emirates University, United Arab Emirates

ARTICLE INFO

Keywords:
Scientific discoveries
Technological inventions
Knowledge diffusion
ERC

ABSTRACT

As societal challenges loom larger, discoveries are in greater demand, and evaluating the impact of publicly funded programs attracts increasing attention. We contribute to this debate by focusing on the spatial influence of scientific discoveries funded through grants targeting frontier research. Our dataset includes information on 6671 EU ERC-funded projects between 2007 and 2016, 172,683 scientific publications generated by these grants, and 34,513 patents citing such publications. Building on linkages between scientific papers and patents via non-patent literature citations, we use the project as the unit of analysis and employ a two-stage regression model to examine the probability that ERC-funded publications are cited by patents and how these citations diffuse across space and time. The analyses on our final sample of 4977 ERC-funded projects, generating 151,574 publications that are cited by 34,007 patents confirmed our hypothesis that higher quality research leads to a broader and faster geographical diffusion and partially confirm the hypotheses that diffusion paths and speed differ by applicants, although these differences do not always show the same patters. Moreover, we also find that c) projects generating scientific output (publications) and technological outputs (patents) diffuse more broadly and faster; and d) projects led by more mobile and scientifically productive scientists diffuse more broadly and faster; We discuss these findings and show how they enhance and extend our understanding of the impact of science and its implications for policymakers and innovation scholars.

1. Introduction

The freedom to make discoveries and advance societal knowledge without targeting a specific goal or a well-identified problem characterizes frontier research. From the early days of public policies inspired by market failures in innovation processes to the development of innovation ecosystems focused on building new institutions, financing frontier research has consistently remained critical in supporting growth by generating new knowledge and ideas (Schot and Steinmueller, 2018). While business-driven spending contribution may vary significantly over time and by industry (National Science Board, 2024; OECD, 2024), public-sector spending has always acted as the main driver, given the weak appropriability of the results, their non-rival nature, and the serendipitous paths leading to eventually relevant applications (Mazzuccato, 2013). If, how, where, how, and when those discoveries find a way to impact society, therefore, are pertinent questions that have been attracting a significant amount of theoretical and empirical research (NATIONAL BUREAU OF ECONOMIC RESEARCH, 1962; Lerner and Stern, 2012).

In this paper, we contribute to this debate in two ways. First, we focus on the relationship between different outputs of idea generation and invention phases to follow the paths of publicly supported frontier research projects toward commercially targeted solutions. Building on the seminal contributions of Non-Patent-Literature citations (Carpenter and Narin, 1983; Jaffe et al., 1993) and their more recent applications using information from patent citations to publicly-supported scientific publications (Azoulay et al., 2019; Fleming et al., 2019; Li et al., 2017; Marx and Fuegi, 2020; Nagar et al., 2024), we link publicly funded projects and patents through the scientific findings generated by scientists and later cited by inventors. Second, we trace the geographical distribution of publicly funded frontier science in commercially viable discoveries. More specifically, we investigate the extent to which the

* Corresponding author.
E-mail addresses: laura.toschi@unibo.it (L. Toschi), federico.munari@unibo.it (F. Munari), msobrero@uaeu.ac.ae (M. Sobrero), herica.moraisrighi@unibo.it (H.M. Righi), sebastiano.leonelli2@unibo.it (S. Leonelli).

https://doi.org/10.1016/j.respol.2026.105528
Received 28 May 2025; Received in revised form 24 March 2026; Accepted 6 May 2026
Available online 23 May 2026

quality of new science-based ideas influences their embeddedness into new technologies, the geographic diffusion of these technologies and the speed at which they give rise to their first patent citation. Our conceptual and empirical approaches allow us to explore the relationship between scientific and industrial diffusion, the spatial patterns of distribution, and the time taken for science to be incorporated into practice.

The initial dataset includes 6671 projects financed between 2007 and 2016 by the European Research Council (ERC), the EU agency established in 2007 to support frontier research in all fields through competitive public funding. Based on projects' PI, we used Scopus and Patstat as data sources for publications and patents. By relying on several disambiguation efforts to correctly identify all the relevant information for both the author(s) and the applicant(s), we identified first 172,683 project-related publications and then 34,513 patents, citing at least one of those publications. In our analyses, we rely on a two-stage empirical strategy that first models, for a sample of 4977 ERC projects, the probability that an ERC project receives at least one patent citation and then, for the 2740 projects with at least one patent citation, we examine the spatial diffusion of citations, conditional of being cited. Moreover, we complemented these investigations with a duration model to capture the timing of first citation.

Our findings highlight interesting patterns. First, the quality of research significantly shapes the geographic reach of science within the technological domain. This is evidenced by citing patents that are (i) geographically distant from the origin of science, (ii) drawn from a diverse range of national contexts, and (iii) not confined to the local innovation ecosystem of scientific research. Collectively, these dynamics highlight the significant contribution of high-quality research to global technological progress. Second, we show that high-quality research significantly accelerates the pace at which a project influences technological innovation, as evidenced by a shorter time to reach the first citation in a patent. Third, we document that these patterns vary depending on project, individual, and context-level characteristics. These results are robust to several econometric specifications and additional tests discussed in the paper and reported in the appendices.

The rest of the paper is organized as follows. In section 2, we discuss the value of science, the role of public and private institutions, and the resulting policy debate, developing a set of hypotheses. Section 3 presents the ERC context, data sources, and disambiguation procedures. Section 4 describes the variables. Section 5 presents the analyses. Section 6 summarizes the main conclusions of our work, its relevance to scholars and policy-makers, its limitations, and potential future developments.

2. Theoretical background and hypotheses development

2.1. Basic science and its contribution to innovation

Several significant societal advancements are bound to the intellectual efforts deployed by individuals and groups moved by curiosity. Nobel prize winners' discoveries opened the way to treat diabetes, made the transistor-based electronic revolution possible, and revolutionized gene editing through CRISPR-Cas9, to name a few (Hargittai, 2002; Norrby, 2010). While some originated in company-funded labs, like in the transistor case or the 2024 Chemistry prize for the AlphaFold2 model (Royal Swedish Academy of Science, 2024), most discoveries occurred in public institutions and were funded by government grants. The path from science to technology holds not only for breakthrough discoveries opening up new high-technology fields but also unfolds through incremental improvements and adaptations affecting low-tech industries (Rosenberg, 1983; Pursell, 2007).

Even though the benefits could be extraordinary, funding frontier research suffers from the classical problems of indivisibility, appropriability, uncertainty, and the corresponding risk of long-term sub-optimal investments (Nelson, 1959; Arrow, 1962). Therefore, financing and supporting frontier research through public resources and different policies is necessary to overcome market failures and generate future growth options (Mazzuccato, 2013). Universities and Public Research Labs are the primary beneficiaries of the funds supporting basic science. Pushing new knowledge more effectively out of their labs to avoid the Ivory-Tower effect became central in the academic and policy debate. New laws and regulations were introduced accordingly in the last forty years to support patenting by public institutions (Mowery et al., 2004; Baldini et al., 2006; Azoulay et al., 2009), incentivize their organizational change (Clarysse et al., 2011; Grimaldi et al., 2011), enrich internal competencies and roles associated with so-called third-mission activities, (Clarysse et al., 2005; Schoen et al., 2014; Munari et al., 2017) support the creation of spin-offs and start-ups (Perkmann et al., 2013), and engage scientists and students in the innovation race (Åstebro et al., 2012; Meoli et al., 2020; Easley and Lee, 2021).

The impact journey of scientific discoveries might take various paths. It might follow a classical linear development marked by different phases presided over by specialized agents (Godin, 2017). It might depend on more complex dynamics showing a punctuated equilibrium pattern, embedding the idea of paradigm shifts and the corresponding conflicts between old and new solutions (Tushman and Anderson, 1986; Anderson and Tushman, 1990). It might depend on a complex web of technical and societal conditions and even rely heavily on the role of chance or unpredictable exogenous shocks (Kline, 1985; Bijker, 1997).

Therefore, searching for how discoveries become applications might require different tools and strategies. In the following section, we focus on those based on connecting scientific publications to patents.

2.2. Linking science to innovation by patent to publication citations

Tracing the contribution of science to innovation poses several methodological and conceptual challenges. Scientific papers are the typical output that conveys new knowledge generated by science. Analyzing where they are published and how they are cited carries information on their reputation and impact (Moed, 2005). Thanks to the increasing availability of large and longitudinal bibliometric data, different measures have been used in the literature and policy practice to consider publication quality as an impact measure. Different studies highlighted the opportunities and biases of relying on citation-based data to measure research quality e.g. (Hicks et al., 2015), especially for novel science (Wang et al., 2017; Veugelers and Wang, 2019), and recent research has started exploring different approaches based on multiple measures and text analyses (Haddawy et al., 2016; Arts et al., 2023; Colquitt et al., 2024).

Patent documents, like scientific publications, include references to delimit prior art and prove the invention's novelty to existing technological developments. These references mainly concern earlier patents but may include non-patent literature (NPL), such as scientific publications. Pioneering work by Narin and colleagues (Carpenter and Narin, 1983) and Jaffe et al. (Jaffe et al., 1993) analyzed patent-to-paper citations and sparked a wave of empirical works using NPL data to study the dynamics of knowledge flows from science to technology.

One recent and promising segment of this research stream traces the reliance of patents on public funding sources, exploiting information from patent citations to publicly funded scientific publications (Azoulay et al., 2019; Fleming et al., 2019; Li et al., 2017; Marx and Fuegi, 2020; Nagar et al., 2024). In a recent review of this literature, Van Raan (Van Raan, 2019) stated that only a small minority (around 3–4%) of publications are cited by patents, but the value increases (15%) for publications based on university-industry collaborations. Veugelers and Wang (Veugelers and Wang, 2019), found higher values, with 11% (on average) of the sampled publications cited in subsequent patents. The study by Ahmadpoor and Jones (Ahmadpoor and Jones, 2017), found that around 10% of scientific publications were directly cited by patents. This percentage increases when considering multiple scientific links (i.e., the original publication is cited by another publication, which is then cited by a patent). Importantly, their study documented dramatic variation by technological fields in the patent propensity to cite science. Similar evidence has been provided by Jefferson et al. (Jefferson et al., 2018), focused on data from 1980 to 2015, showing an average of around 10% of publications cited in patents.

In a more recent study based on European Research Council-funded projects, Nagar et al. (Nagar et al., 2024) show that 10% of the publications from these projects were cited by USPTO or EPO patents. Their control group of publications in similar fields, years, and journals showed a similar value (9%). Their subsequent analysis, however, highlighted that for both groups, publication quality influenced the likelihood of being cited and that, overall, the ERC group received slightly more citations, with significant differences among disciplines.

These studies point to the relevance of scientific publications in influencing patenting activities, as publication quality increases the likelihood of being later incorporated into a patent, with significant differences among fields, and greater relevance of the patents based on scientific literature. However, the speed at which ideas spread from the lab to the corporate world, their geographical distribution, and who picks them up first in the patent race are still unexplored. In the next section, we turn to the spatial analyses of knowledge diffusion to contribute to this ongoing debate and formulate our hypotheses on these different aspects.

2.3. Geographical diffusion of knowledge flows

The role of geography has been a central theme in knowledge diffusion literature, particularly concerning how proximity and borders influence the spread of scientific discoveries and technological advancements (Döring and Schnellenbach, 2006). The seminal work of Jaffe (Jaffe, 1989) laid the foundation for studying the spatial dimension of knowledge spillovers coming from publicly funded research. Exploiting panel data at the US state level to assess university research funding and corporate patents, he found evidence that firms in regions characterized by high academic research tended to have higher patenting activity. The findings suggested that informal interactions influence knowledge diffusion, and geographic proximity may be necessary to capture the benefits of these spillovers.

Jaffe et al. (Jaffe et al., 1993) subsequently developed a matching method to test localized knowledge spillovers by comparing the geographical locations of citing and cited patents. Their findings indicated a higher likelihood of inventions being cited within the same or nearby regions, reinforcing that knowledge diffusion is spatially constrained and that spillovers are more localized when tacit knowledge and personal interactions are more critical. However, this method was contested by Thompson and Fox-Kean (Thompson and Fox-Kean, 2005), who did not find significant evidence supporting localization at the state or metropolitan levels after refining the control patents. This sparked a debate about knowledge spillovers' geographical localization (Henderson et al., 2005; Murata et al., 2014). Belenzon and Schankerman (Belenzon and Schankerman, 2013) focused on the role played by university policies and the characteristics of the local economies. Using US data, they found that citations to university patents decline sharply with distance and are significantly constrained by state borders. This effect, however, is heterogeneous and influenced by factors such as university type (public vs. private), state policies, the strength of local development initiatives, and varies by technological fields.

Jaffe and Trajtenberg (Jaffe and Trajtenberg, 1999) examined cross-border knowledge flows, extending the analysis to international contexts and showing that domestic patents are cited more frequently and quickly than foreign inventions. These findings suggest that national borders are barriers to knowledge diffusion, and local knowledge is more accessible for innovations in proximal areas. Singh and Marx (Singh and Marx, 2013) offered additional evidence by demonstrating that while spatial proximity increases the likelihood of knowledge spillovers, political borders serve as significant constraints, even when inventors are geographically close but situated in different countries. Similarly, Ribeiro et al. (Ribeiro et al., 2014) used patent citations to map global innovation networks, demonstrating that while innovation and knowledge creation are increasingly international, the diffusion of knowledge remains uneven. Their study showed that multinational enterprises are critical facilitators in linking innovation streams across countries. However, knowledge flows are still predominantly concentrated among certain regions, notably the United States and Europe. This aligns with the findings of Gomez et al. (Gomez et al., 2022), who noted a global citation inequality in knowledge diffusion through scientific citations. Countries from the Global North, which are wealthy and have established scientific infrastructures, show over-citation relative to countries from the Global South, even when their research is of comparable quality. Inequalities in knowledge diffusion become barriers to scientific progress, as valuable insights from peripheral countries are overlooked.

2.4. The effects of scientific quality on the geography of knowledge flows: Hypotheses development

Proximity, borders, and informal interactions influence the geographical diffusion of knowledge. We also argue that the quality of scientific research plays a decisive role in shaping the geography of knowledge flows and the timing of their incorporation into technological inventions.

Foundational scientific research tends to address universal questions, making its insights broadly relevant across fields and geographies (Fleming and Sorenson, 2004; Yegros-Yegros et al., 2015). It often leads to paradigm-shifting discoveries that transcend local contexts and resonate globally. In contrast, incremental research, though valuable in specific contexts, is typically narrower in scope, limiting its appeal and impact beyond proximal regions. From a geographic perspective, corporate inventors may thus find it easier to access knowledge from local sources through personal connections and direct interactions. However, when seeking knowledge from distant locations, adopting a more targeted strategy emphasizing highly knowledgeable scientists and reputable institutions is likely more effective.

Information quality also reduces the search cost by limiting entropy and becomes particularly relevant as the search space increases (Shannon, 1948). The academic literature has seen remarkable volume and publication rate growth, a trend further accelerated by the digital dissemination of articles. For example, Fortunato et al. (Fortunato et al., 2018) report that the volume of scientific literature has been growing exponentially, with an average doubling period of approximately 15 years. In an era of information overload, corporate inventors can benefit from prioritizing high-quality scientists and journals as sources of inspiration, facilitating efficient attention management, access to impactful ideas, and alignment with emerging trends (Bickard and Marx, 2019).

High-quality research is usually published in reputable, widely circulated journals. Increasing its visibility among international research communities and enhancing the likelihood of use in patentable innovations across diverse regions. These processes might be further accelerated in scientific communities where the most prestigious conference proceedings and communications pre-empt relevant discoveries. Breakthrough findings frequently command immediate attention from both academic and industrial audiences. This rapid recognition facilitates their faster incorporation into technological inventions by firms eager to introduce new products in markets characterized by shorter product life cycles and the need to constantly redefine their competitive edge.

All these different reasons support the idea that new knowledge generated from high-quality science inspires patented inventions from a more distant and broader range of geographic locations. For similar reasons, we also expect a faster diffusion process for high-quality science outcomes into new technical inventions.

Consistently, we advance the following hypotheses:

Hypothesis 1. *The higher the science –quality, the more widespread the geographical location of the citing technological inventions.*

Hypothesis 2. *The higher the science –quality, the faster it is citated by technological inventions.*

The geography and pace of knowledge flows stemming from high-quality science might differ depending on who the inventors are. Research has shown that the knowledge transfer process from science to technology follows distinct patterns, depending on the institutional characteristics of the organizations involved. In particular, various studies highlight different knowledge diffusion dynamics (in time and space) between academia and industry (Nagar et al., 2024; Belenzon and Schankerman, 2013). However, the theoretical predictions regarding the impact of the institutional nature of the recipients (academic vs industrial) on the geography of knowledge flows are not straightforward.

Different knowledge generation and dissemination regimes characterize the academic and corporate environment (Dasgupta and David, 1994). Academics are supposed to share values and operate in an open science regime, where dissemination is encouraged by the norms of the profession and the reward structure. They are supposed to activate a wide set of long-range collaborations, with a community of peers sharing similar interests that can also be located across borders, thus reducing barriers to accessing distant, high-quality knowledge sources. Moreover, academics engaged in technology transfer activities possess the absorptive capacity to effectively understand, integrate, and utilize scientific advancements in their patented inventions at the frontier of knowledge (Zahra and George, 2002). They can, therefore, incorporate new discoveries regardless of their distance without necessarily resorting to direct, frequent, and face-to-face interactions favoured by proximity.

In contrast, science-based corporate inventions, emerging in the proprietary knowledge regime of private corporations and facing more severe restrictions on knowledge sharing, could require more direct interactions. This, in turn, calls for higher degrees of formalization to promote knowledge sharing and greater attention to the coordination costs associated with managing distant relationships. More controlled, formalized links are therefore easier to establish with closer academic counterparts to be fully developed, especially when they refer to high-quality research results that lie at the frontier of scientific advancements. In line with this view, previous research showed that corporate inventions are more likely to cite prior patents from their own country, reflecting localized knowledge flows and domestic collaborations. The study by Azoulay et al. (Azoulay et al., 2011), for instance, suggests that to be realized, knowledge flows to the industry may require more face-to-face interaction than in academia. This may reflect the importance of physical proximity to university laboratories for helping industrial firms develop their inventions relying in science.

Based on these perspectives, we can formulate the following hypotheses:

Hp.3a. *The geographic spread of diffusion of higher-quality science into technological inventions is greater for academic inventions than for corporate inventions.*

Hp.4a. *The speed of diffusion of higher-quality science into technological inventions is greater for academic inventions than for corporate inventions.*

However, if we adopt the theoretical perspective based on the efficient allocation of attention and effort that we described in the discussion of Hypothesis 1, we can reach a different conclusion. We expect that corporate inventors adopt a more targeted strategy when seeking knowledge from distant locations, favoring highly knowledgeable scientists and reputable institutions in their knowledge transfer process. Their incentive to adopt high-quality science more rapidly is higher given the greater competitive pressure and the expectation of directly benefiting from the development of successful innovations. On the contrary, academic institutions divide their attention between their traditional missions of teaching and researching and the different demands of the different kinds of technology transfer activities, which fall under the larger category of so-called third mission activities.

Corporations may be advantaged compared to academic institutions in accessing geographically dispersed knowledge due to their strategic deployment of R&D hubs in global innovation clusters. Multinationals often establish partnerships with leading institutions in innovative regions like Silicon Valley, Cambridge, or Bangalore, allowing them to tap into local expertise while bridging international knowledge flows (Ribeiro et al., 2014). Their speed of action and resource availability might be sensibly higher than academia, making it more likely a partner than a competitor in the race to innovate.

Other operational aspects might account for the different capacities of private firms to tap into a broader knowledge base more quickly. First, there is a transparent allocation of the property rights deriving from the invention, while in academia, different regimes might operate and require specific negotiations between the institution and the individual. Second, ideas generated in companies are screened, examined, and eventually protected using professional services and dedicated resources. While patenting and licensing offices have significantly developed in the last thirty years in academic institutions all over the world, their comparative efficiency is still limited by several factors, such as the attractiveness of the positions for qualified professionals, the dependency on public administration regulations, and the need to cater to very different fields.

We can, therefore, advance the following competing hypotheses:

Hp.3b. *The geographic spread of diffusion of higher-quality science into technological inventions is greater for corporate inventions than for academic inventions.*

Hp.4b. *The speed of diffusion of higher-quality science into technological inventions is greater for corporate inventions than for academic inventions.*

3. The data

3.1. The context of the study: ERC and the characteristics of the projects examined

The European Research Council (ERC) is the premier funding agency for frontier research. Established in 2007, it offers individual, long-term grants for high-risk and high-reward projects, selected through highly competitive processes, with an acceptance rate of around 14%. Since 2007, more than 12,000 projects and over 10,000 researchers have been funded.

The ERC administers five primary grants: Starting Grants (STG), Advanced Grants (ADG), Consolidator Grants (COG), Proof of Concept Programme (PoC), and Synergy Grants (SYG). It supports early-career scientists and established scholars, clustering projects into three overarching fields: Life Sciences (LS), Physical Sciences and Engineering (PSE), and Social Sciences and Humanities (SSH). The first three grants target individuals, while the Synergy Grant targets interdisciplinary projects proposed by at least two and at most four PIs. The Proof-of-Concept Programme supports the technological and market development of previously funded projects.

3.2. The publication and patent set and the disambiguation procedures

We started by identifying all ERC-funded grants through Cordis,[1] corresponding to 6671 projects. We identified 172,683 scientific publications originating from these grants by integrating data from Cordis,

[1] Cordis is the European Commission's primary source of results from the projects funded by the EU's framework programs for research and innovation. https://cordis.europa.eu/.

Scopus, and the ERC databases, and matching the DOI and/or title and collecting detailed bibliographic information, including the number of citations as of October 2023.

We then relied on the 2021-Autumn Patstat edition to link publications and patents through Non-Patent Literature (NPL) citations and collect additional patent information.[2] Patstat organizes these citations in a specific table (tls214), which documents references to scientific publications categorized as NPL. We recorded a link between a patent application and an ERC publication when the publication was cited in the NPL section of the patent. The entries in this table were cross-referenced with the ERC publication dataset, using three criteria to identify a match: 1) having the same first author (surname), 2) having the same title, and 3) having the same DOI. We retained those with at least two matches and manually checked the publications that only featured the same title or DOI. For each patent, we then collected the application year, the patent office of the application, the IPC classification, the grant status, the applicant's name, country, and address.

Patent citations include both references reported by the applicants and those added by the patent examiners. Following the recommendations of previous patent-citation-based studies (Thompson, 2006; Kuhn et al., 2020), we utilized PATSTAT to distinguish between the two, controlling for potential biases in our estimates that may be introduced by citations made by patent examiners, and use this information to conduct robustness checks on our results.[3]

For the initial sample of 6671 ERC projects, we identified 34,513 patent applications citing the publications identified in the previous step. These patents cite 12,871 publications (out of the 172,683 ones previously identified). Then, to finalize our sample for the analyses, we applied a set of filters. First, we selected only STG, ADG, and COG categories for 2008–2016 (excluding SYG and PoC), as they target single PI proposals focused on frontier research. Second, we restricted the dataset to projects in the PE and LS domains, excluding SSH projects due to their limited relevance for patent generation. Third, we excluded 19 projects that did not produce any publication. After these steps, our final sample includes 4977 projects generating 151,574 publications, 12,558 of which are cited by 34,007 patents. Among these, we have 2740 projects with at least one patent citation, 2179 projects without patent citations, and 58 projects with only patent self-citations. Fig. 1 summarizes these various steps.

The 2740 projects with at least one patent citation generated 92,661 scientific publications, of which 11,795 are cited by 32,570 patents. In terms of distribution, 81% of such 2740 projects belong to the FP7 Program and 19% to the H2020 Program. By grant type, 49% of them are Starting Grants, 11% Consolidator Grants and 40% Advanced Grants, while in terms of scientific fields, 51% fall within the Life Sciences and 49% within the Physical and Engineering domain.

The other 2237 projects, instead, generated 60,844 scientific publications. In terms of distribution, 58.6% belong to the FP7 Program and 41.4% to the H2020 Program. By grant type, 50.7% are Starting Grants, 20.4% Consolidator Grants and 28.9% Advanced Grants, while in terms of scientific fields, 36.0% fall within the Life Sciences and 64.0% within the Physical and Engineering domain.

4. The variables

4.1. Explanatory variable: Assessing the scientific quality of research projects

To measure the scientific impact of each ERC project, we adapted the H-Index (Hirsch, 2005), a common bibliometric indicator used to evaluate individual researchers, to develop a *Project H-Index*. For each project, we ranked its papers from the most cited to the least cited, and we computed the highest *h*, where the h^{th} publication in the list has been cited at least *h* times. For instance, if a research project has generated 10 publications and only 5 were cited at least 5 times, its Project H-Index will be 5. A higher Project H-Index suggests a greater scientific influence and impact.

We used Scopus to retrieve the citations and considered only those received within three years after each publication's date to maintain consistency across the projects and disciplines. We log-transformed the *Project H-Index* to correct for right-skewness and ensure comparability across fields. We also constructed two alternative measures of project scientific quality, which we describe in detail in the "Additional Analyses" section.

4.2. Dependent variables: Assessing the geographic distribution of citing patents

To capture the geographic distribution of the citations to ERC publications from patented inventions, we first geo-localized patent applicants and projects' Host Institutions (HIs). We relied on Rassenfosse et al. (De Rassenfosse et al., 2019) to identify the geographic coordinates of the applicants of the citing patents, using Google's Geocoding API to upload their country and address/city and determine the corresponding latitude and longitude coordinates. We followed the same procedure to geo-localize the projects' HI using the detailed addresses available in Cordis.

For 1913 records, representing 5.5% of the full sample of 34,513 patents, we missed the address data. This issue was particularly pronounced for individual applicants, with additional identification challenges due to the risk of homonymy. We approached this problem in two steps. First, we integrated our data using Rassenfosse et al. (De Rassenfosse et al., 2019) data, for the following cases: (i) if the information on the two variables applicant_id and person_id were present in their dataset, we used their corresponding latitude and longitude (73 cases) and (ii) if the person_id was unique in their dataset (123 cases), we retrieved the geolocation and completed the address/city field. For the remaining 1717 cases, where only the country was specified, we assigned a default value corresponding to the country's geographic center.

After finalizing the geocoding procedure, we constructed different variables. First, we calculated the distance in kilometers based on the coordinates of the patent applicant and those of the project's HI,[4] using Karney's (Karney, 2013) iterative algorithm, accounting for the Earth's ellipsoidal shape and providing robust solutions. We computed the variable *Mean Distance* of citing patents by summing the distances between the patents citing a project's publications and the location of the Host Institution and dividing them by the number of citing patents.

We then constructed two variables to account for the heterogeneity of the geographic sources of citations. The first one, *Number of Countries,* counts the number of countries of origin for applicants' patents that cite a research project and measures its geographical spread: the higher the value, the more global the diffusion. The second one, *Heterogeneity of Countries,* measures the breadth of the countries from which patent applicants cite a research project. We distinguish three categories, all measured as ratios, using the total number of patent applicants citing the project's publications as the common denominator: *Patents* in the *Same Country*, *Patents Within Europe*, and *Patents Outside Europe*. *Patents Same*

[2] Patstat is a database released by the European Patent Office (EPO) and updated twice a year that provides access to patent data from more than 40 patent authorities worldwide.

[3] We are grateful to one of the reviewers for this suggestion.

[4] Multiple applicants in a single patent application can cause problems calculating the geographical distance between a citing patent and the project's host institution. In these cases, following Murata et al. (2014) and Bottazzi & Peri (2008), we calculated the average distance between the different applicants' locations and the Host Institution's location, using the city if a specific address was not available.

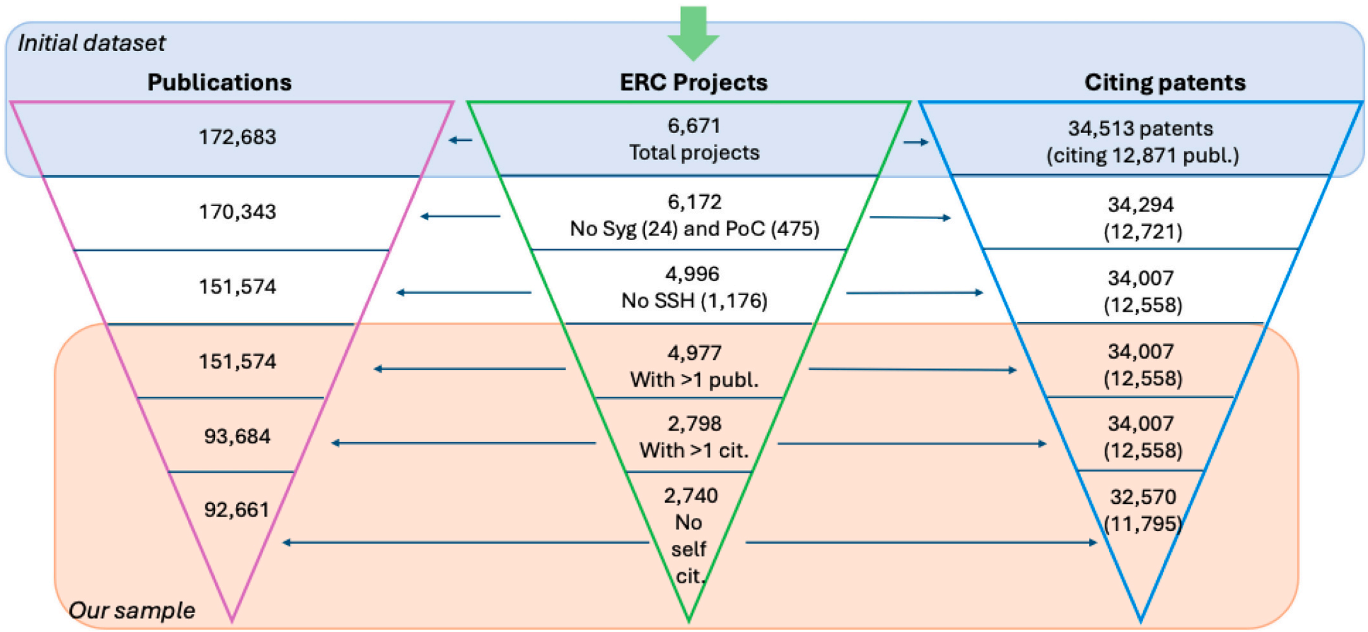

Fig. 1. Procedure to build our final sample.

Country uses as the numerator the number of applicants coming from the research project's country. A higher value suggests that the research is primarily relevant domestically. *Patents Within Europe* uses the number of European applicants as the numerator. A higher value suggests a stronger regional influence in Europe, which would be a desirable outcome for European-funded projects. Finally, *Patents Outside Europe* uses the number of non-European applicants as the numerator. A higher value suggests a stronger global technological influence of the project.

Finally, to test Hp. 3 and Hp. 4, we computed these variables, distinguishing between patent citations from corporate applicants or universities and research institutions based on Patstat applicants' classification.

4.3. Control variables

In our models, we included different control variables at the project, PI, and regional levels. At the project level, the dummy *H2020* distinguishes between projects funded by the H2020 Program (classified as 1) and those funded by the FP7 Program (classified as 0). A set of dummy variables controls for the type of grant (*Consolidator Grant, Starting Grant, Advanced Grant*) and for the scientific discipline of the projects (referring to the ERC classification of scientific fields, which ranges from fields PE1 – PE11 for Physical and Engineering, and from LS1 to LS9 for Life Sciences). The variable *Project Budget* indicates the amount of financial resources allocated to each research project, normalized using mean and standard deviation by grant type as a proxy of project scale. The variable *International co-authorships* controls for the geographical span of international collaboration. To build this measure, we calculated, for each publication generated by the ERC project, the share of co-authors affiliated with institutions outside the PI's country relative to the total number of coauthors. We, then, averaged these values to obtain a project-level indicator. Finally, the variable *Self-Reported Patents* captures the number of patents generated by the project and declared at the ERC by the PIs, normalized using the mean and standard deviation within our sample.

At the PI level, we controlled for their international mobility, expecting that projects with mobile PIs should have a broader geographic influence (Agrawal et al., 2006). We identified through Scopus the historic institutional affiliations of each PI, as reported in their articles published five years before the project initiation. The dummy *PI International Mobility* takes the value 1 for those PIs with affiliations in two or more countries and 0 otherwise. The variable *Number of PI Publications* is used to control for PI's heterogeneity in scientific productivity. To account for differences across scientific sectors, we took all publications available in Scopus for each PI in the five years preceding the grant and normalized them using the mean and standard deviation of all publications from all PIs of our sample within the same ERC subclass in the Life Science or Physical and Engineering domains.

Finally, we controlled for possible differences due to regional heterogeneities in inventive activities. We used information from OECD Regpat databases to calculate the variable *Regional Patent Activity,* which reports the normalized total number of patents in the NUTS 3 area of the host institution in the year of the project's grant.

5. Analyses

5.1. Descriptive statistics

Table 1 presents the descriptive statistics for our main variables across the 4977 research projects in our sample, and the 2740 projects that received at least one patent citation, excluding the 58 that received only self-citations. For this last group, we also include the pool of variables related to the geographical dimensions of patent citations (mainly *Mean Distance, Number of Countries, Patents Same Countries, Patents Within Europe, Patents Outside Europe*). Table 2 shows the correlations of the main variables.

Fig. 2 provides the distribution of ERC-funded research projects based on their H Index. The red line, representing the whole sample, reveals an asymmetric distribution, with most projects clustering around H-Index values of 8–10 and a few reaching high H-Index levels. The blue and green lines represent projects that have received patent citations or not. For lower H-Index values, the blue curve consistently lies above the green curve, suggesting that projects with lower H-Index values are less likely to attract attention from the industrial sector and are therefore less frequently cited. For higher values, this relationship reverses, and the green curve rises above the blue curve. This distribution supports the intuition that high-quality research projects contribute significantly to academic knowledge through scientific publications and have a greater chance of influencing technological developments in industry.

Fig. 3 illustrates the average time before an ERC research project

Table 1
Summary Statistics of the main variables.

All Projects					
Variable	Obs.	Mean	Std. Dev.	Min	Max
Project H-Index (log)	4977	2.29	0.59	0.00	3.93
FP7	4977	0.71	0.45	0.00	1.00
H2020	4977	0.29	0.45	0.00	1.00
Starting Grant	4977	0.50	0.50	0.00	1.00
Consolidator Grant	4977	0.15	0.36	0.00	1.00
Advanced Grant	4977	0.35	0.48	0.00	1.00
Project Budget (normalized)	4977	0.00	1.00	−4.66	3.18
International Co-authorship (share)	4977	0.29	0.19	0.00	1.00
Self-Reported Patents (normalized)	4977	0.00	1.00	−0.20	44.17
PI International Mobility	4977	0.80	0.40	0.00	1.00
Number of PI Publications (normalized)	4977	0.00	1.00	−0.87	17.92
Regional Patent Activity (normalized)	4977	0.00	1.00	−0.57	3.96
Projects Cited by at least one Patent					
Variable	Obs.	Mean	Std. Dev.	Min	Max
Project H-Index (log)	2740	2.48	0.48	0.00	3.93
FP7	2740	0.81	0.39	0.00	1.00
H2020	2740	0.19	0.39	0.00	1.00
Starting Grant	2740	0.49	0.50	0.00	1.00
Consolidator Grant	2740	0.11	0.32	0.00	1.00
Advanced Grant	2740	0.40	0.49	0.00	1.00
Project Budget (normalized)	2740	0.12	0.83	−4.20	3.18
International co-authorships (share)	2740	0.26	0.18	0.00	0.99
Self-Reported Patents (normalized)	2740	0.14	1.32	−0.20	44.17
PI International Mobility	2740	0.81	0.39	0.00	1.00
Number of PI Publications (normalized)	2740	0.14	1.06	−0.87	15.25
Regional Patent Activity (normalized)	2740	−0.01	0.97	−0.57	3.96
Mean Distance (log)	2740	8.24	1.27	−2.01	9.77
Number of Countries	2740	3.74	3.36	1.00	28.00
Patents Same Country	2740	1.37	3.74	0.00	59.43
Patents Within Europe	2740	3.79	8.96	0.00	156.52
Patents Outside Europe	2740	10.92	26.71	0.00	599.45

receives its first patent citation as a function of the project's H Index. As the H-Index increases, the time to the first patent citation decreases, suggesting that higher-quality research projects capture industrial interest more quickly, reinforcing its relevance to innovation.

Fig. 4 shows the mean number of applicants from different countries that cite ERC-funded scientific projects plotted against the projects' H Index. The trend is positively linear: as a project's H Index rises, so does the geographical diversity of its patent citations. This suggests that high-quality research attracts international industrial attention, highlighting its broad applicability across multiple regions.

5.2. Econometric estimates

To test our hypotheses, we combine a two-stage Heckman selection model with a survival analysis and a set of robustness tests, which are presented in the next section. In the first stage of the selection model, we estimated the probability that an ERC project receives at least one NPL patent citation, using a probit selection equation that includes all projects, PIs, and regional controls, fixed effects for ERC subclasses, and *IDR Variety* as an exclusion restriction. This variable captures the degree of boundary spanning orientation of the ERC research (Yegros-Yegros et al., 2015; D'Este et al., 2019), computed as the count of unique Scopus subject areas (i.e., scientific disciplines) represented across all backward citations in the publications of each ERC project (Munari et al., 2024). We suggest that, ceteris paribus, a higher level of interdisciplinarity increases the probability that an ERC project will be cited in the NPL section of a patent, as this type of research expands its accessible technological market by integrating insights from multiple fields of knowledge. Moreover, the geographic breadth of knowledge diffusion in the technology domain is primarily driven by the level of technological opportunity structures and the geography of patenting rather than by the disciplinary composition of the underlying scientific publication (Kwon et al., 2022; Wang and Zheng, 2023). Moreover, the existing research suggests that the disciplinary composition of scientific knowledge is not strongly geographically segmented in a way that systematically translates into the spatial dispersion of subsequent patent citations (Meyer and Persson, 1998; Wuestman et al., 2019). Combining these two reasonings, scientific interdisciplinarity is expected to affect the extensive margin of citation (whether a publication is cited by patents) rather than the conditional geographic spread of citations once the citation occurs. Thus, our exclusion restriction suggests that any direct relationship between scientific interdisciplinarity and patenting geographic diffusion outcomes is second order relative to the selection mechanism. The results of the first stage confirm a positive and significant (p-value <0.01) effect of the boundary-spanning nature of scientific research on the probability of receiving at least one patent citation (as shown in Table 3).

The inverse Mills ratio of this selection equation is then included in the second-stage models, where we assess the geographical diffusion of citations conditional on being cited at least once. With the *Mean Distance* and the origin of patent applicants for the categories *Patents Same Country*, *Patents Within Europe*, and *Patents Outside Europe* as our dependent variables, we employed an Ordinary Least Squares (OLS) regression with robust standard errors, given the presence of heteroskedasticity as suggested by the Breusch-Pagan test. With the *Number of Countries* as the dependent variable, we use a Zero-Truncated Negative Binomial Regression model, which accounts for the fact that the estimation sample is restricted to cited projects and therefore the dependent variable is mechanically greater than or equal to one. For this model, we exclude the inverse Mills ratio directly into the second stage as it is not the canonical Heckman two-step model. In linear outcome equations, the Heckman correction has a well known structure under joint normality assumptions. For a nonlinear count outcome, the validity of simply including this term as an additional regressor is not automatic and requires additional assumptions. Finally, to explore citation timing and identify factors that accelerate or delay the impact of research on innovation, we employed a survival analysis using a Cox regression model, where the dependent variable is the probability that the research project will receive its first patent citation.

Models 1 and 2 in Table 4 present the results of the OLS regression with the *Mean Distance* between the location of the research institution and the locations of the citing patents as the dependent variable. Model 1 includes only the control variables, while Model 2 adds the *Project H-Index*. Its coefficient is positive and significant (p-value<0.01), supporting our hypothesis that higher-quality research attracts attention from inventors operating in more geographically distant regions. Among the controls, the variable capturing the international composition of co-authors has a positive and significant coefficient (p-value<0.01), suggesting that projects with international teams are more likely to be cited by geographically distant patents, due to the PIs' broader professional networks and increased visibility of their research.

Models 3 and 4 present the results of the Zero Truncated Negative Binomial Regression, where the dependent variable is the number of distinct countries represented by the applicants of patents citing research projects (*Number of Countries*), capturing the intensity of geographic diffusion conditional on a project receiving at least one patent citation. Once again, *Project H-Index* is positive and significant (p-value<0.01), indicating that higher-quality research significantly enhances the international diffusion of scientific ideas, attracting citations from a more diverse set of geographic locations. We also find consistent

Table 2
Correlation matrix of the main variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Mean Distance (log)	1.00								
(2) Number of Countries	0.16*	1.00							
(3) Patents Same Country	−0.07*	0.48*	1.00						
(4) Patents Within Europe	0.01	0.68*	0.41*	1.00					
(5) Patents Outside Europe	0.14*	0.69*	0.41*	0.64*	1.00				
(6) Project H-Index (log)	0.14*	0.39*	0.16*	0.23*	0.26*	1.00			
(7) FP7	0.08*	0.20*	0.10*	0.12*	0.13*	0.06*	1.00		
(8) H2020	−0.08*	−0.20*	−0.10*	−0.12*	−0.13*	−0.06*	−1.00	1.00	
(9) Starting Grant	0.02	0.00	0.00	−0.01	0.00	−0.15*	0.11*	−0.11*	1.00
(10) Consolidator Grant	−0.05	−0.12*	−0.06*	−0.08*	−0.09*	−0.03	−0.36*	0.36*	−0.35*
(11) Advanced Grant	0.01	0.08*	0.04	0.06*	0.06*	0.18*	0.12*	−0.12*	−0.79*
(12) Project Budget (normalized)	−0.03	0.01	0.01	0.01	−0.01	0.04	−0.12*	0.12*	0.01
(13) International co-authorships (share)	0.08*	0.02	−0.04	0.02	0.03	0.12*	0.01	−0.01	0.03
(14) Self-Reported Patents (normalized)	0.00	0.19*	0.15*	0.11*	0.13*	0.04	0.07*	−0.07*	−0.01
(15) PI International Mobility	0.07*	0.09*	0.03	0.04	0.06*	0.11*	−0.01	0.01	0.13*
(16) Number of PI publications (normalized)	0.04	0.15*	0.06*	0.08*	0.08*	0.26*	−0.04	0.04	−0.37*
(17) Regional Patent Activity (normalized)	−0.01	−0.01	0.03	0.00	−0.01	−0.13*	−0.03	0.03	0.04

Variables	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(10) Consolidator Grant	1.00							
(11) Advanced Grant	−0.29*	1.00						
(12) Project Budget (normalized)	0.03	−0.02	1.00					
(13) International co-authorships (share)	0.00	−0.03	−0.03	1.00				
(14) Self-Reported Patents (normalized)	−0.03	0.03	0.03	−0.05	1.00			
(15) PI International Mobility	−0.03	−0.11*	0.07*	0.17*	0.02	1.00		
(16) Number of PI publications (normalized)	−0.02	0.39*	0.02	−0.04	0.07*	0.12*	1.00	
(17) Regional Patent Activity (normalized)	0.01	−0.05*	0.01	−0.05*	0.01	−0.02	−0.09*	1.00

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

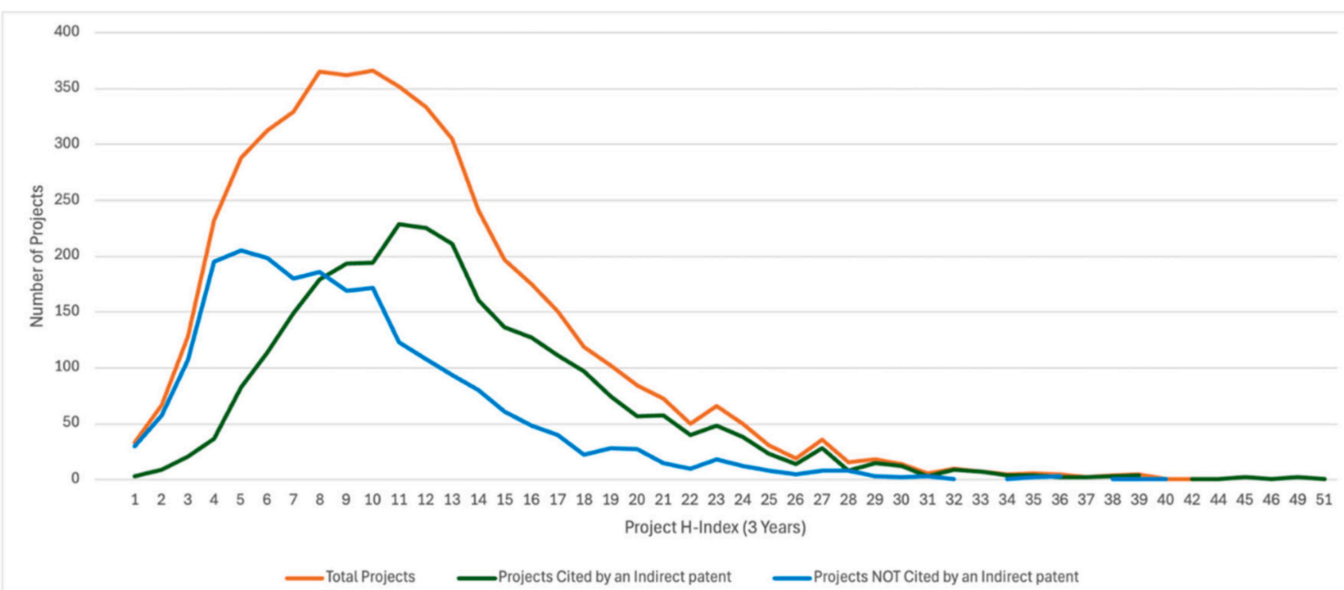

Fig. 2. Number of ERC Research Projects by H-Index (2008–2016).

effects regarding directionality and significance, which are comparable to those obtained in Models 1 and 2. Similarly, the coefficient for *Regional Patent Activity* is positive and significant (p-value<0.01), suggesting that research conducted in highly innovative regions is more likely to influence patents developed further away, possibly due to their global reputation and connectivity. Moreover, the positive and significant coefficients of the *Number of PI Publications* (p-value<0.01) and *Self-Reported Patents* (p-value<0.01) suggest that the PIs' overall scientific productivity and the presence of patents as project outputs also contribute to increasing the international diffusion of their results in industrial applications.

Models 5–10 of Table 4 consider the breadth of the geographical spillover, focusing on different areas, and always estimating first a model with only the controls and then a model with *Project H-Index*. Models 5 and 6 show the impact of high-quality research on patents mainly generated by applicants in the same country of the PI's institution. Models 7 and 8 focus on patents originating in European countries different from the PI's institution, and Models 9 and 10 on patents outside Europe.

In all cases, the *Project H-Index* coefficient is positive and statistically significant (*p*-value<0.01), pointing to the impact of high-quality research ideas. Still, their magnitude differs, reflecting varying levels of geographic influence. In Model 6 the coefficient of the variable *Patents Same Country* is 1.412, suggesting that the impact on domestic

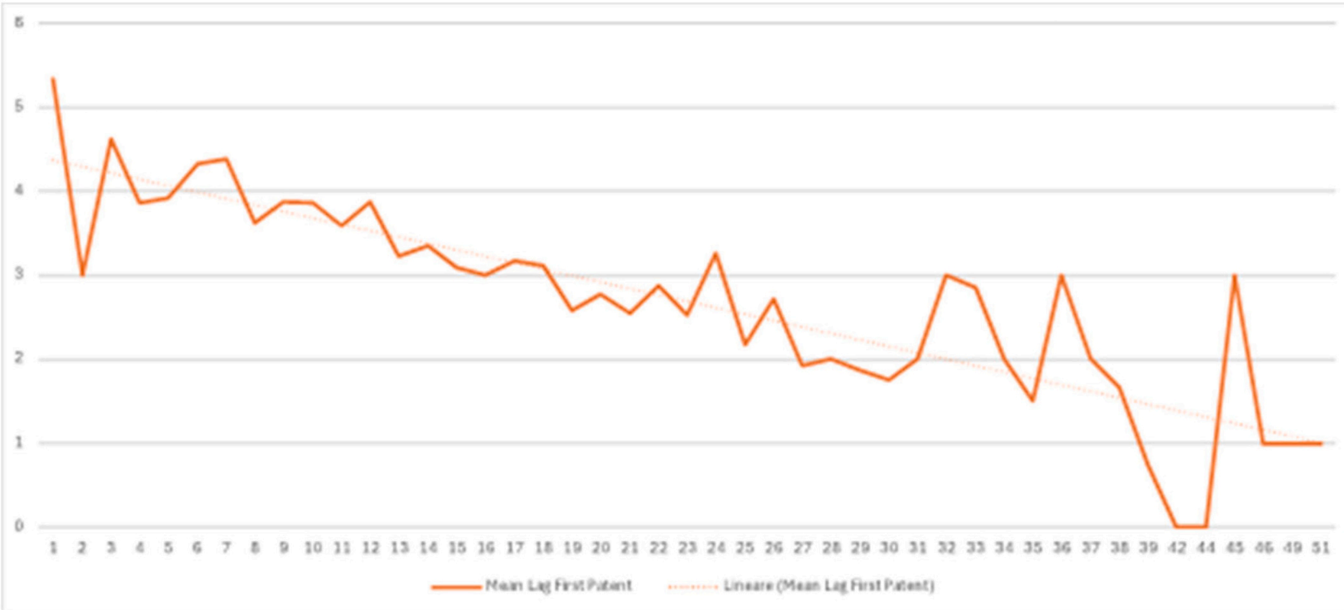

Fig. 3. Mean time for ERC Research Projects to receive the first patent citation by H-Index (2008–2016).

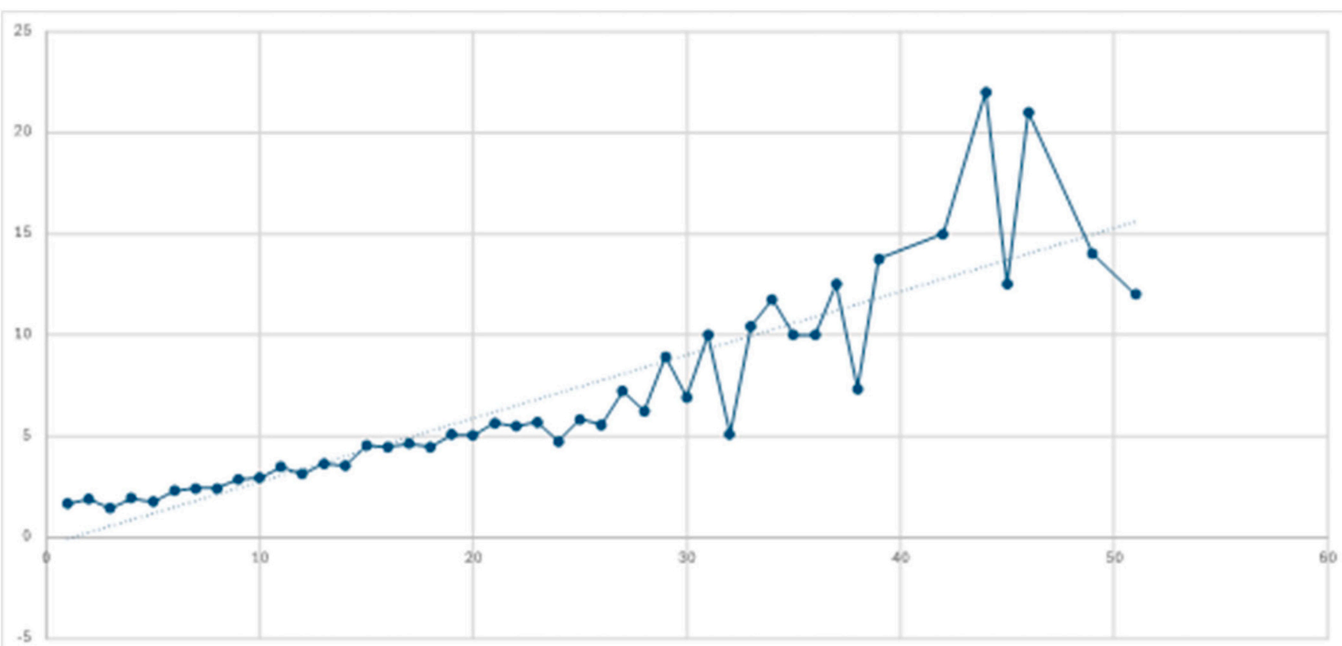

Fig. 4. Mean Number of Applicant's Countries by H-Index (2008–2016).

technological innovation could be due to proximity effects, easier knowledge transfer, and a better alignment with local industrial needs. However, the relatively small magnitude of this coefficient indicates that the influence of high-quality research is not heavily concentrated in the domestic landscape. For patent applicants within Europe (but outside the country of origin), the coefficient is 4.705 (Model 8). This larger coefficient suggests that high-quality research projects are well-integrated into the European innovation ecosystem, promoting regional collaboration and the adoption of scientific knowledge across European borders.

The strongest association, however, is observed for patent applicants from countries outside Europe, where the *Project H-Index* coefficient is 16.703, showing that high-quality research has a distant impact. The increasing magnitude of the coefficients across the three categories (from *Patents Same Country* to *Patents Outside Europe*) indicates that high-quality research has a broader reach as we move from domestic to regional to global scales. The difference among these three coefficients is statistically significant, as suggested by the high value of the Wald test (322.576; p-value<0.01). We thus find that impactful scientific projects are not confined to their local innovation ecosystems but contribute significantly to global technological advancements.

Upon examining the various control variables, we find overall consistency with the previous estimates and additional insights, albeit with less robust single-coefficient estimates. The regional effect is confined to a single nation (*Regional Patent Activity* $p < 0.01$) but does not hold for Europe or the rest of the world (n.s.). The PIs' overall scientific

Table 3
First stage of the Heckman model.

	(M0)
	Project cited by at least one patent (Probit)
IDR Variety	2.498***
	(0.166)
H2020	0.148
	(0.374)
Starting Grant	−0.111
	(0.069)
Advanced Grant	0.107
	(0.072)
Project Budget	0.095***
	(0.026)
International co-authorships	−0.080
	(0.119)
Self-Reported Patents	0.565***
	(0.069)
PI International Mobility	0.057
	(0.053)
Number of PI Publications	0.137***
	(0.026)
Regional Patent Activity	0.002
	(0.021)
Constant	−2.723***
	(0.410)
Start Year of the Project	YES
ERC Panel	YES
Observations	4977
Pseudo R^2	0.305

Standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

productivity has a positive effect in Model 8 capturing citations by European Patents *(Number of PI Publications p*-value<0.1). The presence of patents as project outputs (*Self-Reported Patents* p-value<0.01) has a positive and significant influence at the national, European, and global levels.

In Table 5, we test H2, which focuses on the speed of the diffusion process from science to industry through a Cox model. A positive coefficient implies a higher hazard of patent citation and a shorter expected duration of the diffusion process. In line with our second hypothesis, we find that *Project H-Index* has a positive and significant effect (*p*-value<0.01). Higher-quality research has a higher likelihood of receiving citations faster than lower-quality research, highlighting the critical role of scientific quality in accelerating the diffusion of research into technological applications. The analysis also shows that *Project Budget*, projects generating their own patents (*Self-Reported Patents*) and whose PI has a dense publication activity (*Number of PI Publications*) are more likely to be cited sooner (*p*-value<0.01), underscoring the importance of direct innovation outputs and the critical role of the PI's scientific output in enhancing the visibility and impact of a research project within technological and industrial domains. None of the other controls shows any significant effect.

We now turn to test the competing hypotheses (H3a-b and H4a-b) related to analyzing the institutional nature of the users of scientific results, distinguishing between private and public inventors (Table 6). Regarding H3a-b, in Models 14 and 16, we find that high-quality science tends to reach a more geographically distant audience when the citing patents are generated by universities (0.512, *p*-value<0.01) rather than corporations (0.357, p-value<0.01). However, the differences are not statistically significant according to the *Z*-test. In Models 18 and 20, we analyze the number of distinct countries of the applicants of patents citing research projects. In this case, the impact is higher for corporations (1.056, p-value<0.01), when compared to universities (1.045, p-value<0.01). Also in this case, the Z-test is not significant.

A slightly different scenario emerges when considering the heterogeneity of citing patents countries (Models 21–32 of Table 6). In this case, high-quality research seems to inspire more domestic patents when the applicant is a university (0.819, *p*-value<0.01) rather than a corporation (0.648, p-value<0.01), suggesting that university-generated knowledge tends to be more deeply embedded within national innovation ecosystems. In contrast, corporate patents exhibit higher coefficients when considering European and Global patents (respectively 2.877 and 10.930 for corporations and 2.086 and 7.423 for universities, *p*-values<0.01), suggesting a broader international diffusion of corporate-generated knowledge. The Wald test confirms a statistically significant difference between the two groups when European and global patents are considered (3.370, p-value 0.1 and 8.039, p-value<0.01 respectively).

Finally, in Table 7, we test for H4a-b. The speed of diffusion of high-quality research is slightly higher for corporate-based patents (1.19, p-value<0.01) than for universities (1.15, p-value<0.01), but the difference is not statistically significant according to the *Z*-test. These results suggest that higher-quality projects are systematically more likely to be cited by patents, regardless of whether they are developed by companies or by universities.

The analyses of the different controls show results that partially confirm the estimates obtained in previous models. The presence of patents as outputs of the projects has a general positive effect on increasing the number of countries, the overall geographical breadth, and the speed of diffusion of the cited discoveries for corporations and universities. The international pool of co-authorships has a positive and significant effect on the mean distance, particularly for university citations, and on the number of countries, particularly in the case of corporate citations of patents. When analyzing the survival specification, its effect on the speed of diffusion is positive and significant only for corporate patents.

The PI's publications' productivity has a positive and significant effect on the number of countries for both corporate and university patents. It also shows a positive effect for corporate patents granted outside Europe, as well as for extra-European and global patents granted by a university. It also increases the speed of citations by both corporate and university patents. Taken together, these results do not present robust evidence of different effects of our PI level controls when comparing the geographical diffusion patterns of corporate and university citing patents. The same holds for the *Regional Patenting* control.

6. Additional analyses and robustness checks

In this section, we present a set of additional analyses conducted to assess the robustness of our results to different methods of identifying the origins of patent citations in our sample, as well as to alternative operationalizations of the explanatory variable that captures the scientific quality of research projects.

With reference to the first point, using citations included in patents without distinguishing who introduced them and when can underscore different dynamics. In particular, several studies have documented that a significant share of backward NPL citations during the patenting process is introduced by the patent examiners to reflect their relevance for patentability (Thompson, 2006; Kuhn et al., 2020; Azagra-Caro and Tur, 2018).While still relevant with respect to a general measure of the diffusion of a specific study, these citations could not be strictly interpreted as a sign of knowledge flows from the research project to the applicant or the inventor. To account for that, we retrieved the information available in PATSTAT's table "TLS212_CITATION: Citation", which includes details on both the type and the origin of citations

Table 4
Spatial influence of ERC-funded projects.

	(M1) Mean Distance (OLS)	(M2) Mean Distance (OLS)	(M3) Number of Countries (ZT-NBREG)	(M4) Number of Countries (ZT-NBREG)
Project H-Index		0.392***		1.022***
		(0.058)		(0.042)
H2020	0.751	0.715	0.583	0.380
	(0.517)	(0.513)	(0.572)	(0.517)
Starting Grant	−0.058	−0.043	−0.127	−0.038
	(0.093)	(0.093)	(0.087)	(0.075)
Advanced Grant	−0.051	−0.037	−0.117	−0.111
	(0.094)	(0.094)	(0.087)	(0.075)
Project Budget	0.006	0.016	0.056**	0.028
	(0.032)	(0.032)	(0.026)	(0.022)
International co-authorships	0.620***	0.473***	0.148	−0.159
	(0.142)	(0.143)	(0.126)	(0.105)
Self-Reported Patents	−0.018	−0.006	0.120***	0.082***
	(0.019)	(0.019)	(0.020)	(0.014)
PI International Mobility	0.129**	0.105	0.172***	0.078
	(0.064)	(0.064)	(0.057)	(0.048)
Number of PI Publications	0.009	−0.005	0.176***	0.051***
	(0.028)	(0.028)	(0.024)	(0.019)
Regional Patent Activity	0.003	0.016	−0.005	0.050***
	(0.025)	(0.025)	(0.022)	(0.018)
Inverse Mills ratio	−0.202	0.134		
	(0.124)	(0.133)		
Constant	7.313***	5.712***	−2.299***	−4.574***
	(0.648)	(0.686)	(0.699)	(0.648)
Ln(alpha)			−0.437***	−1.131***
			(0.05)	(0.07)
Start Year of the Project	YES	YES	YES	YES
ERC Panel	YES	YES	YES	YES
Observations	2740	2740	2740	2740
R-squared	0.053	0.068	–	–
Pseudo R^2	–	–	0.053	0.100

	(M5) Patent Same Country (weight) (OLS)	(M6) Patent Same Country (weight) (OLS)	(M7) Patent within Europe (weight) (OLS)	(M8) Patent within Europe (weight) (OLS)	(M9) Patent Outside Europe (weight) (OLS)	(M10) Patent Outside Europe (weight) (OLS)
Project H-Index		1.412***		4.705***		16.703***
		(0.170)		(0.399)		(1.162)
H2020	0.310	0.177	0.227	−0.216	1.015	−0.558
	(1.512)	(1.493)	(3.586)	(3.498)	(10.572)	(10.192)
Starting Grant	−0.076	−0.023	−0.374	−0.197	−1.701	−1.073
	(0.273)	(0.270)	(0.648)	(0.633)	(1.911)	(1.843)
Advanced Grant	−0.143	−0.093	−0.465	−0.299	−0.771	−0.180
	(0.276)	(0.273)	(0.655)	(0.639)	(1.93)	(1.861)
Project Budget	0.070	0.109	0.136	0.266	0.931	1.393**
	(0.093)	(0.092)	(0.220)	(0.215)	(0.649)	(0.626)
International co-authorships	−0.607	−1.135***	1.495	−0.262	5.427*	−0.812
	(0.417)	(0.416)	(0.988)	(0.975)	(2.913)	(2.841)
Self-Reported Patents	0.317***	0.359***	0.506***	0.648***	1.984***	2.488***
	(0.056)	(0.056)	(0.133)	(0.130)	(0.393)	(0.380)
PI International Mobility	0.067	−0.019	0.146	−0.142	1.737	0.717
	(0.189)	(0.187)	(0.447)	(0.437)	(1.319)	(1.273)
Number of PI Publications	0.129	0.076	0.703***	0.529***	1.48**	0.862
	(0.083)	(0.082)	(0.197)	(0.193)	(0.581)	(0.562)
Regional Patent Activity	0.148**	0.197***	0.053	0.217	−0.283	0.297
	(0.073)	(0.073)	(0.174)	(0.170)	(0.512)	(0.496)
Inverse Mills ratio	−1.291***	−0.080	−2.773***	1.261	−5.875**	8.447***
	(0.363)	(0.387)	(0.862)	(0.908)	(2.541)	(2.645)
Constant	1.886	−3.877*	2.384	−16.822***	0.166	−68.014***
	(1.896)	(1.997)	(4.498)	(4.679)	(13.258)	(13.633)
Start Year of the Project	YES	YES	YES	YES	YES	YES
ERC Panel	YES	YES	YES	YES	YES	YES
Observations	2740	2740	2740	2740	2740	2740
R-squared	0.068	0.091	0.089	0.134	0.108	0.172
Wald test (M6-M8-M10)	322.576***					

Standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
Survival analysis.

	Likelihood to citation	
	(M11)	(M12)
	Coeff.	Coeff.
Project H-Index		1.07***
		(0.05)
H2020	−0.01	−0.01
	(0.41)	(0.41)
Starting Grant	−0.12	−0.02
	(0.08)	(0.08)
Advanced Grant	0.10	0.06
	(0.08)	(0.08)
Project Budget	0.09***	0.09***
	(0.02)	(0.02)
International co-authorships	0.06	−0.34***
	(0.11)	(0.12)
Self-Reported Patents	0.09***	0.08***
	(0.01)	(0.01)
PI International Mobility	0.09*	−0.01
	(0.05)	(0.05)
Number of PI Publications	0.16***	0.09***
	(0.02)	(0.02)
Regional Patent Activity	−0.02	0.02
	(0.02)	(0.02)
Start Year of the project	YES	YES
ERC Panel	YES	YES
Observations	4977	4977
Likelihood Ratio (LR) Test		644.71***

Standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

contained in a patent document.[5]

To further validate our results, we used this additional information to repeat all the analyses, focusing only on applicant-added citations (and excluding examiner-added ones), which more accurately proxy knowledge flows than those provided by examiners. We report the results of these additional analyses in the Supplementary Materials Tables A1 to A4. They demonstrate that excluding examiner-added citations from the analysis does not impact our main results and continues to reveal a positive and statistically significant association between a project's scientific impact and the geographical breadth of the technological inventions that build upon it. Across specifications, the magnitude and direction of the main effects remain stable, confirming that findings are not driven by examiner practices.

To address the same issue, we also performed additional analyses (reported in the Supplementary Materials Tables A5 and A6) to provide separate estimates for USPTO- and EPO-citing patents. This distinction is relevant because of institutional differences in citation practices between the two offices, due to the stricter disclosure requirements for applicants at the USPTO (the so-called "duty of candor") (Callaert et al., 2006; Alcácer et al., 2009).

We thus replicated our analyses in two different sub-samples: the sub-sample of projects cited at least once by a patent directly filed at the USPTO and the sub-sample of projects cited at least once by a patent directly filed at the EPO.[6] Our additional estimates show that across all models (both in the USPTO and the EPO subsample), the project H index is positive and strongly significant, thus reinforcing our key findings that projects producing more influential science are cited more distantly, independently of examination-specific practices.

We also run additional estimates to investigate alternative specifications for the construction of our key explanatory variable. In our main models, we chose to work at the project level and proposed a variation of the H-Index to consider the whole set of publication output. However, the measure can be sensitive to the extent number of publications associated with a given project. Therefore, it is a measure not independent to scale. While this is a common limitation of the H-index in general, it may be more relevant when it is not calculated at the individual level, but rather at the project level.

As an additional robustness check, we therefore replicated our estimates by adopting two alternative specifications of the dependent variable. In the first specification, to isolate the role of quality from project scale or panel-specific citation patterns, we constructed and used a new variable, the *Mean Citations per Publication* (Supplementary Materials Tables A7 to A10). This was computed as a project-level average, based on the number of citations each publication received within the first three years from its publication date, and then normalized by the average number of citations received by ERC projects starting in the same year and belonging to the same ERC panel (to account for differences in citation patterns across scientific disciplines). In the second specification, we focused on the quality of the journals in which the project publications appeared. Using Scopus data, we computed a variable, *Share Q1 publications,* for each project, measuring the share of its publications in Q1 journals (Supplementary Materials Tables A11to A14). Both alternatives, like all bibliometric indicators, have their specific limitations; however, they represent two distinct ways in which institutions measure publication quality for different purposes.

In the Supplementary Materials, we repeated all our analyses using these two alternative measures of project quality. Our result show that, while alternative proxies of science quality provide support for parts of the main narrative, the strength and precision of the associations vary across outcomes and specifications. In particular, we note that the results based on *Share Q1 publications* are generally weaker and less consistently estimated for the distance and timing dimensions, compared with those based on citation-based measures of quality. One possible explanation is that *Share Q1 publications* captures the prestige or quality of the journals in which project outputs are published, and therefore represents a broader and more indirect proxy of research quality than indicators such as the H-index or citation counts, which more directly reflect the impact and recognition of the research itself. As a result, the Q1-based measure may be less closely linked to the mechanisms through which scientific outputs attract and diffuse technological attention.

7. Discussion

The results of our analysis provide evidence of the role of scientific quality in the spatial diffusion of novel ideals into industrial applications, across all models, considering simple spatial effects, a more fine-grained analysis of inter-country flows, and the timing of diffusion. Consistent with Hypothesis 1, projects characterized by a higher scientific impact are also associated with a broader geographical diffusion of technological inventions. Citing patents that build on the knowledge of such projects are more likely to originate from distant regions, beyond the host country, and even Europe. This supports the view that scientific

[5] In particular, we used the field "CITN_ORIGIN" from this table, which specifies the source and the procedural stage at which the citation was created. This field indicates whether a citation was introduced by the applicant or by the examiner, and whether it arose during the search, examination, or opposition phases. Specifically, we used the citation category "APP" in this field to identify citations introduced by applicants and to distinguish them from those added by examiners, which are coded differently according to the "Exchange of Patent Information" document published by the EPO. Patent-to-publication citations introduced by applicants represent the largest share of citations included in our sample. More precisely, they account for over 70% of all publication–patent links (8789 out of 12,474 cited publications). If we focus strictly on applicant-added citations, the number of ERC projects whose publications are cited by patents decreases to 2349 (out of 2740 cited projects).

[6] In order to identify the patent office where a citing patent was originally filed we referred to information available in Patstat in the APPLN_AUTH table (using the US vs EP code respectively).

Table 6
Spatial influence of ERC-funded projects by Type of Applicant (Corporations vs. Universities and Research Institutions).

	Mean Distance				Number of Countries			
	(M13)	(M14)	(M15)	(M16)	(M17)	(M18)	(M19)	(M20)
	Corporations *(OLS)*	Corporations *(OLS)*	Universities and Res Instit *(OLS)*	Universities and Res Instit *(OLS)*	Corporations *(Zero-Truncated Negative Binomial)*	Corporations *(Zero-Truncated Negative Binomial)*	Universities and Res Instit *(Zero-Truncated Negative Binomial)*	Universities and Res Instit *(Zero-Truncated Negative Binomial)*
Project H-Index		0.357***		0.512***		1.056***		1.045***
		(0.074)		(0.074)		(0.064)		(0.049)
H2020	0.705	0.533	0.821	0.772	0.646	−0.011	1.082	0.876
	(0.947)	(0.943)	(0.600)	(0.594)	(1.235)	(1.137)	(0.784)	(0.740)
Starting Grant	0.058	0.074	−0.157	−0.141	−0.153	−0.052	−0.100	−0.025
	(0.122)	(0.122)	(0.121)	(0.120)	(0.132)	(0.116)	(0.107)	(0.093)
Advanced Grant	0.094	0.111	−0.137	−0.127	−0.154	−0.133	−0.071	−0.076
	(0.123)	(0.122)	(0.123)	(0.122)	(0.132)	(0.116)	(0.107)	(0.093)
Project Budget	0.049	0.057	0.011	0.024	0.064*	0.031	0.054*	0.025
	(0.039)	(0.039)	(0.040)	(0.040)	(0.038)	(0.032)	(0.030)	(0.025)
International co-authorships	0.596***	0.430**	0.676***	0.518***	0.260	−0.136	0.204	−0.114
	(0.182)	(0.185)	(0.180)	(0.179)	(0.185)	(0.158)	(0.141)	(0.118)
Self-Reported Patents	0.029	0.038*	−0.053**	−0.038*	0.116***	0.080***	0.093***	0.058***
	(0.021)	(0.021)	(0.023)	(0.022)	(0.025)	(0.018)	(0.020)	(0.013)
PI International Mobility	0.046	0.033	0.099	0.068	0.175**	0.104	0.174***	0.078
	(0.082)	(0.081)	(0.082)	(0.081)	(0.086)	(0.075)	(0.065)	(0.055)
Number of PI Publications	−0.041	−0.054*	0.005	−0.014	0.184***	0.060**	0.154***	0.030
	(0.033)	(0.033)	(0.035)	(0.034)	(0.033)	(0.027)	(0.025)	(0.021)
Regional Patent Activity	0.101***	0.113***	−0.006	0.016	0.005	0.063**	−0.014	0.038*
	(0.032)	(0.031)	(0.032)	(0.032)	(0.032)	(0.027)	(0.025)	(0.021)
Inverse Mills Ratio	0.002	0.305*	−0.343**	0.079				
	(0.157)	(0.168)	(0.161)	(0.171)				
Constant	7.417***	6.144***	6.898***	4.810***	−2.924**	−4.745***	−3.913***	−6.216***
	(1.097)	(1.122)	(0.806)	(0.854)	(1.420)	(1.328)	(1.088)	(1.047)
Ln(alpha)	–	–	–	–	−0.004	−0.720***	−0.607***	−1.478***
	–	–	–	–	(0.09)	(0.13)	(0.10)	(0.18)
Start Year of the Project	YES	YES	YES	YES	YES	YES	YES	YES
ERC Panel	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2021	2021	2321	2321	2021	2021	2321	2321
R-squared	0.048	0.059	0.057	0.076	–	–	–	–
Pseudo R^2	–	–	–	–	0.053	0.091	0.054	0.106
Z test |Mean Distance (M14-M16)	1.475							
Z test |Number of Countries (M18-M20)					-0.132			

	Heterogeneity of Countries											
	Panel A: Corporations						Panel B: Universities and Research Institutions					
	(M21)	(M22)	(M23)	(M24)	(M25)	(M26)	(M27)	(M28)	(M29)	(M30)	(M31)	(M32)
	Patents Same Country *(Weight)* *(OLS)*	Patents Same Country *(Weight)* *(OLS)*	Patents Within Europe *(Weight)* *(OLS)*	Patents Within Europe *(Weight)* *(OLS)*	Patents Outside Europe *(Weight)* *(OLS)*	Patents Outside Europe *(Weight)* *(OLS)*	Patents Same Country *(Weight)* *(OLS)*	Patents Same Country *(Weight)* *(OLS)*	Patents Within Europe *(Weight)* *(OLS)*	Patents Within Europe *(Weight)* *(OLS)*	Patents Outside Europe *(Weight)* *(OLS)*	Patents Outside Europe *(Weight)* *(OLS)*
Project H-Index		0.648***		2.877***		10.930***		0.819***		2.086***		7.423***
		(0.167)		(0.385)		(1.124)		(0.112)		(0.192)		(0.516)
H2020	0.432	0.119	−0.903	−2.294	1.561	−3.722	0.191	0.113	0.638	0.439	0.850	0.144
	(2.116)	(2.111)	(4.948)	(4.885)	(14.563)	(14.242)	(0.907)	(0.897)	(1.570)	(1.531)	(4.298)	(4.117)
Starting Grant	−0.026	0.005	−0.367	−0.233	−1.283	−0.776	−0.017	0.009	−0.062	0.004	−0.492	−0.258
	(0.273)	(0.272)	(0.638)	(0.630)	(1.878)	(1.836)	(0.183)	(0.181)	(0.317)	(0.309)	(0.869)	(0.832)

(*continued on next page*)

Table 6 (*continued*)

	Heterogeneity of Countries											
	Panel A: Corporations						Panel B: Universities and Research Institutions					
	(M21)	(M22)	(M23)	(M24)	(M25)	(M26)	(M27)	(M28)	(M29)	(M30)	(M31)	(M32)
	Patents Same Country *(Weight)* *(OLS)*	Patents Same Country *(Weight)* *(OLS)*	Patents Within Europe *(Weight)* *(OLS)*	Patents Within Europe *(Weight)* *(OLS)*	Patents Outside Europe *(Weight)* *(OLS)*	Patents Outside Europe *(Weight)* *(OLS)*	Patents Same Country *(Weight)* *(OLS)*	Patents Same Country *(Weight)* *(OLS)*	Patents Within Europe *(Weight)* *(OLS)*	Patents Within Europe *(Weight)* *(OLS)*	Patents Outside Europe *(Weight)* *(OLS)*	Patents Outside Europe *(Weight)* *(OLS)*
Advanced Grant	−0.093	−0.063	−0.474	−0.341	−0.337	0.168	−0.036	−0.021	−0.097	−0.057	−0.294	−0.152
	(0.274)	(0.274)	(0.642)	(0.633)	(1.888)	(1.846)	(0.186)	(0.184)	(0.322)	(0.314)	(0.881)	(0.843)
Project Budget	0.012	0.026	0.083	0.144	0.569	0.803	0.032	0.053	0.066	0.119	0.344	0.534*
	(0.087)	(0.087)	(0.204)	(0.202)	(0.602)	(0.589)	(0.061)	(0.060)	(0.106)	(0.103)	(0.289)	(0.277)
International co-authorships	−0.125	−0.426	0.555	−0.781	4.174	−0.902	−0.621**	−0.875***	1.079**	0.432	2.126*	−0.175
	(0.408)	(0.414)	(0.953)	(0.957)	(2.805)	(2.791)	(0.272)	(0.271)	(0.470)	(0.463)	(1.288)	(1.244)
Self-Reported Patents	0.071	0.088*	0.222**	0.296***	0.962***	1.244***	0.193***	0.216***	0.196***	0.256***	0.734***	0.948***
	(0.047)	(0.047)	(0.109)	(0.108)	(0.322)	(0.316)	(0.034)	(0.034)	(0.059)	(0.058)	(0.162)	(0.156)
PI International Mobility	0.073	0.049	0.338	0.232	0.996	0.594	0.034	−0.016	−0.101	−0.227	0.942	0.493
	(0.183)	(0.182)	(0.428)	(0.422)	(1.259)	(1.231)	(0.123)	(0.122)	(0.214)	(0.209)	(0.585)	(0.561)
Number of PI Publications	0.044	0.020	0.415**	0.310*	0.232	−0.164	0.059	0.028	0.231**	0.152*	0.881***	0.600**
	(0.074)	(0.074)	(0.172)	(0.170)	(0.507)	(0.497)	(0.052)	(0.052)	(0.090)	(0.089)	(0.248)	(0.238)
Regional Patent Activity	−0.035	−0.014	0.141	0.233	−0.329	0.020	0.190***	0.225***	−0.066	0.023	−0.115	0.202
	(0.070)	(0.070)	(0.165)	(0.163)	(0.485)	(0.475)	(0.048)	(0.048)	(0.083)	(0.082)	(0.228)	(0.219)
Inverse Mills ratio	−0.914***	−0.365	−1.721**	0.717	−3.946	5.320**	−0.616**	0.059	−1.705***	0.016	−2.773**	3.352***
	(0.350)	(0.376)	(0.818)	(0.871)	(2.408)	(2.539)	(0.244)	(0.258)	(0.422)	(0.441)	(1.156)	(1.186)
Constant	1.042	−1.269	2.891	−7.369	1.070	−37.911**	1.152	−2.188*	1.119	−7.390***	−0.743	−31.022***
	(2.450)	(2.513)	(5.729)	(5.816)	(16.861)	(16.957)	(1.219)	(1.289)	(2.110)	(2.202)	(5.776)	(5.919)
Start Year of the Project	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
ERC Panel	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2021	2021	2021	2021	2021	2021	2321	2321	2321	2321	2321	2321
R-squared	0.031	0.038	0.058	0.083	0.088	0.130	0.064	0.085	0.108	0.152	0.106	0.180
Wald test | Same Country (M22-M28)	0.724											
Wald test | Within Europe (M24-M30)	3.370*											
Wald test | Outside Europe (M26-M32)	8.039**											

Standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7
Survival analysis by Type of applicant (Corporations versus University and Research Institution Patents).

	Likelihood to citation			
	Panel A: Corporations		Panel B: Universities and Research Institutions	
	(M33)	(M34)	(M35)	(M36)
	Coeff.	Coeff.	Coeff.	Coeff.
Project H-Index		1.19***		1.15***
		(0.05)		(0.05)
H2020	0.73	0.75	−0.33	−0.40
	(0.71)	(0.71)	(0.42)	(0.42)
Starting Grant	−0.15	−0.05	−0.09	0.04
	(0.09)	(0.09)	(0.08)	(0.08)
Advanced Grant	0.04	−0.02	0.10	0.08
	(0.09)	(0.09)	(0.08)	(0.08)
Project Budget	0.09***	0.09***	0.10***	0.11***
	(0.03)	(0.03)	(0.03)	(0.03)
International co-authorships	−0.06	−0.52***	0.13	−0.29**
	(0.13)	(0.14)	(0.12)	(0.13)
Self-Reported Patents	0.09***	0.08***	0.10***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)
PI International Mobility	0.13**	0.01	0.09	−0.03
	(0.06)	(0.06)	(0.06)	(0.06)
Number of PI Publications	0.18***	0.10***	0.17***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)
Regional Patent Activity	−0.03	0.02	−0.01	0.04
	(0.02)	(0.02)	(0.02)	(0.02)
Start Year of the project	YES	YES	YES	YES
ERC Panel	YES	YES	YES	YES
Observations	4977	4977	2321	2321
Likelihood Ratio (LR) Test		559.32***		606.17***
Z test (M34-M36)	-0.53			

Standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

success can play a decisive role in shaping knowledge paths in the technological domain, as foundational research tends to address universal questions and produce insights that are globally relevant.

Our results contribute to the extensive body of literature, beginning with Jaffe et al. (Jaffe et al., 1993), by focusing on the geographic reach of knowledge spillovers and providing new evidence-based testing a set of specific theory driven hypotheses. The findings suggest that high-quality research can overcome geographical constraints, attracting the attention of inventors operating in distant countries (Fleming and Sorenson, 2004; Yegros-Yegros et al., 2015; Bickard and Marx, 2019). We confirm Nagar et al.'s (Nagar et al., 2024) analysis, which compared ERC-funded and non-ERC-funded projects, documenting that high-quality publications were more likely to be cited by international patents, and we expand it by providing evidence and understanding on how high-quality ERC projects lead to more geographically dispersed patents.

Spatial effects are only one part of diffusion processes. Another important aspect is the time it takes for science to be embedded in innovative solutions, especially when technologically intensive industries face greater pressures to sustain competitive positions through new products (Giachetti and Marchi, 2017), and several markets significantly reward first movers (Arora et al., 2023). Our study offers a specific and original contribution showing that high-quality science is cited more rapidly by technological inventions. The breadth and speed of discovery diffusion indirectly represent a more global and interconnected world with increased competitive opportunities beyond the boundaries of the funding agency, challenging National Innovation systems perspectives, or more recent perspectives based on innovation ecosystems. When science-related public goods can travel easily and quickly across boundaries, the incentives to invest locally may decrease, and the attention may shift to creating greater absorptive capacity to appropriate the investments in discoveries made by others. The introduction of direct and indirect limitations to the diffusion of ideas, or more favorable conditions for proximal diffusion, could also be alternative mechanisms to maximize local benefits. At a more conceptual level, our evidence, along with many recent studies on how science translates into innovation, calls for a more thorough cross-boundary understanding of the classical Arrow's paradox and its potential effects on global investments in science.

For any given level of scientific quality, our results also provide some preliminary evidence of the role of different factors in supporting these dynamics: the project, the PI, and regional differences. We show that projects generating scientific output (in the form of publications) and technological outputs (in the form of patents) diffuse more broadly and faster. This might suggest a simultaneous effect of different information channels, or a reinforcing signal on the quality of ideas provided by combining the two outputs. Future research could help disentangle these two components. People are one of the key components of knowledge transfer (Argote and Ingram, 2000; Franzoni et al., 2018). In our analyses, those scientists who were more mobile before securing the ERC grants contributed more to the breadth and speed of diffusion of project results into innovative solutions. It might reflect a general reputation effect or specific long-term relationship-building efforts. Our inclusion of the PI's general publication productivity and the positive effect of the international pool of co-authorships in some of our models seems to provide support for the reputation effect. In a world where information circulates freely and everyone can choose based on knowledge quality relationships may still be useful to accelerate the process or might be critical to select among possible different alternatives. Future research using more detailed data on individual networks could improve our understanding of the two dynamics and further focus on the relational component.

Our evidence on the role of the context where ideas are generated is less conclusive. While working in areas characterized by high levels of reputation and connectivity might offer an initial advantage, we find only limited evidence that research conducted in highly innovative regions is more likely to influence patents developed further away when measured by absolute distance. Still, these results do not replicate across models and do not appear to influence the diffusion speed.

We also offer an additional contribution by highlighting different adoption patterns depending on who is engaged in the innovation race. We contrasted theoretical perspectives based on the differences between academic and corporate environments in terms of knowledge generation and dissemination regimes (H3a and H4a) with more general models that focus on the efficient allocation of attention and effort (H3b and H4b). Our findings offer mixed support to the idea that high-quality science tends to reach a more geographically distant audience when the citing patents are developed by universities, as compared to corporations. While this is true when considering the number of countries, extra-European corporate patents tend to utilize high-quality research more often than extra-European academic patents. When examining diffusion speed, however, academic patents tend to absorb high-quality research more quickly than corporate patents. We interpret our results as evidence of differences between economic systems, market efficiencies, and the corresponding capabilities of companies to absorb new knowledge and transform it into innovation potential. As most corporate entities citing patents in our dataset hold US patents, our results align with Nagar et al.'s (Nagar et al., 2024) evidence of the greater absorptive capacity of the US ecosystem compared to the European one.

8. Conclusions

Our study has investigated the spatial diffusion of knowledge generated by publicly funded scientific research, focusing on the geographical reach and speed of technological diffusion stemming from ERC-funded projects. We offer a range of theoretical and empirical contributions.

First, we contribute to the literature on the economic impact of scientific research by adding a spatial dimension and exploring its conceptual and policy implications. Second, we extend the literature linking scientific publications to patent citations by geolocating their diffusion paths and providing novel insights into how high-quality science transcends geographical boundaries and influences technological advancements. Third, we highlight that the visibility of results in prestigious scientific outlets and the international collaboration network represent different, yet often intertwined, channels that facilitate the geographic spread of knowledge stemming from high-quality research projects into the technology domain. Fourth, we contrast and compare different theoretical expectations regarding the roles played by corporate and academic institutions in absorbing new scientific discoveries. Fifth, we introduce a novel measure of scientific quality that extends the notion of the H-index and applies it at the grant level.

Our contributions have direct implications for science policies and corporate decisions. They reinforce the notion that scientific activity is, by its nature, open, cumulative, and international. We show the importance of funding high-quality research and its economic impact beyond borders, providing evidence for the global relevance of science-based common goods. Greater resources available in different parts of the world to support scientific discoveries may be a blessing if there is an increasing effort to level the absorptive capacity of various ecosystems. However, it might become a curse if opportunistic behavior in public funding emerges as an alternative to exploit others' investments or if various forms of restriction in the circulation of ideas are introduced to raise barriers and preserve less efficient ecosystems.

Established companies and new start-ups face greater opportunities to tap into research funded by public institutions in other countries if they adopt an open-innovation mindset and invest in searching and parsing through scientific discoveries. In this process, they can focus their scouting efforts on high-quality and highly reputable knowledge sources to reduce search costs. These approaches can be critical to secure a competitive advantage when market cycles are shortening, and first-mover advantages in using scientific discoveries are more relevant.

While we have carefully constructed our dataset and the corresponding empirical analyses to ensure that our study offers theoretical, empirical, and practical implications, we acknowledge that it is also subject to various limitations that should be considered when interpreting its evidence. First, we do not include a comparable sample of scientific activities not funded by the ERC to control for any differences between the two groups, nor do we compare ERC grants with those supported by other EU research and innovation funding programs. While our focus was not on determining the ERC program's relative effectiveness compared to other financing forms, we were able to leverage the variety of projects supported by the ERC, spanning the entire spectrum of scientific disciplines and supporting researchers from a broad range of research institutions across Europe. Future work could consider comparing multiple programs, including those with a more applied focus, and incorporating a spatial dimension into the comparison.

We traced the effect of science on technology by linking publications to patents and we distinguished in our robustness tests those introduced by the inventors from those introduced by the examiners, given their well-known limitations (Thompson, 2006). From a technical perspective, we did not consider the in-text citations (Bryan et al., 2020). Given that they have been identified as a more representative measure of knowledge flows, however, our results might be conservative, rather than overscoring the geographical reach of research ideas. On a more conceptual level, discoveries can become innovations in many ways, and patents may never lead to new products. We therefore share the same limitations as other studies using a similar approach. Future works using different measures, such as research contracts or the analysis of new science-based companies, and extending the analysis to in-text citations could widen this perspective, including a geographical dimension.

Linking publications to patents presents several technical challenges, including name disambiguation, consolidation of multiple data sources, and localization of individuals and institutions. We paid great attention to all these aspects and developed several specific procedures, building on previous research. While we are confident that we have minimized inconsistencies, we cannot fully exclude the possibility that our data may still be prone to some.

Estimating the geographical impact and operationalizing this high-level construct poses specific challenges. We have attempted to address these difficulties by working at various conceptual levels and using different dependent variables, while reflecting on the meaning of distance, geographical variety, and country boundaries. Future work could further test their robustness and propose more efficient alternatives.

Evaluating the quality of scientific discoveries associated with complex, articulated, and long-term projects, such as those funded through the ERC programs, is not straightforward. We calculated an indicator based on an extension of the H-index and applied it to the entire project. We complemented this with other project-level indicators, such as field-weighted citation impact and journal prestige. However, further research is needed to assess the usefulness and representativeness of a project-level H-index and future research could explore more fine-grained measures of project quality, which may allow for a more precise assessment of how different dimensions of scientific quality shape the diffusion of knowledge into technological domains. Moreover, in our construction of the control variable for PI's scientific productivity, we normalized on our sample and not on the broader population of scientists, and we used high-level aggregations for the scientific fields. Future research could adopt more fine-grained measures in this respect.

Finally, our study uses a cross-sectional sample and therefore offers a correlational evidence of the effects that we examine. We share this limitation with other studies (e.g. Nagar et al. 2024) and all results should be interpreted accordingly. Nevertheless, we believe that the efforts taken in the sample selection, the different type of estimation techniques, and the various robustness tests contribute to offer evidence which could inspire future studies designed to overcome this limitation.

Overall, our results and limitations offer the opportunity to improve our understanding of how scientific excellence translates into industrial applications. The results support and extend previous studies and provide unique evidence for scholars, policymakers, and practitioners. The limitations suggest directions for future research and how it could further contribute to our understanding of how novel ideas travel through space and time.

CRediT authorship contribution statement

Laura Toschi: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Federico Munari:** Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **Maurizio Sobrero:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hérica Morais Righi:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Sebastiano Leonelli:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this paper the authors used ChatGPT in order to proofread the text. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Some of the authors (Federico Munari, Herica Morais Righi, Maurizio Sobrero, Laura Toschi) have been involved in the group of independent experts for the preparation of the report "Assessing the Influence of ERC-funded Research on Patented Inventions" for the European Research Council Executive Agency (ERCEA). The analyses, interpretation and findings of this article, including possible omissions or errors, are the sole responsibility of the Authors.

Acknowledgments

The authors have been involved in the group of independent experts for the preparation of the report "Assessing the Influence of ERC-funded Research on Patented Inventions" for the European Research Council Executive Agency (ERCEA), to which they are most grateful. The analyses, interpretation and findings of this article, including possible omissions or errors, are the sole responsibility of the Authors.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.respol.2026.105528.

Data availability

Data will be made available on request.

References

Agrawal, A., Cockburn, I., McHale, J., 2006. Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships. J. Econ. Geogr. 6 (5), 571–591. https://doi.org/10.1093/jeg/lbl016.

Ahmadpoor, M., Jones, B.F., 2017. The dual frontier: patented inventions and prior scientific advance. Science 357 (6351), 583–587. https://doi.org/10.1126/science.aam9527.

Alcácer, J., Gittelman, M., Sampat, B., 2009. Applicant and examiner citations in U.S. patents: an overview and analysis. Res. Policy 38 (2), 415–427. https://doi.org/10.1016/j.respol.2008.12.001.

Anderson, P., Tushman, M., 1990. Technological discontinuities and dominant designs: a cyclical model of technological change. Adm. Sci. Q. 35 (1), 604–633.

Argote, L., Ingram, P., 2000. Knowledge transfer: a basis for competitive advantage in firms. Organ. Behav. Hum. Decis. Process. 82 (1), 150–169. https://doi.org/10.1006/obhd.2000.2893.

Arora, A., Belenzon, S., Dionisi, B., 2023. First-mover advantage and the private value of public science. Res. Policy 52 (9), 104867. https://doi.org/10.1016/j.respol.2023.104867.

Arrow, Kenneth, 1962. Economic welfare and the allocation of resources for invention. In: The Rate and Direction of Inventive Activity: Economic and Social Factors. National Bureau of Economic Research. Princeton University Press, Princeton, NJ, pp. 609–626 [Online]. Available: https://www.nber.org/books-and-chapters/rate-and-direction-inventive-activity-economic-and-social-factors.

Arts, S., Melluso, N., Veugelers, R., Aristodemou, L., 2023. Publication text: code, data, and new measures. Zenodo. https://doi.org/10.5281/ZENODO.8283353.

Åstebro, T., Bazzazian, N., Braguinsky, S., 2012. Startups by recent university graduates and their faculty: implications for university entrepreneurship policy. Res. Policy 41 (4), 663–677. https://doi.org/10.1016/j.respol.2012.01.004.

Azagra-Caro, J.M., Tur, E.M., 2018. Examiner trust in applicants to the European patent office: country specificities. Scientometrics 117 (3), 1319–1348. https://doi.org/10.1007/s11192-018-2894-4.

Azoulay, P., Ding, W., Stuart, T., 2009. The impact of academic patenting on the rate, quality and direction of (public) research output. J. Ind. Econ. 57 (4), 637–676.

Azoulay, P., Graff Zivin, J.S., Manso, G., 2011. Incentives and creativity: evidence from the academic life sciences. RAND J. Econ. 42 (3), 527–554.

Azoulay, P., Graff Zivin, J.S., Li, D., Sampat, B.N., 2019. Public R&D Investments and private-sector patenting: Evidence from NIH funding rules. Rev. Econ. Stud. 86 (1), 117–152. https://doi.org/10.1093/restud/rdy034.

Baldini, N., Grimaldi, R., Sobrero, M., 2006. Institutional changes and the commercialization of academic knowledge: a study of Italian universities' patenting activities between 1965 and 2002. Res. Policy 35 (4), 518–532. https://doi.org/10.1016/j.respol.2006.01.004.

Belenzon, Sharon, Schankerman, M., 2013. Spreading the word: geography, policy, and knowledge spillovers. Rev. Econ. Stat. 95 (3), 884–903. https://doi.org/10.1162/REST_a_00334.

Bickard, Michaël, Marx, Matt, 2019. Bridging academia and industry: how geographic hubs connect university science and corporate technology. Manag. Sci. 66 (8), 3425–3443. https://doi.org/10.1287/mnsc.2019.3385.

Bijker, W.E., 1997. Of Bicycles, Bakelites, and Bulbs: Toward a Theory of Sociotechnical Change. MIT Press, Cambridge, MA [Online]. Available: https://mitpress.mit.edu/9780262522274/of-bicycles-bakelites-and-bulbs/.

Bryan, K.A., Ozcan, Y., Sampat, B., 2020. In-text patent citations: a user's guide. Res. Policy 49 (4), 103946. https://doi.org/10.1016/j.respol.2020.103946.

Callaert, J., Van Looy, B., Verbeek, A., Debackere, K., Thijs, B., 2006. Traces of prior art: an analysis of non-patent references found in patent documents. Scientometrics 69 (1), 3–20. https://doi.org/10.1007/s11192-006-0135-8.

Carpenter, M.P., Narin, F., 1983. Validation study: patent citations as indicators of science and foreign dependence. World Patent Inf. 5 (3), 180–185. https://doi.org/10.1016/0172-2190(83)90139-4.

Clarysse, B., Wright, M., Lockett, A., Van de Velde, E., Vohora, A., 2005. Spinning out new ventures: a typology of incubation strategies from European research institutions. J. Bus. Ventur. 20 (2), 183–216. https://doi.org/10.1016/j.jbusvent.2003.12.004.

Clarysse, B., Tartari, V., Salter, A., 2011. The impact of entrepreneurial capacity, experience and organizational support on academic entrepreneurship. Spec. Issue 30 Years Bayh-Dole Reassessing Acad. Entrep Res. Policy 40 (8), 1084–1093. https://doi.org/10.1016/j.respol.2011.05.010.

Colquitt, J.A., Long, D.M., Gentry, R.J., 2024. Syllabus share: a new metric for gauging journal status. J. Manag. Educ. 48 (1), 7–51. https://doi.org/10.1177/10525629231205484.

Dasgupta, P., David, P.A., 1994. Toward a new economics of science. Spec. Issue Honor Nathan Rosenb. 23 (5), 487–521. https://doi.org/10.1016/0048-7333(94)01002-1.

De Rassenfosse, G., Kozak, J., Seliger, F., 2019. Geocoding of worldwide patent data. Sci. Data 6 (1), 260. https://doi.org/10.1038/s41597-019-0264-6.

D'Este, P., Llopis, O., Rentocchini, F., Yegros, A., 2019. The relationship between interdisciplinarity and distinct modes of university-industry interaction. Res. Policy 48 (9), 103799. https://doi.org/10.1016/j.respol.2019.05.008.

Döring, T., Schnellenbach, J., 2006. What do we know about geographical knowledge spillovers and regional growth?: a survey of the literature. Reg. Stud. 40 (3), 375–395. https://doi.org/10.1080/00343400600632739.

Easley, C.E., Lee, Y.S., 2021. Do university entrepreneurship programs promote entrepreneurship? Strateg. Manag. J. 42 (4), 833–861. https://doi.org/10.1002/smj.3246.

Fleming, L., Greene, H., Li, G., Marx, M., Yao, D., 2019. Government-funded research increasingly fuels innovation. Science 364 (6446), 1139–1141. https://doi.org/10.1126/science.aaw2373.

Fleming, Lee, Sorenson, O., 2004. Science as a map in technological search., 25(8–9), pp.909–928. Strateg. Manag. J. 25 (8–9), 908–928. https://doi.org/10.1002/smj.384.

Fortunato, S., et al., 2018. Science of science. Science 359 (6379), eaao0185. https://doi.org/10.1126/science.aao0185.

Franzoni, C., Scellato, G., Stephan, P., 2018. Context factors and the performance of Mobile individuals in research teams. J. Manag. Stud. 55 (1), 27–59. https://doi.org/10.1111/joms.12279.

Giachetti, C., Marchi, G., 2017. Successive changes in leadership in the worldwide mobile phone industry: the role of windows of opportunity and firms' competitive action. Res. Policy 46 (2), 352–364. https://doi.org/10.1016/j.respol.2016.09.003.

Godin, B., 2017. Models of Innovation: The History of an Idea. MIT Press, Cambridge, MA [Online]. Available: https://mitpress.mit.edu/9780262035897/models-of-innovation/.

Gomez, C.J., Herman, A.C., Parigi, P., 2022. Leading countries in global science increasingly receive more citations than other countries doing similar research. Nat. Hum. Behav. 6, 919–929. https://doi.org/10.1038/s41562-022-01351-5.

Grimaldi, R., Kenney, M., Siegel, D.S., Wright, M., 2011. 30 years after Bayh–Dole: reassessing academic entrepreneurship. Spec. Issue 30 Years Bayh-Dole Reassessing Acad. Entrep Res. Policy 40 (8), 1045–1057. https://doi.org/10.1016/j.respol.2011.04.005.

Haddawy, P., Hassan, S.-U., Asghar, A., Amin, S., 2016. A comprehensive examination of the relation of three citation-based journal metrics to expert judgment of journal quality. J. Inf. Secur. 10 (1), 162–173. https://doi.org/10.1016/j.joi.2015.12.005.

Hargittai, I., 2002. The road to Stockholm: Nobel prizes, science, and scientists. Oxford University Press. https://doi.org/10.1093/oso/9780198509127.001.0001.

Henderson, M., Jaffe, A.B., Trajtenberg, M., 2005. Patent citations and the geography of knowledge spillovers: a reassessment: comment. Am. Econ. Rev. 95 (1), 461–464. https://doi.org/10.1257/0002828053828644.

Hicks, D., Wouters, P., Waltman, L., de Rijcke, S., Rafols, I., 2015. Bibliometrics: the Leiden manifesto for research metrics. Nature 520 (7548), 429–431. https://doi.org/10.1038/520429a.

Hirsch, J.E., 2005. An index to quantify an individual's scientific research output. Proc. Natl. Acad. Sci. 102 (46), 16569–16572. https://doi.org/10.1073/pnas.0507655102.

Jaffe, A.B., 1989. Real effects of academic research. Am. Econ. Rev. 79 (5), 957–970.

Jaffe, A.B., Trajtenberg, M., 1999. International knowledge flows evidence from patent citations. Econ. Innov. New Technol. 8 (1–2), 105–136. https://doi.org/10.1080/10438599900000006.

Jaffe, A.B., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations*. Q. J. Econ. 108 (3), 577–598. https://doi.org/10.2307/2118401.

Jefferson, O.A., et al., 2018. Mapping the global influence of published research on industry and innovation. Nat. Biotechnol. 36 (1), 31–39. https://doi.org/10.1038/nbt.4049.

Karney, C.F.F., 2013. Algorithms for geodesics. J. Geodyn. 87 (1), 43–55. https://doi.org/10.1007/s00190-012-0578-z.

Kline, S.J., 1985. Innovation is not a linear process. Res. Manag. 28 (4), 36–45. https://doi.org/10.1080/00345334.1985.11756910.

Kuhn, J., Younge, K., Marco, A., 2020. Patent citations reexamined. RAND J. Econ. 51 (1), 109–132. https://doi.org/10.1111/1756-2171.12307.

Kwon, H.-S., Lee, J., Lee, S., Oh, R., 2022. Knowledge spillovers and patent citations: trends in geographic localization, 1976–2015. Econ. Innov. New Technol. 31 (3), 123–147. https://doi.org/10.1080/10438599.2020.1787001.

Lerner, J., Stern, S. (Eds.), 2012. The Rate and Direction of Inventive Activity Revisited. University of Chicago Press. https://doi.org/10.7208/9780226473062.

Li, D., Azoulay, P., Sampat, B.N., 2017. The applied value of public investments in biomedical research. Science 356 (6333), 78–81. https://doi.org/10.1126/science.aal0010.

Marx, M., Fuegi, A., 2020. Reliance on science: worldwide front-page patent citations to scientific articles. Strateg. Manag. J. 41 (9), 1572–1594. https://doi.org/10.1002/smj.3145.

Mazzuccato, M., 2013. The Entrepreneurial State. Anthem Press.

Meoli, A., Fini, R., Sobrero, M., Wiklund, J., 2020. How entrepreneurial intentions influence entrepreneurial career choices: the moderating influence of social context. J. Bus. Ventur. 35 (3), 105982. https://doi.org/10.1016/j.jbusvent.2019.105982.

Meyer, M., Persson, O., 1998. Nanotechnology-interdisciplinarity, patterns of collaboration and differences in application. Scientometrics 42 (2), 195–205. https://doi.org/10.1007/BF02458355.

Moed, H.F., 2005. *Citation Analysis in Research Evaluation*, vol. 9. In: Information Science and Knowledge Management, 9. Springer, New York, NY. https://doi.org/10.1007/1-4020-3714-7 [Online]. Available:

Mowery, D.C., Nelson, R.R., Sampat, B.N., Ziedonis, A.A., 2004. Ivory Tower and Industrial Innovation: University-Industry Technology Transfer before and after the Bayh-Dole Act. Stanford University Press, Palo Alto, CA [Online]. Available: https://www.sup.org/books/business/ivory-tower-and-industrial-innovation.

Munari, F., Sobrero, M., Toschi, L., 2017. Financing technology transfer: assessment of university-oriented proof-of-concept programmes. Tech. Anal. Strat. Manag. 29 (2), 233–246. https://doi.org/10.1080/09537325.2016.1241874.

Munari, F., et al., 2024. Public research funding and science-based innovation: an analysis of ERC research grants, publications and patents. Res. Eval. https://doi.org/10.1093/reseval/rvae012.

Murata, Y., Nakajima, R., Okamoto, R., Tamura, R., 2014. Localized knowledge spillovers and patent citations: a distance-based approach. Rev. Econ. Stat. 96 (5), 967–985. https://doi.org/10.1162/REST_a_00422.

Nagar, J.P., Breschi, S., Fosfuri, A., 2024. ERC science and invention: does ERC break free from the EU paradox? Res. Policy 53 (8), 105038. https://doi.org/10.1016/j.respol.2024.105038.

NATIONAL BUREAU OF ECONOMIC RESEARCH, 1962. The Rate and Direction of Inventive Activity. Princeton University Press. Accessed: Oct. 18, 2024. [Online]. Available: http://www.jstor.org/stable/j.ctt183pshc.

National Science Board, 2024. Research and Development: U.S. Trends and International Comparisons. Science and Engineering Indicators. Alexandria, VA, NSB-2024-6. [Online]. Available: https://ncses.nsf.gov/pubs/nsb20246/.

Nelson, R.R., 1959. The simple economics of basic scientific research. J. Polit. Econ. 67 (3), 297–306.

Norrby, Erling, 2010. Nobel Prizes and Life Sciences. World Scientific Publishing Company, Singapore. https://doi.org/10.1142/7677 [Online]. Available:

OECD, 2024. Main Science and Technology Indicators. R&D and Related Highlights [Online]. Available: https://www.oecd.org/sti/msti2024march.pdf.

Perkmann, M., et al., 2013. Academic engagement and commercialisation: a review of the literature on university–industry relations. Res. Policy 42 (2), 423–442. https://doi.org/10.1016/j.respol.2012.09.007.

Pursell, Carol W., 2007. The Machine in America : A Social History of Technology, 2nd edition. Johns Hopkins University Press, Baltimore, NC.

Ribeiro, L.C., Kruss, G., Britto, G., Bernardes, A.T., da Motta e Albuquerque, E., 2014. A methodology for unveiling global innovation networks: patent citations as clues to cross border knowledge flows. Scientometrics 101 (1), 61–83. https://doi.org/10.1007/s11192-014-1351-2.

Rosenberg, N., 1983. Inside the Black Box. Cambridge University Press, Cambridge, UK. https://doi.org/10.1017/CBO9780511611940 [Online]. Available:

Royal Swedish Academy of Science, 2024. They cracked the code for proteins' amazing structures [Online]. Available: https://www.nobelprize.org/prizes/chemistry/2024/press-release/. (Accessed 19 October 2024).

Schoen, A., van Pottelsberghe de la Potterie, B., Henkel, J., 2014. Governance typology of universities' technology transfer processes. J. Technol. Transf. 39 (3), 435–453. https://doi.org/10.1007/s10961-012-9289-0.

Schot, J., Steinmueller, W.E., 2018. Three frames for innovation policy: R&D, systems of innovation and transformative change. Res. Policy 47 (9), 1554–1567. https://doi.org/10.1016/j.respol.2018.08.011.

Shannon, C.E., 1948. A mathematical theory of communication. Bell Syst. Tech. J. 27 (3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x.

Singh, J., Marx, M., 2013. Geographic constraints on knowledge spillovers: political borders vs. spatial proximity. Manag. Sci. 59 (9), 056–2078. https://doi.org/10.1287/mnsc.1120.1700.

Thompson, P., 2006. Patent citations and the geography of knowledge spillovers: evidence from inventor- and examiner-added citations. Rev. Econ. Stat. 88 (2), 383–388. https://doi.org/10.1162/rest.88.2.383.

Thompson, P., Fox-Kean, M., 2005. Patent citations and the geography of knowledge spillovers: a reassessment. Am. Econ. Rev. 95 (1), 450–460. https://doi.org/10.1257/0002828053828509.

Tushman, M.L., Anderson, P., 1986. Technological discontinuities and organizational environments. Adm. Sci. Q. 31 (3), 439–465. https://doi.org/10.2307/2392832.

Van Raan, A.F.J., 2019. Measuring science: Basic principles and application of advanced bibliometrics. In: Springer handbook of science and technology indicators. Springer, New York, NY, pp. 237–280 [Online]. Available: https://link.springer.com/book/10.1007/978-3-030-02511-3.

Veugelers, R., Wang, J., 2019. Scientific novelty and technological impact. Res. Policy 48 (6), 1362–1372. https://doi.org/10.1016/j.respol.2019.01.019.

Wang, J., Veugelers, R., Stephan, P., 2017. Bias against novelty in science: a cautionary tale for users of bibliometric indicators. Res. Policy 46 (8), 1416–1436. https://doi.org/10.1016/j.respol.2017.06.006.

Wang, Q.R., Zheng, Y., 2023. Patent regime and the geography of cumulative innovation. Res. Policy 52 (7), 104809. https://doi.org/10.1016/j.respol.2023.104809.

Wuestman, M.L., Hoekman, J., Frenken, K., 2019. The geography of scientific citations. Res. Policy 48 (7), 1771–1780. https://doi.org/10.1016/j.respol.2019.04.004.

Yegros-Yegros, A., Rafols, I., D'Este, P., 2015. Does interdisciplinary research Lead to higher citation impact? The different effect of proximal and distal Interdisciplinarity. PLoS One 10 (8), e0135095. https://doi.org/10.1371/journal.pone.0135095.

Zahra, S.A., George, G., 2002. Absorptive capacity: a review, reconceptualization, and extension. Acad. Manag. Rev. 27 (2), 185–203. https://doi.org/10.2307/4134351.