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Across disciplines, to make an impact. The technological impact of boundary-spanning research projects

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ABSTRACT

Boundary spanning research is increasing recognition among scholars and policymakers due to its potential in generating novel and breakthrough scientific contributions. However, while previous research mainly investigated its effect for the scientific domain, less is known about how boundary spanning approaches in science are related to technology transfer activities. To investigate this issue, we examine 6081 research projects in the Life Sciences, Physical & Engineering, and Social Sciences & Humanities sectors funded by the European Research Council under the 7th Framework Programme and Horizon 2020 Programme in the period 2008–2016. Our results show that boundary spanning research projects and the probability to generate technological impact through patent citations are linked through an inverted U-shape relation, thus recognizing both benefits and costs to this research approach. Moreover, as research integrates knowledge from more diverse scientific domains, its technological applications expand correspondingly across a broader range of technical fields. Finally, we show that these relations change according to the seniority of the researcher performing the scientific activity.

1. Introduction

For over three decades, management studies have been investigating the consequences of spanning boundaries in different fields, such as strategy and finance (Bergh, 1995; Murray, 1989; Yang et al., 2014), innovation (Fleming, 2001; Hargadon, 2002; Schilling and Green, 2011; Leone et al., 2022), entrepreneurship (Gartner, 1985; Kilduff et al., 2000). These studies have described boundary spanning as a strategy characterized by two main opposing dynamics. On the one hand, it allows to see connections across different domains: bridging disconnected knowledge spaces results in better and more creative ideas (Lo and Kennedy, 2015). On the other hand, it implies penalties: investing in multiple areas disperses competences and increases costs of knowledge integration and coordination (Bromham et al., 2016; Kotha et al., 2013; Leahey et al., 2016; Yegros-Yegros et al., 2015).

In the field of academia, researchers have mainly focused on two dynamics of boundary spanning: (i) at the individual level, the evaluation by the scientific audience of boundary spanning profiles to test the effects in terms of career progression (Fini et al., 2023; Jacobs and Frickel, 2009; Leahey et al., 2016) and (ii) at a broader level, the consequence of boundary spanning in terms of generation of scientific impact (Yegros-Yegros et al., 2015). If these studies have increased our understanding of how the combination of knowledge among different fields may play an important role, they mainly disregarded two elements: (i) the assessment of boundary spanning at the level of research projects, rather than at the individual level, and (ii) the link between boundary spanning scientific activity and technological impact, rather than scientific impact.

In this paper, we address these gaps by focusing on the boundary spanning nature of research projects (Boudreau et al., 2016; Bromham et al., 2016; Criscuolo et al., 2016) that we define as researchers' ability to access and flexibly integrate different sources of knowledge which derives from outside the boundaries of their own disciplinary field. With this definition in mind, we intend to answer the following research question: *Are boundary spanning research projects more likely sources of technological impact?*

This investigation is relevant for the following reasons. First, literature suggests that the process of scientific research is increasingly becoming the output of a team activity, thus shifting the locus of scientific discovery from the single researcher to networks of researchers (Paruchuri, 2010). This joint production effort, involving multiple specialists with different expertise, can be easily captured in the nature of scientific research projects, where the use of collective knowledge to solve a problem is a key feature (Boudreau et al., 2016; Bromham et al.,

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2016; Kotha et al., 2013). Second, the clue that science is a social system focused on the production of knowledge, but also interconnected with the wider society (Sauermann and Stephan, 2013) has been a long-standing topic of investigation in the innovation and technology transfer literature (Cohen et al., 2002; Dabić et al., 2021; Dasgupta and David, 1994; Hameri, 1996). Indeed, the interrelation between science and industry is recognized as crucial for increasing innovative performance, accelerating growth and supporting competitiveness of organizations and countries (Dumont, 2017; Freeman, 1987; Jaffe, 1989; Mendonça et al., 2004).

Moreover, we intend also to analyze whether and how the relation between boundary spanning research and technological impact is moderated by the academic seniority of the scientists leading the research projects. In this way, we contribute to the open debate on the role of academic seniority in innovation and technology transfer processes, on the one hand, and in the adoption of boundary-spanning research, on the other hand. Extant studies are not unanimous in defining which is the best stage of development in the academic career for assuring value creation in university-industry relations and in effectively managing a research approach spanning multiple disciplines (Colyvas and Powell, 2007; D'Este and Patel, 2007; Haeussler and Colyvas, 2011; Munari and Toschi, 2021; Stuart and Ding, 2006).

We investigate our research questions exploring the scientific outcomes from 6081 projects in Life Sciences, Physical & Engineering, and Social Sciences & Humanities funded by the European Research Council (ERC) under the 7th Framework Programme (FP7) and Horizon 2020 (H2020) for the period 2008–2016. We identify the patents relied on the knowledge produced by these projects and investigate to which extent boundary spanning projects are related to technology development. We measure boundary spanning using the diversity of subject areas (identified on the SCOPUS database) represented by the backward citations of the publications derived by each ERC-funded project. We assess technological impact in terms of i) a boundary-spanning research project's probability of having its scientific publications cited by at least one subsequent patent and ii) a boundary-spanning research project's ability to inspire patents that span across broad technological domains. In this paper, we are thus interested in tracing knowledge flow from science to technology and assessing whether and how the technological community understands and makes sense of boundary spanning scientific research for the further generation of innovation.

We find that the relationship between boundary spanning and technological impact is not linear. Boundary spanning research projects are more likely to generate technological impact but there is a turn point where the increment on the knowledge range starts to hinder technological impact. Moreover, our results show that the researchers' academic seniority moderates the relationship. In particular, we find that for medium-low levels of boundary-spanning, when the scientific projects are led by junior researchers, the inverted U-shaped relationship is more pronounced. On the other hand, for high levels of boundary-spanning, senior researchers seem to be more able than early-stage researchers to contribute to technological progress through their boundary-spanning research. We also show that as research integrates knowledge from more diverse scientific domains, its technological applications expand correspondingly across a broader range of technical fields. In other words, we find a positive relationship between the scientific boundary spanning orientation of a research project and the boundary spanning orientation of its citing patents.

In the following sections, we first develop our theoretical arguments. Then, we describe more precisely our setting, and we present our data, econometric models and results. Finally, we discuss the implications of our study.

2. Theoretical background

2.1. Boundary spanning in science

In their scientific activity, researchers may decide to accumulate specialized knowledge in order to demonstrate high levels of competences in a specific area or spanning knowledge among different areas. The former approach suggests that superior knowledge in an area allows to perform one type of action efficiently and provides strong evidence of focused expertise (Hsu, 2006; Hsu et al., 2009). The latter divides capacities across many different kinds of activities and involves the development of a diverse knowledge stock, leading to less obvious and more articulated research outputs (Caccamo et al., 2023; Hsu, 2006; Huang and Su, 2019). Each of these approaches implies a different use of knowledge. In the first case, the focus is on exploitation of existing learning processes, while boundary spanning is more characterized by learning from distinctive cognitive sets (Paolella and Durand, 2016) in order to explore new knowledge in different domains (Bingham and Davis, 2012; Leone et al., 2022), integrating "perspectives, information, data, techniques, tools, concepts, and/or theories from two or more disciplines'' (National Academies of Science, National Academy of Engineering, and Institute of Medicine, 2005: 188). This last concept has been adopted in management studies with different terms: interdisciplinarity, scientific breath, scientific scope, exploration, boundary or category spanning.

There are both advantages and costs associated with conducting research activities in academia that span different scientific fields. As far as the advantages, there is substantive evidence suggesting that scientists whose research encompasses multiple disciplinary fields benefit from more academic visibility and scientific impact (Chen et al., 2015, 2021; Larivière and Gingras, 2010; Leahey et al., 2017; Rinia et al., 2001; Schilling and Green, 2011; Uzzi et al., 2013; Wang et al., 2015). In academia, impact is typically gauged via citations as it measures how a paper is received by the scientific community. For instance, using data from 32,000 published articles, Leahey et al. (2017) showed that boundary-spanning research improves scientists' cumulative citations count. Larivière and Gingras (2010) suggest that this positive relation occurs only for articles with a medium-level of interdisciplinarity.

Other researchers, on the other hand, suggest that elaborating ideas from different fields may be risky, complex and time-consuming as it implies cognitive and coordination costs (Leahey et al., 2017; Yegros-Yegros et al., 2015). Leahey et al. (2017) found that interdisciplinary research is associated with lower productivity as it requires additional time, commitment, and effort. In same extreme cases, an interdisciplinary approach may also create epistemological and/or methodological conflict (van Rijnsoever and Hessels, 2011) between members of different fields, slowing progress toward publication. Moreover, quality may suffer as it is not obvious for researchers to accommodate the concepts and perspectives of multiple fields and produce output that is standard in form and content for all the domains considered. Finally, some works suggest a negative effect also on the individual scientific career due to the departmental structure of universities where processes of social closure, typical of professional occupations, occurs to restrict access to individual not meeting the standard of the discipline (Fini et al., 2023; Weeden, 2002).

These studies, although very informative, mainly focused on the effect of interdisciplinarity on scientific discovery process which occurs within the academia (i.e., scientific productivity), disregarding the impact that boundary spanning research may have on commercialization process of scientific discoveries within the industry.

2.2. Boundary spanning from science to technology

The extant literature is rich of studies focusing on the importance of science as trigger of innovation, able to promote economic growth and social development in organizations, industries and countries (Dumont,

2017; Freeman, 1987; Jaffe, 1989; Mendonça et al., 2004). The crucial value generated by the interconnection between science and industry is documented in different ways (Dabić et al., 2021; Rajalo and Vadi, 2017). As far as stakeholders belonging to industry, corporations are increasingly employing open innovation practices, with a particular interest in the creation of collaborations with university and research-oriented institutions to leverage public science as knowledge source for their technological innovations (Gambardella, 1992; Cockburn and Henderson, 1996; Mansfield, 1998; Laursen and Salter, 2006; Arora et al., 2015). From the science side, universities and public research organizations are increasingly engaged in the so called "Third Mission", shifting from mainly focusing on teaching and research to actively contributing to society with knowledge transfer activities (Branscomb et al., 1999; Compagnucci and Spigarelli, 2020; D'Este et al., 2012; Dasgupta and David, 1994; Etzkowitz and Leydesdorff, 2000). In this context, being boundary spanner is growing interest.

Research on recombinant innovation (Fleming, 2001; Fleming and Sorenson, 2004; Schilling and Green, 2011; Uzzi et al., 2013) has convincingly pointed out that bringing together ideas from diverse knowledge domains and integrate them into original combinations is a pathway for the creation of impactful and breakthrough innovations. In this view, discoveries that recombine knowledge from similar knowledge domains are more likely to be incremental, and therefore less valuable in terms of subsequent technological developments and commercial applications. On the other hand, scientific efforts that involve the combination of dissimilar knowledge domains are more likely to spark new insights and generate radically new innovative outputs.

Moreover, boundary-spanning scientific discoveries are recognized as particularly successful "to solve challenging scientific and practical problems" (Kotha et al., 2013: 499). Industrial and societal challenges are typically not confined within specific academic domains, but are "tackled more effectively by bringing together disconnected knowledge spaces" (D'Este et al., 2019: 1). Researchers have documented that spanning among different disciplines encourages a more reflexive approach to research, and a higher researchers' awareness of the social impact and technical feasibility of their research activities, a mindset which better meets the complex problems posed by the society nowadays (Molas-Gallart et al., 2014).

In line with this view, some studies - although limited in number - have started to investigate whether interdisciplinarity-oriented researchers tend to engage more frequently in knowledge-exchange activities with industry (Carayol and Thi, 2005; D'Este et al., 2019; Kotha et al., 2013). In these works, the results suggest that connections across fields are significantly associated to scientists' engagement with non-academic actors. However, performing interdisciplinary research has to deal with coordination issues which may undermine its potential and effectiveness. The existence of an adequate mutual knowledge is the *conditio* sine *qua non* for successfully performing complex tasks. In interdisciplinary teams such a condition could not be satisfied as there are different knowledge, beliefs, languages, and norms of working, that make it difficult to understand each other. In the paper by Kotha et al. (2013), studying the probability of interdisciplinary researchers to engage in licensing activities, this problem arises not only at the team level, as suggested by previous studies, but also between the academic team, who starts the development of the invention, and the licensee firm, the downstream part who continues the technology transfer process till the commercialization of the invention.

Although these studies contribute to our understanding of the link between interdisciplinarity in science and technology transfer, they mainly adopt the perspective of the researchers engaged in interdisciplinary projects to understand their deliberative actions in terms of technology transfer (i.e., likelihood to engage in licensing activities, spin-off creation, or, more generally, university-industry interactions). The issue of how others outside the academia make sense of boundary-spanning in science, received limited attention. In particular, the extent to which industrial actors clearly perceive a fit with scientific discoveries needs to be taken into consideration to better understand the ability of researchers to inspire technology progress further developed by players positioned outside the academia.

With our paper, we intend to trace knowledge flow from science to technology with the idea that the scientific publications cited in patents play a valuable indirect role as source of relevant background information for the generation of innovation. In this way, we follow the approach suggested by Munari et al. (2024), Narin et al. (1997), and Veugelers and Wang (2019) which uses scientific non-patent literature (i.e., the backward citations to the scientific literature included in patents) as relevant prior art for the patented inventions to measure technological impact. Veugelers and Wang (2019), in particular, investigated how the degree of novelty of science is related to technological impact. They assess novel science in terms of publications which include new combinations of journals in their references, and trace links between science and technology through scientific references in patent applications. The authors find that novel scientific publications are significantly more likely to generate technological impact than non-novel publications. This work makes a step forward in shifting from the assessment of scientific impact to the importance to study how science is able to create a different type of impact, not only for the academic audience but for the whole society, that is technological impact.

We intend to contribute to this literature by assessing the relation between the boundary spanning nature of science and the generation of technological impact, as we will discuss in the next section.

3. Hypotheses development

3.1. The effect of boundary spanning research on technological impact

The role of boundary spanning approaches in academia has been mainly investigated from the lens of the producers of scientific knowledge, mostly focusing on the researchers' scientific activity and related publications (Jacobs and Frickel, 2009; Leahey et al., 2016; Yegros-Yegros et al., 2015). In our contribution we shift the attention on the recipients of the new scientific discoveries, the external organizations that use such new knowledge to deploy novel technological solutions. Focusing on the users within industry and society, who may be responsible for the further development of the scientific discovery into practical applications, allows us to assess whether boundary-spanning science is more likely to be a knowledge source for technological innovation and whether the technological impact of boundary-spanning science displays a special profile different from that of focused science.

Scientific research that adopts a boundary spanning approach expands its accessible technological market by engaging with a wider spectrum of challenges and opportunities. The integration of insights from multiple fields of knowledge, indeed, addresses various needs and preferences within the technological community, creating multiple opportunities for technological advancement. Thus, through their engagement in multiple fields, researchers produce different kinds of knowledge to perform their research activities which can be of interest to different users within the technological domains. Moreover, as combining dissimilar scientific knowledge fields is widely recognized as a key driver for generating radically innovative outputs (Fleming, 2001; Fleming and Sorenson, 2004; Pontikes, 2012), being boundary-spanner can signal researchers' ability to develop novel ideas that the technological community can perceive as highly valuable, fostering innovations with significant societal impact. In other words, researchers conducting boundary-spanning studies should present a more pronounced awareness of the potential technical and social influence of their scientific activities (Kotha et al., 2013; Yegros-Yegros et al., 2015). Such explanations, centred on expected positive outcomes in terms of market size and scientific originality, and potential applicability of boundary-spanning research, support the expectations of beneficial implications for boundary-spanning research in terms of technological impact.

However, several studies have also cautioned about excessively positive narratives of the benefits of boundary-spanning, highlighting its potential costs. One main problem is related to the potential difficulties of reception by external users (Leahey et al., 2017; Yegros-Yegros et al., 2015), who may have difficulties in understanding discoveries stemming from disparate and atypical combinations of diverse fields of knowledge (Kotha et al., 2013). This has been extensively documented in the organizational, sociological and categorical literatures which suggest that actors spanning different categories suffer from a valuation penalty because evaluators are confused by their profile and have concerns about their unobservable quality (Fini et al., 2023; Negro and Leung, 2013; Zuckerman et al., 2003). At the research level, it has been documented that some novelty is important in the search for new products and services, but too much can be difficult to interpret and categorize (Criscuolo et al., 2016). Related to this, we know that "grant evaluation processes are biased against interdisciplinary projects, because proposals may be assigned to a panel or reviewers who are ill-equipped to evaluate all parts of the project (Woelert and Millar, 2013), while more narrowly focused proposals may be better matched to assessor expertise" (Bromham et al., 2016: 685). These negative effects may be more relevant especially when the exercise to evaluate boundary-spanning science goes beyond the scientific field (i.e., academia) to enter an interrelated domain (i.e., industry/technology). The conceptualization of industry and academia is often depicted by the extant literature as domains guided by conflicting institutional logics (Sauermann and Stephan, 2013) which could increase the cognitive gap between the two and undermine mutual understanding.

Therefore, by recognizing both benefits and costs of spanning the boundaries of knowledge domains in conducting research, we argue that scientific discoveries stemming from intermediate levels of boundary-spanning should have an advantage in generating technological impact, as compared to those generated from extreme levels of boundary-spanning (either very low or very high). In other words, we hypotheses that:

Hypothesis 1. There will be an inverted U-shaped relationship between the scientific boundary spanning orientation of a research project and the likelihood of having technological impact.

3.2. The relationship between boundary spanning research and boundary spanning inventions

The ability of external users—and in particular corporate researchers and engineers—to effectively utilize academic knowledge to create novel technical advancements is influenced by various factors. Among these is absorptive capacity, which refers to the ability to recognize the value of new external information, assimilate it, and apply it to technological and commercial outcomes (Zahra and George, 2002). We posit that this capacity is enhanced by an organization's engagement in boundary-spanning inventive activities within the technology domain. Such engagement fosters a superior ability to scan, interpret, and assimilate the results of interdisciplinary science (Fabrizio, 2009).

In the literature, boundary-spanning inventive activity has often been studied by examining patents that integrate knowledge from diverse technological domains (Whalen, 2018). These patents are typically identified through classifications in multiple technological categories, such as the different IPC classes to which a patent is assigned (Rousseau, 2014) or broader categorizations like WIPO technical fields (Schmoch, 2008).[1] Such categorizations are used to infer whether an invention spans knowledge boundaries.[2]

Engaging in search processes that combine dissimilar knowledge domains during the creation of patented inventions is likely to enhance the identification and integration of upstream research perspectives. This contributes to the development of science-based inventions that address critical technological bottlenecks and possess significant market potential (Kotha et al., 2013; Vural et al., 2013).

On one hand, firms that cross and integrate technical boundaries in their inventive processes often have teams and systems in place to manage knowledge from diverse domains (e.g., biology and computer science in bioinformatics, or engineering, software, and materials science in autonomous vehicles). This organizational setup inherently makes such firms more adept at understanding and applying the interdisciplinary knowledge that universities frequently produce. Moreover, developing inventions that integrate multiple technologies requires a capacity to manage complexity and perform knowledge translation (Zobel et al., 2024). Knowledge translation involves not only understanding insights from diverse fields but also adapting them to solve specific technical problems. This aligns closely with the interdisciplinary nature of academic research and underscores the potential for firms engaged in boundary-spanning inventive activity to leverage university research effectively.

Building on these arguments, we hypothesize that scientific knowledge stemming from interdisciplinary research projects is more likely to be cited by boundary-spanning patents. Therefore:

Hypothesis 2. There will be a positive relationship between the scientific boundary spanning orientation of a research project and the boundary spanning orientation of its citing patents.

3.3. The effect of the researcher's academic seniority

A set of conditions may facilitate (or hinder) the undertaking of boundary-spanning research and its desired outcomes in terms of technological impact (Carayol and Thi, 2005; Leahey et al., 2017; van Rijnsoever and Hessels, 2011). We expect that the ultimate magnitude of the effect exerted on subsequent technological developments may depend on academic seniority in terms of the researchers' motivation and capacity to engage in boundary-spanning research. They might change in the different stages of the researcher's academic career, thus having varying effects on the ability to generate useful research results that can inspire subsequent technological development.

In this sense, some studies showed that boundary-spanning may be beneficial for early researchers as they may benefit from more academic visibility and impact (Leahey et al., 2017; Schilling and Green, 2011; Uzzi et al., 2013). Moreover, as previously pointed out, the "recombinant search" approach suggests that discipline-spanning is more and more a primary route to innovation (Fleming, 2001; Fleming et al., 2007) and society demands increasingly complex innovations for whom a boundary-spanning approach is at the base. In such a context, younger researchers – who are exposed from the beginning of their scientific career to this logic - may be more open, confident and skilled to perform boundary-spanning research in respect to their peers in later stages of the career, who started their research activities when a specialization of skills was the master of success. Early-career researchers may be also more attuned to the latest scientific advancements and technological trends, enabling them to integrate cutting-edge knowledge into their interdisciplinary work, which resonates with broad technological applications. From this perspective, it is thus plausible to expect higher

[1] The International Patent Classification (IPC) is a hierarchical system developed to classify patents based on their technical subject matter. WIPO fields are based on aggregated IPC classifications, making them less granular. When a patent is classified under more than one IPC class, it indicates that the invention spans multiple technological domains.

[2] In the literature other approaches have been used to identify boundary spanning patents, in addition to the classification of a patent in terms of IPC or WIPO classes. For instance, Whalen (2018) uses semantic similarity analysis, analyzing the full text of patent documents to assess the semantic distance between them.

technological impact from boundary-spanning scientific projects lead by younger researchers, who possess the right mindset, motivations and abilities to match the needs of the industrial audience.

However, we should also consider that adopting a boundary-spanning perspective might be complex and risky in an early-stage of the career as researchers who cross the boundaries are less recognized than peers who contribute to the core of a discipline (Bonaccorsi et al., 2022). In the first stages of academic career, scientists tend to prefer developing a safe career path, by strengthening their academic reputation through scientific publications in their discipline to enhance their scientific prestige and reputation (Carayol and Thi, 2005; Munari and Toschi, 2021). More experienced researchers, on the contrary, could more freely (perceiving less career pressures) engage with ideas and colleagues from other scientific fields, also distant ones.

Moreover, ideas emerging from highly diverse domains (if compared to more related knowledge domains) requires time to be, first, developed and then effectively integrated and communicated (Bromham et al., 2016). Reaching effectively across boundaries in knowledge search may be increasingly challenging due to the difficulty of searching unfamiliar domains (Uzzi et al., 2013). Also, high levels of interdisciplinarity can be difficult to be communicated to and understood by external users, especially when scientists lack collaboration experience and visibility in different communities of practice (D' Este and Patel, 2007). Adopting an orientation toward activities of "Third Mission", which includes building strong networks with the industrial sector, may allow researchers to better understand market needs and develop research that is practically relevant. By engaging with industry, researchers gain insights into real-world challenges and user requirements, which guide them in shaping their scientific efforts to align with technological and societal demands. This connection with industry enhances the likelihood that research outputs will be translated into tangible applications, increasing its utilization by end-users outside academia.

From these considerations, we can suggest the following hypotheses:

Hypothesis 3. The researcher's academic seniority will moderate the relationship between boundary spanning research and technological impact, such that,

a) from low to moderate (high) levels of boundary spanning, when the project is led by an early-stage (senior) researcher, the inverted U-shaped relationship will be more pronounced.
b) when the project is led by an early-stage (senior) researcher, the linear relationship will be more (less) pronounced.

4. The context of the study: the ERC grant scheme

Our paper focuses on data related to the European Research Council (ERC) Grant Schemes. The analyses consider the whole set of ERC-funded projects activated during the FP7 programme (2008–2013) and H2020 programme (2014–2016). The ERC was established in 2007 to support the highest-quality frontier research in Europe across all fields and to strengthen the European research system. Through competitive funding, it provides individual long-term grants for ground-breaking, high-risk/high-gain research. A particularity of ERC funding grants is that the projects are assigned to the Principal Investigator (PI) and not to the Host Institution, which means more mobility to the researchers without interrupting the progress in case of transfer.

The Council offers five main types of grants that represent the core of its activities: Starting Grants (StG), Consolidator Grants (CoG), Advanced Grants (AdG), Synergy Grants (SyG) and Proof of Concept Program (PoC). The division into five categories allows the possibility to support early-career researchers until established researchers develop their idea and contribute to the science state-of-art. Table A1 in the Appendix describes the main characteristics of these grant categories. Moreover, three macro fields aggregate the range of disciplines: Life Sciences, Physical & Engineering, and Social Sciences & Humanities.

The selection of beneficiary projects in such funding schemes is based on a high-quality, international peer-review process, with the sole selection criterion being scientific excellence. Since 2007, ERC has already funded more than 14.000 research projects[3] spread on the different categories of grants.

5. Data and methods

To address our research question, we used the scientific production of research projects funded by the ERC FP7 and H2020 grant programmes and we identified patents citing the papers produced by the projects developed in Life Science, Physical & Engineering and Social Sciences & Humanities sectors.

5.1. Data source

We used a database built following the approach recently explored by the innovation literature which refers to research projects' contribution to the development of patents by tracing the patent citations to scientific publications (Azoulay et al., 2019; Fleming et al., 2019; Li et al., 2017). The methodology we followed is described in greater detail in the article by Munari et al. (2024).

Our first step was to collect the projects funded by the ERC FP7 and H2020 grant programmes until 2016 using the E.U. Open Data Portal data (6671 projects). We identified 4556 FP7 research projects and 2115H2020 research projects from the Physical & Engineering (46.2%), Life Science (35.69%) and Social Science & Humanities (18.11%) sectors.

The second step consisted in identifying the publications produced by these research projects using the combination of Cordis and Scopus information for this purpose.[4] We merged the information of both datasets using DOI and/or title of each publication. After data treatment, we were able to find 172,683 publications linked to the ERC projects included in our dataset. We collected information about authors, journal, year of publication, and subject area for each publication.

Our third step consisted of identifying the patents that cited the research projects' publications. Using the list of publications, we identified on Patstat database the patent applications that cited the publications generated by these grants.[5] We matched the publications with the Non-Patent Literature (NPL) field from Patstat, i.e., the dedicated field that allows identifying scientific publications cited on the patent's front page or during the examination process.[6] The match between NPL

[3] This information is available at ERC website (https://erc.europa.eu/project-statistics/project-database).

[4] More precisely, on CORDIS, each ERC-project has a dedicated page. We first retrieved the list of publications reported in the section "Results". We then used Scopus' research looked for publications that declared on their "Acknowledgments" section that the study was funded by the ERC funding program, using the project number we got from the first step. Scopus analyses the funding sources cited in the scientific publications' acknowledgments and inserts them in a dedicated metadata field. We downloaded from Scopus all the publications citing an ERC grant number reported in the dataset identified in the first step. We then merged the publications retrieved from Scopus and from Cordis, avoiding duplicates. Please see the Annex of the paper by Munari et al. (2024) for a more detailed explanation of the process.

[5] Patstat is a database released by the European Patent Office (EPO) and provides access to patents' data from more than 40 patent authorities worldwide, including the World Intellectual Property Office (WIPO). We used the 2021 Autumn Edition of Patstat.

[6] Metadata for NPL papers in Patstat are present on two configurations. There are structured entries, with a separate field for every information (e.g., title, authors, DOI, or year). Those consist of about nine million entries. Conversely, unstructured data are the majority (about 35 million), where combines all the information about the publication into a single free-text field.

and the corresponding scientific publication considered three criteria: having the same first author's surname, same title, and same DOI. We selected those with at least two matches, and manually checked the publications that only featured the same title or DOI.[7] The identified NPL conducted us to the patents that cited the scientific publications produced by the ERC research projects. We then collected information about these patents like application year, patent office, IPC classification, grant status, etc. Using the original project of each publication it was then possible to link each patent to its respective project, gathering a total of 34,513 patent applications.

In order to define our final sample, we applied a set of filters. First, we excluded from the analyses the projects funded under the Synergy Grant scheme, as they represent a small number of projects in respect to the total number of projects of the database (24 projects) and they are different in nature as they address ambitious challenges where two or more PIs work together and receive higher amount of funding (up to a maximum of € 10 million for a period of 6 years in respect to an average of up to € 2 million for a period of 5 years for the other grants). Second, we excluded from the analyses the projects funded through the Proof of Concept programme (475 projects), as it represents an additional funding with a focus on valorisation for those who had previous grantees of ERC frontier research main grants (Starting, Consolidator, Advanced or Synergy). After the application of these two filters, we obtained 6172 projects. Third, considering our interest in measuring boundary-spanning research, we included in our final sample only those projects which generated at least one publication.[8] Applying this filter, we dropped 91 projects (representing less than 1.5% of the group of 6172 projects), and we obtained a final sample of 6081 granted projects, of which 4289 FP7 and 1792H2020 projects. Table 1 presents the distribution of these projects between type of scheme, sectors and type of programmes. For this sample of projects, we obtained 170,323 publications generated by the ERC-funded projects and 34,294 patents citing these publications.

Table 1
Projects according to type of scheme (FP7 vs. H2020), type of research grant (Advanced, Consolidator and Starting) and scientific field (Life Science, Physical & Engineering, Social Science & Humanities).

Panel A

Type of Research Grant	Life Sciences	Physical & Engineering	Social Sciences & Humanities	Total
Advanced Grant	772	969	367	2108
Consolidator Grant	332	439	172	943
Starting Grant	1090	1375	565	2108
Total	**2194**	**2783**	**1104**	**6081**

Panel B

Type of Research Grant	FP7	H2020	Total
Advanced Grant	1683	425	2108
Consolidator Grant	308	635	943
Starting Grant	2298	732	3030
Total	**4289**	**1792**	**6081**

Panel C

Sector	FP7	H2020	Total
Life Sciences	1570	624	2194
Physical & Engineering	1958	825	2783
Social Sciences & Humanities	761	343	1104
Total	**4289**	**1792**	**6081**

5.2. Measures

Our main objective is to investigate the impact of boundary spanning research projects on the inspiration of new patents. In the following section, we describe our main variables.

- Dependent Variables

Our main outcome is the set of patent applications that rely on ERC FP7 and H2020 Research Projects. To measure technological impact, we test two different variables. The first one (*Dummy Citing Patent*), used for H1, is a dummy variable and investigates the probability of a research project to be cited by at least one patent application. It identifies if at least one patent cited a publication generated by a research project (0 if the project was not cited by a patent and 1 if the project was cited by at least one patent).

Second, we assess if boundary spanning research projects influence patents with a broader technological extent, according to H2. To this purpose, we created a variable measuring the mean number of WIPO technological fields associated to the citing patent applications of each project (*Mean WIPO Technological Fields)*.[9] This variable offers an idea of the technological scope characterizing the citing patents linked to the research projects: a low value of the variable means a narrow technological focus, while a high level is associated with boundary spanning inventions covering diverse technology fields.

- Explanatory Variables

We aim to investigate the relationship between boundary spanning and the probability of being cited by a patent application. To obtain the degree of boundary spanning of each project, we used one measure of boundary spanning research indicated in the literature: variety (Rafols and Meyer, 2010; Rafols et al., 2012; Wang et al., 2015; Yegros-Yegros et al., 2015; Bromham et al., 2016; D'Este et al., 2019). To build this variable, we used Scopus' database to identify the scientific disciplines (Scopus subject areas) linked to the journals in which each backward citation reported in the paper was published (Porter and Rafols, 2009; Yegros-Yegros et al., 2015). More precisely, Boundary Spanning Variety (*BS Variety*) refers to the number of Scopus subject areas (Rafols and Meyer, 2010; Rafols et al., 2012; Wang et al., 2015; Yegros-Yegros et al., 2015; Bromham et al., 2016; D'Este et al., 2019). We calculated this variable as the total number of unique subject areas of all the backward citations reported in the publications of each project. Considering the high variance between projects, we normalized the indicator by each project's publications[10].

- Moderating Variable

[7] In our approach, a publication can match the related Patstat NPL field on one or more of the following criteria: title, DOI, and author. A higher number of hits means a more confident match (e.g., if a publication matched title, DOI, and author is the best result we can obtain). A priori, we discarded matches based only on the first author surname, given the very high number of results produced and the low significance of homonymy instances. We than considered acceptable the matches with two or more hits, and we manually controlled the publications that matched only title or DOI. Please see the Annex of the paper Munari et al. (2024) for a more detailed explanation of the process.

[8] This approach is in line with other works like the one by Fontana et al. (2022) that analyses the interdisciplinarity level of researchers at the University of Florida, starting from a sample of researchers with at least one publication in a peer-reviewed journal.

[9] The WIPO (World Intellectual Property Organization) Technology classification follows a hierarchical structure. It starts from a list of five technological macro-sectors, divided into 35 technological fields categories, which are developed by grouping IPC subclasses (at the 4-digit level). The 35 categories were used to assess our variable. This classification was developed aiming to allow the comparison between countries and regions regarding their technological competence (Schmoch, 2008).

[10] We normalized the variable as follows: $(X_i\text{-}X_{min})/(X_{max}\text{-}X_{max})$ where X_{min} and X_{max} are the extreme values of original variable variety (X) as suggested by (Yegros-Yegros et al., 2015).

To verify our second hypothesis, we identified the academic seniority of the researcher leading the ERC-funded project, exploiting the type of research grant. Our sample contains research projects funded by four different types of programs. Each type corresponds to a different researcher career stage: Starting Grants (StG) for researchers with 2–7 years of experience since the completion of the PhD, Consolidator Grants (CoG), for researchers with 7–12 years of experience after the PhD, and Advanced Grants (AdG), who are already established leaders in their fields. The variable *Academic Seniority* takes value 1 if the PI obtained a Consolidator Grant or Advanced Grant, and 0 in case of a Starting Grant.

- Control Variables

Other aspects might be associated with the probability of being cited by a patent application. We then introduced to our analysis other research projects' characteristics. First, we controlled for the research orientation of the host institutions with the *Applied Research Institution* dummy variable. Gathering information about the host institutions, we classified as applied oriented institution the polytechnics, medical schools, business schools and those focused on a specific research field. On the other hand, we classified universities and those developing research on multiple scientific fields as generalist. This way, the variable is equal 1 for the host institutions with an applied research orientation and 0 for the generalists.

We also controlled for the type of ERC scheme, distinguishing between FP7 (value 0) and H2020 (value 1), and the knowledge field of the project to take into consideration the heterogeneity between Life Sciences, Physical & Engineering or Social Sciences & Humanities. We also added a fixed effect for the starting year of the project whose range goes from 2008 to 2016 (*Start Year of the Project*), the amount of funding received by the project (*Project Budget*), and we controlled also for the logarithm term of the project's total publications (Log *Publications*) and the quality of the research, measured in terms of citations received after three years of the publication (*Citations*). Finally, at the geographical level, we referred to Eurostat to measure the rate of GDP invested in R&D activities by the geographical NUTS2 level of the Host Institution (*Regional R&D*[11]) and the percentage of total employment in technology and knowledge-intensive sectors by the geographical NUTS2 level of the Host Institution (*Regional Employment*[12]).

5.3. Empirical strategy

Our main objective is to investigate the impact of boundary spanning research projects on the generation of new patents. We first investigate the probability of a research project being cited by a patent application considering their boundary spanning orientation. For this first step, we use a logit model to predict the probability of boundary-spanning research projects being cited by a patent application.

In a second step, we focus on a subsample of projects, those receiving at least one patent citation (representing about the 47% of our sample and corresponding to 2.886 projects). In this case, we move our attention to a different dependent variable, which captures the level of technological scope that the ERC-granted projects are able to generate through its scientific publications. As we have an over count dispersion dataset (Jain and Consul, 1971), we use Ordinary Least Square (OLS).

[11] It is important to highlight that the Nomenclature of Territorial Unit Statistics (NUTS) embodies just Europe and United Kingdom. However, our dataset contains 344 projects coordinated by Israeli Institutions. To these projects, we considered data gathered on OECD.

[12] To Israel's projects we gathered data from official reports released by Israeli government (https://innovationisrael.org.il).

6. Analyses and results

6.1. Descriptive statistics

Tables from 2 to 5 show the descriptive statistics and pairwise correlations, respectively, of the variables included in the analysis: Tables 2 and 3 refer to the full sample of 6081 projects, while Tables 4 and 5 focus on the subsample of 2886 research projects cited at least by one patent.

Around 47% of the whole sample of projects were cited by patent applications (Table 2), and there is not a substantial difference in this proportion comparing projects in Physical & Engineering and Life Sciences (47,7% and 49.2% respectively) as shown in Table 7. However, Social Sciences & Humanities projects represent just 3.1% of the projects cited by a patent. This under-representation can be attributed to the nature of the knowledge generated on these fields, as they are usually more related to conceptual thinking than the direct generation of new technologies (Olmos-Peñuela et al., 2014).

Moreover, on average, the sample research projects have 34,294 patent applications (Table 6) citing at least one publication derived by the ERC project. In terms of boundary spanning, the average level of variety for the whole sample is of 0.33 on a scale from 0 to 1, while the average number of technological fields for the citing patents is 1.74 in a range from 1 to 5 (Table 4).

In order to better understand the institutions involved in patent inventions linked to ERC projects and have a better idea of the recipients of the new knowledge stemming from them, we considered the types of institutions that Patstat uses when categorizing patent applicants: a) firms; b) universities and research institutions (such as public research organizations); c) individuals. Table 6 presents a breakdown of citing

Table 2
Descriptive statistics for the full sample of 6081 research projects.

Variable	Obs	Mean	Std. Dev.	Min	Max
Dummy Citing Patent	6081	0.47	0.5	0	1
BS Variety	6081	0.33	0.17	0	1
Academic Seniority	6081	0.5	0.5	0	1
LogPublications	6081	3.02	0.92	0.1	5.8
Citations (3 Years)	6081	477.87	754.34	0	13712
Applied Research Institute	6081	0.38	0.49	0	1
FP7 Program	6081	0.71	0.46	0	1
H2020 Program	6081	0.29	0.46	0	1
Social Sciences & Humanities	6081	0.18	0.39	0	1
Life Sciences	6081	0.36	0.48	0	1
Physical & Engineering	6081	0.46	0.5	0	1
Project Budget	6081	1.75	0.52	0.16	3.5
Regional R&D	6081	2.69	1.21	0.25	9.34
Regional Employment	6081	6.04	2.32	0.8	11
Start Year of the Project	6081	2012.74	2.4	2008	2016
Variable	Obs	Mean	Std. Dev.	Min	Max
Dummy Citing Patent	6081	0.47	0.5	0	1
BS Variety	6081	0.33	0.17	0	1
Academic Seniority	6081	0.5	0.5	0	1
Log Publications	6081	3.02	0.92	0.10	5.80
Citations (3 Years)	6081	477.87	754.34	0	13712
Applied Research Institute	6081	0.38	0.49	0	1
FP7 Program	6081	0.71	0.46	0	1
H2020 Program	6081	0.29	0.46	0	1
Social Sciences & Humanities	6081	0.18	0.39	0	1
Life Sciences	6081	0.36	0.48	0	1
Physical & Engineering	6081	0.46	0.50	0	1
Project Budget	6081	1.75	0.52	0.16	3.50
Regional R&D	6081	2.69	1.21	0.25	9.34
Regional Employment	6081	6.04	2.32	0.8	11
Start Year of the Project	6081	2012.74	2.40	2008	2016

Table 3
Pairwise correlations for the full sample of 6081 research projects.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Dummy Citing Patent	1.00														
(2) BS Variety	0.33	1.00													
(3) Academic Seniority	0.02	0.10	1.00												
(4) Log Publications	0.29	0.54	0.14	1.00											
(5) Citations (3 Years)	0.24	0.26	0.10	0.52	1.00										
(6) Applied Research Institute	0.12	0.02	0.01	0.00	0.02	1.00									
(7) FP7 Program	0.21	0.06	−0.12	0.19	0.13	0.02	1.00								
(8) H2020 Program	−0.21	−0.06	0.12	−0.19	−0.13	−0.02	−1.00	1.00							
(9) Social Sciences & Humanities	−0.37	−0.15	−0.01	−0.32	−0.20	−0.14	−0.02	0.02	1.00						
(10) Life Sciences	0.26	0.23	0.00	−0.15	−0.01	0.14	0.02	−0.02	−0.35	1.00					
(11) Physical & Engineering	0.04	−0.11	0.01	0.39	0.16	−0.02	0.00	0.00	−0.43	−0.69	1.00				
(12) Project Budget	0.17	0.26	0.71	0.18	0.14	0.02	−0.10	0.10	−0.15	0.16	−0.04	1.00			
(13) Regional R&D	0.08	−0.02	0.00	−0.02	0.01	−0.03	0.00	0.00	−0.12	0.10	0.00	0.05	1.00		
(14) Regional Employment	0.00	−0.09	−0.02	−0.10	−0.06	0.00	−0.02	0.02	−0.04	0.07	−0.04	−0.01	0.44	1.00	
(15) Strat Year of the Project	−0.22	−0.01	0.20	−0.17	−0.11	−0.02	−0.76	0.76	0.03	0.00	−0.03	0.22	0.00	0.01	1.00
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Dummy Citing Patent	1.00														
(2) BS Variety	0.33	1.00													
(3) Academic Seniority	0.02	0.10	1.00												
(4) Log Publications	0.29	0.54	0.14	1.00											
(5) Citations (3 Years)	0.24	0.26	0.10	0.52	1.00										
(6) Applied Research Institute	0.12	0.02	0.01	0.00	0.02	1.00									
(7) FP7 Program	0.21	0.06	−0.12	0.19	0.13	0.02	1.00								
(8) H2020 Program	−0.21	−0.06	0.12	−0.19	−0.13	−0.02	−1.00	1.00							
(9) Social Sciences & Humanities	−0.37	−0.15	−0.01	−0.32	−0.20	−0.14	−0.02	0.02	1.00						
(10) Life Sciences	0.26	0.23	0.00	−0.15	−0.01	0.14	0.02	−0.02	−0.35	1.00					
(11) Physical & Engineering	0.04	−0.11	0.01	0.39	0.16	−0.02	0.00	0.00	−0.43	−0.69	1.00				
(12) Project Budget	0.17	0.26	0.71	0.18	0.14	0.02	−0.10	0.10	−0.15	0.16	−0.04	1.00			
(13) Regional R&D	0.08	−0.02	0.00	−0.02	0.01	−0.03	0.00	0.00	−0.12	0.10	0.00	0.05	1.00		
(14) Regional Employment	0.00	−0.09	−0.02	−0.10	−0.06	0.00	−0.02	0.02	−0.04	0.07	−0.04	−0.01	0.44	1.00	
(15) Strat Year of the Project	−0.22	−0.01	0.20	−0.17	−0.11	−0.02	−0.76	0.76	0.03	0.00	−0.03	0.22	0.00	0.01	1.00

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

Table 4
Descriptive statistics for the subsample of 2886 research projects cited by at least one patent.

Variable	Obs	Mean	Std. Dev.	Min	Max
Mean WIPO Technology Fields	2886	1.74	0.59	1	5
BS Variety	2886	0.39	0.16	0.03	0.96
Academic Seniority	2886	0.51	0.50	0	1
Log Publications	2886	3.30	0.73	0.10	5.71
Citations (3 Years)	2886	669.66	855.47	5	13712
Applied Research Institute	2886	0.44	0.50	0	1
FP7 Program	2886	0.81	0.39	0	1
H2020 Program	2886	0.19	0.39	0	1
Social Sciences & Humanities	2886	0.03	0.17	0	1
Life Sciences	2886	0.49	0.50	0	1
Physical & Engineering	2886	0.48	0.50	0	1
Project Budget	2886	1.84	0.49	0.24	3.50
Regional R&D	2886	2.79	1.19	0.35	9.34
Regional Employment	2886	6.04	2.27	0.80	11
Start Year of the Project	2886	2012.19	2.31	2008	2016

patent applications by type of applicant and ERC Program (FP7 versus H2020). We implemented fractional counting to prevent double counting, in cases where patents have multiple applicants of varied nature. While the majority of citations originate from patents assigned to firms (about 52%), a notable portion of citing patents stem from universities and research organizations (about 42%), thus suggesting the long and cumulative nature of the process of translating new scientific knowledge into technological innovations (Ahmadpoor and Jones, 2017).

Table 7 also presents mean values and comparisons of proportion tests (for dummy variable) and of mean tests (for continuous variables) across the two groups of projects with and without publications cited by patent applications. From these detailed summary statistics, it is possible to notice a statistically significant difference for our main explanatory variables and several control variables, thus, suggesting that the two groups differ. The results show that projects cited by patents present a higher *BS Variety* than those without a patent citation. In other words, on our sample, the projects cited by patents present a higher disciplinary diversity than those with no patent citation. In addition to that, the table shows that the likelihood to have a PI in the early phases of her career is not significantly different in the two groups of projects.

6.2. Results of the regression analyses

Table 8 introduces the results of the probability of a research project of being cited by a patent application using a Logit specification with fixed effect. The first model (M1) presents the influence of control variables on the probability of generating a patent. Our results suggest that projects with more publications (0.555, $p < 0.01$), more citations (0.001, $p < 0.01$) and developed by applied research institutions (0.296, $p < 0.01$) are more likely to receive at least one patent citation. Moreover, the model shows that Physical & Engineering (1.880; $p < 0.01$) and Life Sciences (2.801; $p < 0.01$) projects are more likely to be cited by a patent application than Social Science & Humanities projects. Other two interesting variables which are positive and significant are the project budget (1.034, $p < 0.01$) and the level of regional R&D of the Host Institution where the research is developed (0.097, $p < 0.01$). Considering the academic seniority of the PI, we find that projects lead by researchers with a consolidated academic reputation are less likely to receive a patent citation when compared to projects lead by early-stage researchers (−0.657; $p < 0.01$).

In the second and third models, we investigate the impact of *BS*

Table 5
Pairwise correlations for the subsample of 2886 research projects cited by at least one patent.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Mean WIPO Technology Fields	1.00														
(2) BS variety	0.04	1.00													
(3) Academic Seniority	−0.05	0.10	1.00												
(4) Log Publications	−0.02	0.54	0.14	1.00											
(5) Citations (3 Years)	0.01	0.26	0.10	0.52	1.00										
(6) Applied Research Institute	0.00	0.02	0.01	0.00	0.02	1.00									
(7) FP7 Program	0.03	0.06	−0.12	0.19	0.13	0.02	1.00								
(8) H2020 Program	−0.03	−0.06	0.12	−0.19	−0.13	−0.02	−1.00	1.00							
(9) Social Sciences & Humanities	−0.05	−0.15	−0.01	−0.32	−0.20	−0.14	−0.02	0.02	1.00						
(10) Life Sciences	0.00	0.23	0.00	−0.15	−0.01	0.14	0.02	−0.02	−0.35	1.00					
(11) Physical & Engineering	0.02	−0.11	0.01	0.39	0.16	−0.02	0.00	0.00	−0.43	−0.69	1.00				
(12) Project Budget	−0.05	0.26	0.71	0.18	0.14	0.02	−0.10	0.10	−0.15	0.16	−0.04	1.00			
(13) Regional R&D	−0.01	−0.02	0.00	−0.02	0.01	−0.03	0.00	0.00	−0.12	0.10	0.00	0.05	1.00		
(14) Regional Employment	−0.01	−0.09	−0.02	−0.10	−0.06	0.00	−0.02	0.02	−0.04	0.07	−0.04	−0.01	0.44	1.00	
(15) Star Year of the Project	−0.09	−0.01	0.20	−0.17	−0.11	−0.02	−0.76	0.76	0.03	0.00	−0.03	0.22	0.00	0.01	1.00

***p < 0.01, **p < 0.05, *p < 0.10.

Table 6
Distribution of patents citing ERC-funded publications by type of applicant and ERC Program (fractional count).

Domain	Total Citing Patent Applications	Firms	Universities and Research Institutions	Individuals
FP7 Program	32,530	16,896.96	13,724.36	1908.68
H2020 Program	3033	1572.32	1360.10	100.58
Total*	***34,294***	***17,828.72***	***14,508.82***	***1956.46***

Note: * A patent application can cite publications linked to more than one ERC-funded project (e.g. to a LS and to a PE project). For this reason, in this Table the sum of values related to projects from the various domains is higher than the total number of unique patent application (reported in the final row of the table).

Table 7
Difference test between projects with and without publications cited by patents.

	Projects with no publications cited by patent applications			Projects with publications cited by patent applications			Difference Test	
	Obs.	Mean	S.E.	Obs.	Mean	S.E.	T-test	Sig.
BS Variety	3193	0.275	0.003	2888	0.389	0.003	−0.114	***
Academic Seniority	3193	0.492	0.009	2888	0.512	0.009	−0.020	n.s.
Log Publications	3193	2.762	0.018	2888	3.298	0.014	−0.536	***
Citations (3 years)	3193	304.748	10.605	2888	669.278	15.915	−364.531	***
Applied Research Institution	3193	0.326	0.008	2888	0.441	0.009	−0.115	***
H2020 Program	3193	0.386	0.009	2888	0.193	0.007	0.193	***
Life Sciences	3193	0.242	0.008	2888	0.492	0.009	−0.249	***
Physical & Engineering	3193	0.440	0.009	2888	0.477	0.009	−0.371	*
Social Sciences & Humanities	3193	0.318	0.008	2888	0.031	0.003	0.286	***
Project Budget	3193	1.665	0.009	2888	1.841	0.009	−0.177	***
Regional R&D	3193	2.604	0.217	2888	2.793	0.222	−0.188	***
Regional Employment	3193	6.042	0.417	2888	6.035	0.042	0.007	n.s.

*p < 0.05, **p < 0.01, ***p < 0.001.

Variety (M2) and the moderating role of *Academic Seniority* of the researcher (M3). M2 shows the main effect on the likelihood to be cited by a patent. Our findings indicates that the *BS Variety* coefficient is positive and statistically significant (7.762; p < 0.01), while the coefficient for the squared term is negative and statistically significant (−5.475; p < 0.01). This outcome indicates a consistent inverted U-shaped relationship between variety of publications and the likelihood to be cited by a patent application, thus confirming our first hypothesis. Fig. 1A shows the curvilinear relationship.

The third model presented on Table 8 (M3) shows the interaction between *BS Variety* and *Academic Seniority* to test our third hypothesis (H3a). The interaction terms in the linear dimension show that researchers with a consolidated academic reputation negatively moderate the main relationship between *BS Variety* and the probability of receiving a patent citation (−2.238, p > 0.1), and the squared dimension shows a positive effect (3.251, p < 0.1). These results indicate that the proposed inverted U-shaped relationship between *BS Variety* and technological impact is flattened by high levels of academic reputation. In order to better understand this result, Fig. 1B highlights the tested relationship. Our results reveal that at medium-low levels of variety (from 0 to 0.7), the relationship between boundary-spanning and probability to be cited by a patent is higher for early-stage researchers' projects, while the trend is the opposite from values of variety higher than 0.7. This result suggests that projects with very high variety often face challenges in integration and practical application, as they may address problems that require substantial effort to adapt into useable technologies. Senior researchers might be more likely to take on such ambitious, interdisciplinary projects, while early-stage researchers may focus on manageable levels of variety, where the boundaries are broader but still practical for technological uptake.

Considering the hypothesis proposed in the beginning of this study, the first step of our analysis strong support the first hypothesis, verifying that there is an inverted U-shaped between the boundary spanning orientation of research projects and its technological impact. The first part of the third hypothesis is also confirmed, as we see a more pronounced and significant inverted U-shape for early-stage researchers'

Table 8
Regression analyses: Effect of *BS Variety* on the probability to receive at least one patent citation (Logit).

	(M1)	(M2)	(M3)
	Logit	Logit	Logit
	Dummy Citing Patent	Dummy Citing Patent	Dummy Citing Patent
Log Publications	0.555***	0.096	0.095
	(0.050)	(0.060)	(0.060)
Citations (3 Years)	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)
Applied Research Institute	0.296***	0.319***	0.319***
	(0.063)	(0.064)	(0.064)
H2020 Program	−0.312	−0.241	−0.249
	(0.548)	(0.553)	(0.553)
Physical and Engineering	1.880***	2.289***	2.295***
	(0.125)	(0.132)	(0.132)
Life Sciences	2.801***	2.682***	2.682***
	(0.128)	(0.132)	(0.133)
Project Budget	1.034***	0.747***	0.744***
	(0.093)	(0.097)	(0.097)
Regional R&D	0.097***	0.105***	0.104***
	(0.029)	(0.029)	(0.029)
Regional Employment	−0.020	−0.005	−0.004
	(0.015)	(0.015)	(0.015)
Academic Seniority	−0.657***	−0.427***	−0.118
	(0.093)	(0.097)	(0.287)
BS Variety		7.762***	9.022***
		(0.800)	(1.117)
BS Variety Sq		−5.475***	−7.348***
		(0.970)	(1.427)
BS Variety *Academic Seniority			−2.238
			(1.522)
BS Variety Sq*Academic Seniority			3.251*
			(1.913)
Constant	−4.689***	−5.016***	−5.185***
	(0.263)	(0.286)	(0.313)
Observations	6081	6081	6081
Pseudo R^2	0.234	0.263	0.264
Start Year of the Project	YES	YES	YES

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

project when the level of variety is medium-low, while the effect for senior researchers is more pronounced for high levels of variety.

Our second set of analyses, presented in Table 9, concerns the linear and positive impact of boundary spanning research projects on the technological scope of patents citing the publications developed by the ERC research projects as postulated in our second hypothesis. The first model (M4) presents the influence of control variables on determining the technological scope, Model 5 presents the analysis considering the variety of the papers published by the research projects, and Model 6 the interaction with *Academic Seniority*. Our main explicative variable (*BS Variety*) is positive and statistically significant (0.465, $p < 0.01$). This indicates that as the interdisciplinarity of scientific research increases, the technological scope also broadens. In other words, scientific outputs resulting from the integration of diverse knowledge domains are more likely to find application across a wider array of technological fields. This highlights the capacity of interdisciplinary research to foster innovation by enabling diverse and varied technological applications. Moreover, when we analyze the role of the seniority of the researcher implementing the scientific activity, we find that the technological scope of patents inspired by interdisciplinary research seems to be more pronounced for early-stage researchers, as suggested by our H3b.

6.3. Robustness checks and additional analyses

We performed a set of robustness checks to validate our analyses. First, we built an alternative measure of boundary-spanning research (*BS Balance*), which measures the evenness of the knowledge disciplines distribution (Rafols and Meyer, 2010; Rafols et al., 2012; Wang et al., 2015; Yegros-Yegros et al., 2015; Bromham et al., 2016; D'Este et al., 2019) rather than their variety. We calculated it using Shannon's Entropy index normalized by variety (Wang et al., 2015; Yegros-Yegros et al., 2015). This index varies from 0 to 1, where the higher the index, the higher the subject areas diversification between the research project publications. Results show that the coefficient of *BS Balance* is positive and statistically significant (49.66, $p < 0.001$), and its squared term is negative and statistically significant (−30.63, $p < 0.001$) as shown in Model A2. Also in this case, the results demonstrate that there is an inverted U-shaped relationship between this measure of interdisciplinarity and the likelihood to be cited by a patent application. The capacity to integrate different knowledge fields increases the capability to create new technology and solving problems (D'Este et al., 2019). However, there is a limit where the unevenness can be effective on this process, since a higher discrepancy of scientific fields diminishes the

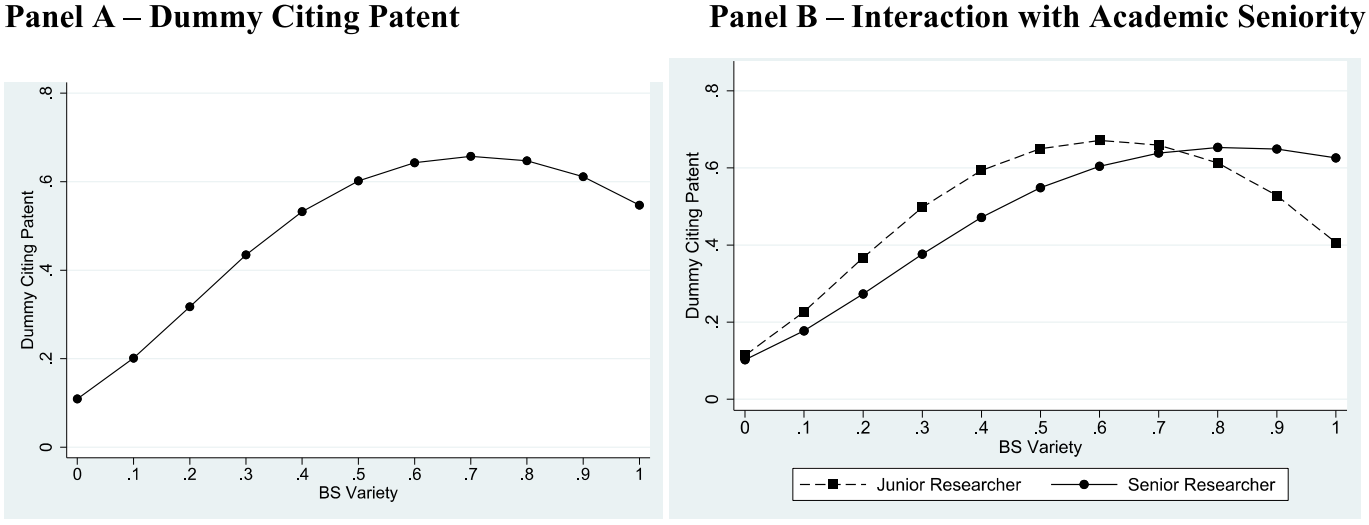

Fig. 1. Curvilinear relationship of *BS Variety* with the probability to receive a patent citation (Panel A) and interaction of *BS Variety* with researcher's academic seniority (Panel B).

Table 9
Regression analyses: Effect of *BS Variety* on the technological scope of the citing patents (OLS).

	(M4)	(M5)	(M6)
	OLS	OLS	OLS
	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields
Log Publications	−0.03*	−0.10***	−0.010***
	(0.02)	(0.02)	(0.02)
Citations (3 Years)	0.01	0.01*	0.01*
	(0.01)	(0.01)	(0.01)
Applied Research Institute	−0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)
H2020 Program	0.34	0.32	0.32
	(0.22)	(0.22)	(0.22)
Physical and Engineering	0.19***	0.26***	0.26***
	(0.06)	(0.07)	(0.07)
Life Sciences	0.16**	0.18***	0.18***
	(0.07)	(0.06)	(0.06)
Project Budget	0.01	0.01	0.01
	(0.04)	(0.04)	(0.04)
Regional R&D	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Regional Employment	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Academic Seniority	−0.05	−0.03	0.08
	(0.04)	(0.04)	(0.06)
BS Variety		0.46***	0.62***
		(0.09)	(0.12)
BS Variety * Academic Seniority			−0.28**
			(0.14)
Constant	1.87***	1.89***	1.82***
	(0.11)	(0.11)	(0.11)
Observations	2886	2886	2886
R-squared	0.02	0.03	0.03
Start Year of the Project	YES	YES	YES

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

probability to a research project of being cited by patent applications. Moreover, the variables *Academic Seniority* is negative and significant (−0.57, p < 0.01), suggesting a lower likelihood to be cited by patents for projects led by senior researchers, according with the results obtained in the regressions using *BS Variety*. Finally, the moderating role of these two variables is negative (Model A3), as in the previous case, but with no statistical significance. The outcome presented on Table A2 (Models A1- A3) are plotted in Figures A1. Models A4-A6, instead, show the results regarding the positive relationship between *BS Balance* and technological scope, confirming the results of the main models using *BS Variety* as measure of interdisciplinarity. Also in this case, the interaction with *Academic Seniority* is negative but not significant.

As second robustness check, we took into consideration the speed of the process leading to the generation of technological impact. For this robustness check, we performed a survival analysis where our dependent variable was the probability that a research project would receive a first patent citation. For each research project, this dependent variable equaled 1 if the event occurred in the year in which the project received the first patent citation. A positive (negative) coefficient thus implied a higher (lower) hazard for that variable occurring (receiving a patent citation) and a lower (higher) expected duration of the overall process of technological development. Table A3 contains the coefficients and the hazard ratios, that predicts projects' time to receive patent citations. The results of the survival analyses largely confirm the findings from Table 8. The variety of knowledge disciplines, as measure of boundary-spanning, continues to have a significant effect on the probability of receiving a patent citation, showing an inverted U shape relationship.

Third, we run the same analyses presented in Tables 8 and 9 but controlling for self-citations (Table A4). We aimed to ascertain how many of the citing patent applications were produced by the same research team responsible for the ERC project, in order to repeat our analyses by focusing only on those citations coming from external (non-project) sources. In order to do this, we distinguished between "direct" and "indirect" citing patents. Direct citing patents have: a) the PI of the ERC project among the applicants and/or inventors of the patent and b) the same Host Institution (Coordinator) of the project listed among the applicants.[13] These patents can be considered as "self-citing" the scientific outcomes of the ERC project. On the other hand, indirect citing patents are assigned to different applicants/inventors, representing a spillover of scientific knowledge generated through the project. From our data we observe that only 2001 patents (out of 34,294 citing patent applications, or 5.83%) can be categorized as directly stemming from the project's research team, according to our definition. Therefore, the vast majority of citations comes from other institutional sources, illustrating a wide dissemination of knowledge. Table A4 and Figure A2, excluding self-citations and focusing on the sole patent citations coming from other institutional sources, show that the results do not present significant changes from the main models.

Finally, we were interested in disentangling the different types of applicants of patents based on ERC research, so to better understand whether there are variations in the effects of interdisciplinary research depending on the institutional origins of citing patents (see Table A5). In order to do that, we created a set of new dependent variables which respectively focused only on citing patents originating from firms (A19-A21), universities and research institutions (A22-A24), individuals (A25-A27). The new variable is a dummy that takes value 1 if the project was cited by at least one firm's patent application and 0 otherwise, and so on for the other types of applicants. The results largely confirm those of Table 8. Moreover, it is interesting to compare the magnitude of the coefficients among these groups. The relationship between boundary spanning research and probability of receiving a patent citation is more pronounced for citations coming from university patents, compared to the other two groups. This suggests that inventors with a strong research orientation are more capable to assimilate the results of boundary spanning science into their technical advancements. In this set of analyses, the interaction related to academic seniority of the researcher is not statistically significant.

With the same logic, in Table A6, we show the results for the analyses where we measure the technological scope of citing patent applications by firms (A28-A30), (b) universities and research institutions (A31-A33), and (c) individuals (A34-A36). Also in this case, the results are largely confirmed: the stronger the scientific interdisciplinarity, the broader the potential technological scope of patents, with some differences emerging among types of applicants.

Finally, we categorized citing patents depending on their reliance on science, referring to the extent through which inventions utilize previous scientific knowledge, considering patent citations to scientific articles (Marx and Fuegi, 2020). In this way, we try to understand whether the effects of interdisciplinary research vary if we focus on inventions that rely more heavily on science. To construct this group of citing patents at the project level, we first categorized each citing patent as science-based or not depending on the percentage of NPL citations over

[13] The procedure to identify "direct patents" is stringent, aiming to circumvent issues of homonymy among PIs. An alternative procedure could involve the use of the PI as inventor/applicant *or*, alternatively, (instead of "and") the Host Institution as applicants of the patent. In such a scenario, the count of direct patents would likely rise, albeit with the potential drawback of introducing errors in accurately identifying the applicants associated with the ERC projects.

the total number of backward citations included in the patent. If this index was higher than 50%, the patent was categorized as science-based. We then aggregated the citing patents at the project level and we defined the *Dummy Science-Based Patents* as 1 if the project received at least one citation by a science-based patent, 0 otherwise. Also in this case, the results (shown in Table A7) confirm our previous findings. The inverted U-shaped effect of boundary-spanning research on the likelihood of being cited by a patent is thus confirmed also when we focus solely on inventions which are deeply rooted in scientific advancements. In Table A8, instead, we show the analyses related to the relationship between interdisciplinary research and boundary spanning inventions for two subsamples. Models A40-A42 show the level of technological scope of patents that primarily cite scientific publications, whereas Models A43-A45 focus on the remaining patents that have a smaller proportion of scientific citations, thus being relatively more rooted in the technology domain. In addition to confirming our previous results with respect to a positive relation, by looking at the magnitude of the coefficients it is noteworthy that the relationship is more pronounced for patents rooted in technical applications as compared to those patents relatively more rooted in scientific discoveries. This suggests that interdisciplinary knowledge is more effectively translated into diverse technological outcomes when the focus is on practical or applied innovation, rather than on fundamental or conceptual advancements. This highlights the role of interdisciplinarity in fostering broader technological impact in applied research contexts.

7. Conclusions

This study aimed to discuss how the boundary spanning orientation of research projects impacts the generation of technological impact. Considering the increasing interest toward the linkage between different scientific fields, the literature investigated how boundary spanning impacts individual performance of the researcher and the process of science development. With our study, we proposed to analyze how boundary spanning research projects impact the development of new technologies. We studied the research grants awarded by the European Research Council in Europe within the FP7 and H2020 programmes in all the different domains - the Life Sciences, Physical & Engineering, and Social Sciences & Humanities. Our final dataset contains 6081 research projects.

Our results indicate that intermediate levels of boundary spanning research have a positive impact on the generation of new patented technologies. The likelihood of a research project being cited by a patent increases with the diversity of the scientific fields at its basis. However, our results showed that there is a limitation on the boundary spanning positive effect. We demonstrated that research projects with an extreme variety distribution tend to decrease the probability of a research project being cited by a patent. When we analyze the link between scientific boundary of research and technological boundary spanning of patents, we find a linear relationship that can be explained by the following reasons. First, interdisciplinary research integrates knowledge from diverse fields, making it directly applicable to a broader range of technological domains. Second, technological boundary-spanning patents inherently demonstrate high absorptive capacity which allows to recognize the value of new external information, assimilate it, and apply it to technological and commercial outcomes (Zahra and George, 2002). We thus provide new evidence on the characteristics of the recipients of such knowledge and the characteristics of the technology they develop. Our findings suggest that a company engagement in boundary-spanning inventive activities within the technology domain fosters a superior ability to scan, interpret, and assimilate the results of interdisciplinary science. Similarly, our additional analyses indicate that the institutional nature of the patent applicant, as well as the technical or scientific origins of its inventions, influence how interdisciplinary knowledge is translated into technological outcomes.

Taking into account the role of individual characteristics, literature shows that the academic seniority of the PIs plays a role in the extent and effectiveness of knowledge transfer activities (Munari and Toschi, 2021). We then investigated if this variable moderates the relationship between boundary spanning research and patent citation. We find support to this moderation role. In particular, we find that younger researchers seem to be more able to generate technological impact when the boundary-spanning level of their research is medium-low, while for high levels of variety, senior researchers obtain higher technological impact. In respect to the technological scope of citing patents, instead, we show that the relationship is more pronounced for early-career researchers.

We consider that the results presented on this study are relevant to improve the understanding about the impact of research projects on the development of new technologies. Our results confirm the importance of integrating different knowledge fields inside research projects in order to leverage problem solving development and consequently new technologies. However they show that too much diversity in research tend to be less influential in inspiring subsequent technological developments, probably because external recipients of novel ideas require a certain level of convention, as highlighted by previous research (e.g., Fleming et al., 2007; Uzzi et al., 2013; Criscuolo et al., 2016). On the other hand, the development of broad patents can be achieved through broad scientific research. Scientific research that spans boundaries, indeed, may unlock solutions relevant to multiple industries. For instance, advances in material science influenced by physics and chemistry can have applications in construction, healthcare, and energy, demonstrating a proportional increase in technological impact with more interdisciplinarity. Regarding the role of academic seniority, our findings indicate that for research projects led by early-stage researchers, greater interdisciplinarity is associated with higher technological influence both in terms of likelihood to contribute to technological development and to foster technological boundary spanning inventions. However, in respect to the probability to receive patent citations, when the degree of interdisciplinarity becomes extremely high, this positive effect diminishes. This outcome may be attributed to the challenges discussed in our third hypothesis: highly interdisciplinary research often demands significant time, effort, and coordination to learn, collaborate, and integrate findings. These factors can delay project outputs and diminish their impact on the technological domain, particularly during the critical early stages of a research career. To address these risks, early-stage researchers should aim to balance interdisciplinary ambitions with the need to establish a strong disciplinary foundation (Yegros-Yegros et al., 2015).

Further investigation is needed in this area, as the moderating effect of academic seniority on the technological impact of interdisciplinary research was not consistently significant in all our analyses. These findings should be interpreted in light of the specific measure of academic seniority employed and the unique research context analyzed—namely, ERC-funded projects.[14] Replicating this type of investigation in diverse research settings would be essential to confirm the robustness of the observed relationship.

In addition to this first point, there are other issues that need a deeper analysis in the future. A first one is related to the investigation of the geographic breadth of knowledge spillovers stemming from boundary spanning research projects, so to better understand whether geographic proximity facilitates private-sector patent activities. A second issue regards the composition of the research team collaborating in the project (Fleming, 2004), to better understand whether teams more diverse, both

[14] Indeed, we resorted to the ERC classification of starting grants that identify early-stage researches as those with less than 7 years of experience since the completion of the PhD. The adoption of a different time window may lead to different results. Moreover, ERC grantees are typically researchers with excellent research track record and a strong “taste for science” (Roach and Sauermann, 2010). This can affect their motivation to engage with applied and practically oriented problems.

in terms of academic seniority and disciplinary expertise, are better off in generating research results that are highly influential for technological applications. Unfortunately, we were not able to have access on information on the actual participants in the project, but just on the principal investigator. Further research in this area could be extremely relevant to better understand the dynamics that favor the translation of boundary-spanning research into valuable technical innovations. A third important avenue for future research is investigating in more detail the characteristics of the receivers of knowledge flows, to better understand what affect their ability to appreciate, assimilate and exploit the results of interdisciplinary research. We made a first step in this direction by disentangling the different types of patent applicants citing scientific publications, distinguishing between corporations, universities and research centres and individuals. Our results show that although the majority of citations to ERC-funded publications come from patents assigned to firms, a significant share of citing patents is still owned by universities and research organizations, thus confirming that the process of translating new scientific knowledge into new patented inventions is complex and cumulative, requiring subsequent steps (Ahmadpoor and Jones, 2017). Future research should analyze in more depth the heterogeneity of corporate receivers, in order to better understand what determines their capacity to absorb and further exploit the results of interdisciplinary research coming from universities and public research centres.

A final concern lies in a more general limitation of the literature analyzing patent-to-paper citations, namely the possibility to understand how intensively the development of the patented technology was affected by the scientific discoveries described in the cited article. Although there is evidence that patents with scientific references are indeed more likely to have been actually inspired by the scientific literature, further evidence is needed on the ability of patent-to-paper citations to signal significant direct flows stemming from science to technology (Callaert et al., 2014).

CRediT authorship contribution statement

Federico Munari: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Hérica Morais Righi:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Laura Toschi:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Formal analysis, Data curation, Conceptualization.

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APPENDIX

Table A1
Main characteristics of the different types of ERC grants

Type of Grant	Researcher	Max Budget	Max duration	Objectives of the Grant
Starting Grant	2–7 years after Ph.D.	€ 1,5 million	up to 5 years	Early-career scientists with an excellent resumè and want to work independently.
Consolidator Grant	7–12 years after Ph.D.	€ 2 million	up to 5 years	Scientists seeking to consolidate their career and build a research team
Advanced Grant	Active researchers in the last ten years	€ 2,5 million	up to 5 years	For established scientist looking for a long term funding to develop novel and risky projects
Synergy Grant	Group of 2–4 Principal Investigators	€ 10 million	up to 6 years	Enhance collaborative projects to work on ambitious projects.
Proof of Concept	Principal Investigator of a previous ERC project	€ 150.00	up to 18 months	For researchers with a preview ERC grant to explore the commercial or societal results

Table A2
Regression analyses: Effect of *BS Balance* on the probability to receive at least one patent citation (Logit) and on technological scope of the citing patents (OLS)

	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)
	Logit	Logit	Logit	Logit	Logit	Logit
	Dummy Citing Patent	Dummy Citing Patent	Dummy Citing Patent	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields
Log Publications	0.56***	0.55***	0.55***	−0.03*	−0.02	−0.02
	(0.05)	(0.06)	(0.06)	(0.02)	(0.02)	(0.02)
Citations (3 Years)	0.01***	0.01***	0.01***	0.01	0.01*	0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Applied Research Institute	0.30***	0.29***	0.30***	−0.01	0.01	0.01
	(0.06)	(0.07)	(0.07)	(0.02)	(0.02)	(0.02)
H2020 Program	−0.31	−0.36	−0.37	0.34	0.32	0.32
	(0.55)	(0.56)	(0.56)	(0.22)	(0.22)	(0.22)
Physical and Engineering	1.88***	2.17***	2.17***	0.19***	0.22***	0.22***
	(0.13)	(0.13)	(0.13)	(0.06)	(0.06)	(0.06)
Life Sciences	2.80***	2.77***	2.77***	0.16**	0.19***	0.19***

(*continued on next page*)

Table A2 (*continued*)

	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)
	Logit	Logit	Logit	Logit	Logit	Logit
	Dummy Citing Patent	Dummy Citing Patent	Dummy Citing Patent	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields
	(0.13)	(0.14)	(0.14)	(0.07)	(0.07)	(0.07)
Project Budget	1.03***	0.90***	0.90***	0.01	0.01	0.01
	(0.09)	(0.10)	(0.10)	(0.04)	(0.04)	(0.04)
Regional R&D	0.10***	0.09***	0.09***	0.01	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
Regional Employment	−0.02	−0.02	−0.02	0.01	0.01	0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Academic Seniority	−0.66***	−0.57***	3.35	−0.05	−0.04	0.33
	(0.09)	(0.10)	(2.62)	(0.04)	(0.04)	(0.24)
BS Balance		49.66***	56.06***		0.74***	1.03***
		(4.39)	(6.29)		(0.17)	(0.25)
BS Balance Sq		−30.63***	−35.24***			
		(3.15)	(4.53)			
BS Balance * Academic Seniority			−11.52			−0.51
			(7.63)			(0.32)
BS Balance Sq * Academic Seniority			8.33			
			(5.56)			
Constant	−4.69***	−24.62***	−26.8***	1.87***	1.26***	1.05***
	(0.26)	(1.52)	(2.17)	(0.11)	(0.18)	(0.22)
Observations	6081	6081	6081	2886	2886	2886
R-squared	.z	.z	.z	0.02	0.03	0.03
Start Year of the Project	YES	YES	YES	YES	YES	YES

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

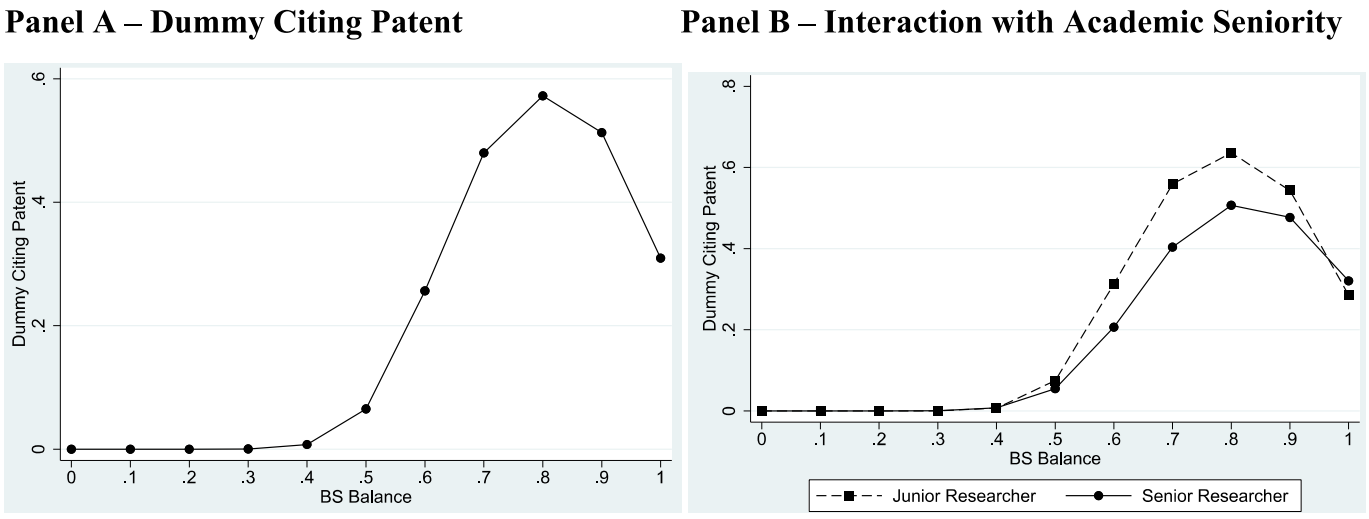

Fig. A1. Curvilinear relationship of *BS Balance* with the probability to receive a patent citation (Panel A) and interaction of *BS Variety* with researcher's academic seniority (Panel B).

Table A3
Survival analysis for *BS Variety*

	(A7)	(A8)	(A9)	(A10)	(A11)	(A12)
	Main Effect	Main Effect	U-Shape	U-Shape	Moderator	Moderator
	Coeff	*Hazard Ratio*	*Coeff*	*Hazard Ratio*	*Coeff*	*Hazard Ratio*
Log Publications	0.371***	1.449***	0.122***	1.130***	0.122***	1.130***
	(0.030)	(0.043)	(0.035)	(0.040)	(0.035)	(0.040)
Citations (3 Years)	0.000***	1.000***	0.000***	1.000***	0.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Applied Research Institute	0.197***	1.218***	0.209***	1.232***	0.208***	1.231***
	(0.038)	(0.046)	(0.038)	(0.047)	(0.038)	(0.047)
H2020 Program	−0.280	0.756	−0.196	0.822	−0.200	0.818
	(0.383)	(0.290)	(0.383)	(0.315)	(0.383)	(0.314)
Physical & Engineering	1.619***	5.048***	1.793***	6.007***	1.793***	6.008***
	(0.111)	(0.561)	(0.112)	(0.671)	(0.112)	(0.671)

(*continued on next page*)

Table A3 (*continued*)

	(A7)	(A8)	(A9)	(A10)	(A11)	(A12)
	Main Effect	Main Effect	U-Shape	U-Shape	Moderator	Moderator
	Coeff	*Hazard Ratio*	*Coeff*	*Hazard Ratio*	*Coeff*	*Hazard Ratio*
Life Sciences	2.161***	8.683***	2.037***	7.668***	2.035***	7.650***
	(0.110)	(0.956)	(0.111)	(0.848)	(0.111)	(0.846)
Project Budget	0.519***	1.680***	0.361***	1.434***	0.357***	1.429***
	(0.054)	(0.090)	(0.055)	(0.080)	(0.056)	(0.079)
Regional R&D	0.057***	1.058***	0.058***	1.060***	0.058***	1.060***
	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)
Regional Employment	−0.009	0.991	−0.003	0.997	−0.002	0.998
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Academic Seniority	−0.326***	0.722***	−0.192***	0.825***	−0.172	0.842
	(0.059)	(0.042)	(0.060)	(0.049)	(0.199)	(0.168)
BS Variety			5.228***	186.479***	5.586***	266.610***
			(0.509)	(94.971)	(0.728)	(194.049)
BS Variety Sq			−4.081***	0.017***	−4.736***	0.009***
			(0.588)	(0.010)	(0.896)	(0.008)
BS Variety * Academic Seniority					−0.472	0.624
					(0.990)	(0.618)
BS Variety Sq * Academic Seniority					0.946	2.576
					(1.183)	(3.048)
Observations	6081	6081	6081	6081	6081	6081
Start Year of the project	YES	YES	YES	YES	YES	YES

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

Table A4
Regression analyses: Effect of *BS Variety* on the probability to receive at least one patent citation (Logit) and on technological scope of the citing patents (OLS), controlling for self-citations of the Principal Investigator and the Host Institution

	(A13)	(A14)	(A15)	(A16)	(A17)	(A18)
	Logit	Logit	Logit	OLS	OLS	OLS
	Dummy Indirect Citing Patent	Dummy Indirect Citing Patent	Dummy Indirect Citing Patent	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields
Log Publications	0.57***	0.14**	0.14**	−0.04*	−0.11***	−0.11***
	(0.05)	(0.06)	(0.06)	(0.02)	(0.02)	(0.02)
Citations (3 Years)	0.01***	0.01***	0.01***	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Applied Research Institute	0.29***	0.31***	0.31***	−0.01	0.01	0.01
	(0.06)	(0.06)	(0.06)	(0.02)	(0.02)	(0.02)
H2020 Program	−0.09	−0.02	−0.03	0.27	0.26	0.27
	(0.56)	(0.56)	(0.56)	(0.25)	(0.24)	(0.24)
Physical and Engineering	1.83***	2.21***	2.22***	0.20***	0.28***	0.28***
	(0.13)	(0.13)	(0.13)	(0.06)	(0.07)	(0.07)
Life Sciences	2.75***	2.63***	2.63***	0.16**	0.18***	0.18***
	(0.13)	(0.13)	(0.13)	(0.07)	(0.07)	(0.07)
Project Budget	1.01***	0.74***	0.74***	0.02	0.01	0.01
	(0.09)	(0.10)	(0.10)	(0.04)	(0.04)	(0.04)
Regional R&D	0.10***	0.11***	0.10***	0.01	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
Regional Employment	−0.03**	−0.02	−0.02	0.01	0.01	0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Academic Seniority	−0.62***	−0.40***	−0.08	−0.06	−0.04	0.07
	(0.09)	(0.10)	(0.29)	(0.04)	(0.04)	(0.07)
BS Variety		7.35***	8.50***		0.50***	0.65***
		(0.80)	(1.12)		(0.09)	(0.12)
BS Variety Sq		−5.19***	−6.83***			
		(0.97)	(1.43)			
BS Variety * Academic Seniority			−2.11			−0.29**
			(1.52)			(0.14)
BS Variety Sq * Academic Seniority			2.90			
			(1.91)			
Constant	−4.63***	−4.93***	−5.10***	1.87***	1.89***	1.82***
	(0.26)	(0.29)	(0.31)	(0.11)	(0.11)	(0.12)
Observations	6081	6081	6081	2829	2829	2829
R-squared	.z	.z	.z	0.02	0.03	0.03
Start Year of the Project	YES	YES	YES	YES	YES	YES

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

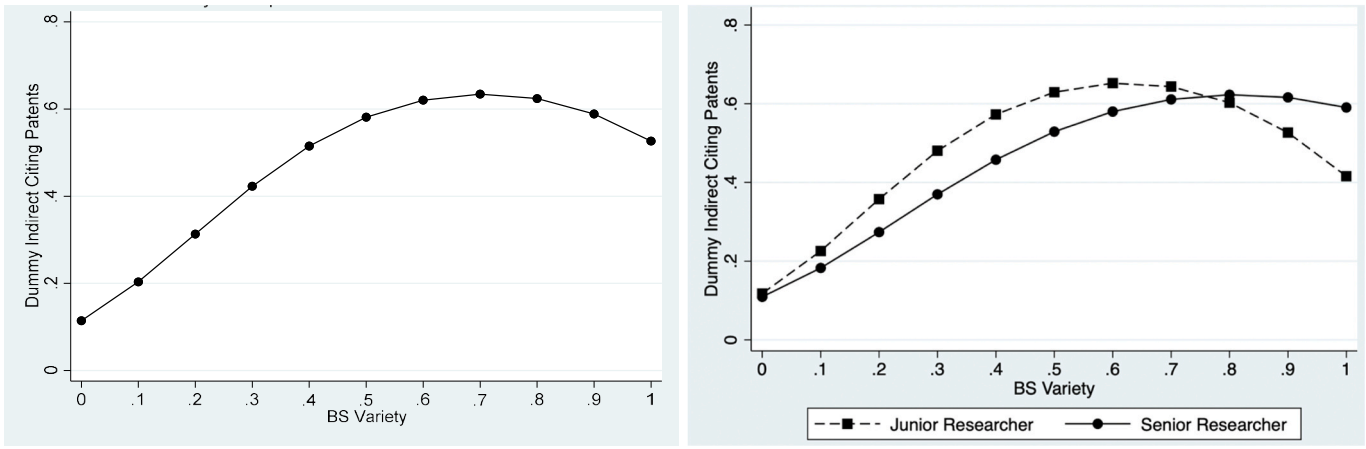

Fig. A2. Curvilinear relationship of *BS Variety* with the probability to receive a patent citation (Panel A) and interaction of *BS Variety* with researcher's academic seniority (Panel B), controlling for self-citations of the Principal Investigator and the Host Institution.

Table A5
Regression analyses: Effect of *BS Variety* on the probability to receive at least one (a) firm's patent citation (A19-A21), (b) university's and research institution's patent citation (A22-A24), and (c) individual's patent citation (A25-A27)

	(A19)	(A20)	(A21)	(A22)	(A23)	(A24)
	Logit	Logit	Logit	Logit	Logit	Logit
	Dummy Citing Patents	Dummy Citing Patents	Dummy Citing Patents	Dummy Citing Patents	Dummy Citing Patents	Dummy Citing Patents
	Firms	Firms	Firms	Universities and Research Institutions	Universities and Research Institutions	Universities and Research Institutions
Log Publications	0.656***	0.320***	0.319***	0.437***	0.001	0.001
	(0.052)	(0.062)	(0.062)	(0.052)	(0.062)	(0.062)
Citations (3 Years)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Applied Research Institute	0.257***	0.273***	0.273***	0.323***	0.348***	0.348***
	(0.063)	(0.064)	(0.064)	(0.063)	(0.064)	(0.064)
H2020 Program	0.645	0.720	0.716	−0.647	−0.602	−0.605
	(0.779)	(0.784)	(0.784)	(0.549)	(0.553)	(0.552)
Physical and Engineering	1.608***	1.885***	1.888***	2.355***	2.703***	2.706***
	(0.141)	(0.145)	(0.145)	(0.166)	(0.170)	(0.170)
Life Sciences	2.274***	2.164***	2.165***	3.210***	3.064***	3.064***
	(0.142)	(0.145)	(0.145)	(0.167)	(0.170)	(0.170)
Project Budget	0.809***	0.596***	0.598***	0.982***	0.718***	0.717***
	(0.093)	(0.097)	(0.097)	(0.094)	(0.098)	(0.098)
Regional R&D	0.102***	0.107***	0.107***	0.079***	0.085***	0.084***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Regional Employment	−0.011	−0.001	−0.001	−0.021	−0.008	−0.008
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Academic Seniority	−0.529***	−0.353***	−0.072	−0.649***	−0.437***	−0.316
	(0.096)	(0.099)	(0.303)	(0.096)	(0.099)	(0.304)
BS Variety		5.989***	6.718***		8.201***	8.669***
		(0.810)	(1.149)		(0.823)	(1.148)
BS Variety Sq		−4.362***	−5.188***		−6.304***	−6.983***
		(0.955)	(1.434)		(0.978)	(1.447)
BS Variety *Academic Seniority			−1.477			−0.835
			(1.553)			(1.572)
BS Variety Sq*Academic Seniority			1.627			1.180
			(1.893)			(1.936)
Constant	−5.025***	−5.303***	−5.436***	−5.049***	−5.473***	−5.538***
	(0.272)	(0.297)	(0.328)	(0.286)	(0.310)	(0.337)
Observations	6081	6081	6081	6081	6081	6081
Pseudo R^2	0.193	0.210	0.210	0.229	0.255	0.255
Start Year of the Project	YES	YES	YES	YES	YES	YES

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

Table A5
(continued) - Regression analyses: Effect of *BS Variety* on the probability to receive at least one (a) firm's patent citation (A19-A21), (b) university's and research institution's patent citation (A22-A24), and (c) individual's patent citation (A25-A27)

	(A25)	(A26)	(A27)
	Logit	Logit	Logit
	Dummy Citing Patents	Dummy Citing Patents	Dummy Citing Patents
	Individual	Individual	Individual
Log Publications	0.499***	0.164*	0.165**
	(0.070)	(0.084)	(0.084)
Citations (3 Years)	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)
Applied Research Institute	0.255***	0.278***	0.279***
	(0.082)	(0.082)	(0.082)
H2020 Program	−0.037	0.015	0.015
	(1.057)	(1.062)	(1.063)
Physical and Engineering	1.715***	1.943***	1.939***
	(0.255)	(0.258)	(0.258)
Life Sciences	2.517***	2.377***	2.373***
	(0.254)	(0.256)	(0.256)
Project Budget	0.661***	0.468***	0.464***
	(0.120)	(0.125)	(0.125)
Regional R&D	0.134***	0.138***	0.138***
	(0.037)	(0.037)	(0.037)
Regional Employment	−0.001	0.005	0.006
	(0.020)	(0.020)	(0.020)
Academic Seniority	−0.481***	−0.319**	−0.743*
	(0.129)	(0.132)	(0.449)
BS Variety		6.690***	5.921***
		(1.113)	(1.516)
BS Variety Sq		−5.235***	−4.531**
		(1.257)	(1.828)
BS Variety *Academic Seniority			1.884
			(2.164)
BS Variety Sq*Academic Seniority			−1.754
			(2.514)
Constant	−5.293***	−5.678***	−5.511***
	(0.381)	(0.419)	(0.455)
Observations	6081	6081	6081
Pseudo R^2	0.226	0.239	0.240
Start Year of the Project	YES	YES	YES

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

Table A6
Regression analyses: Effect of *BS Variety* on the technological scope of citing patent applications by (a) firms (A28-A30), (b) universities and research institutions (A31-A33), and (c) individuals (A34-A36)

	(A28)	(A29)	(A30)	(A31)	(A32)	(A33)	(A34)	(A35)	(A36)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields
	Firm Patents	Firm Patents	Firm Patents	Univ and Res Instit Patents	Univ and Res Instit Patents	Univ and Res Instit Patents	Individuals Patents	Individuals Patents	Individuals Patents
Log Publications	−0.02	−0.09***	−0.08***	−0.04*	−0.11***	−0.11***	−0.01	−0.11*	−0.10*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.05)	(0.06)	(0.06)
Citations (3 Years)	0.01***	0.01***	0.01***	0.01	0.01*	0.01*	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Applied Research Institute	−0.05*	−0.04	−0.04	0.01	0.01	0.01	0.02	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)
H2020 Program	0.07	0.06	0.08	0.38	0.36	0.37	−0.32	−0.24	−0.27
	(0.45)	(0.45)	(0.45)	(0.23)	(0.23)	(0.23)	(0.79)	(0.79)	(0.79)
Physical and Engineering	0.14*	0.21**	0.20**	0.32***	0.39***	0.38***	0.17	0.25	0.24
	(0.08)	(0.08)	(0.08)	(0.09)	(0.10)	(0.09)	(0.19)	(0.19)	(0.19)
Life Sciences	0.09	0.11	0.10	0.30***	0.32***	0.31***	−0.05	−0.04	−0.05

(*continued on next page*)

Table A6 (*continued*)

	(A28)	(A29)	(A30)	(A31)	(A32)	(A33)	(A34)	(A35)	(A36)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields	Mean WIPO Technology Fields
	Firm Patents	Firm Patents	Firm Patents	Univ and Res Instit Patents	Univ and Res Instit Patents	Univ and Res Instit Patents	Individuals Patents	Individuals Patents	Individuals Patents
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.19)	(0.19)	(0.19)
Project Budget	0.06	0.04	0.05	0.02	0.01	0.01	0.01	−0.02	−0.01
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.09)	(0.09)	(0.09)
Regional R&D	0.01	0.01	0.01	0.01	0.01	0.01	−0.02	−0.02	−0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Regional Employment	−0.01	−0.01	−0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Academic Seniority	−0.06	−0.04	0.09	−0.07*	−0.06	0.07	−0.06	−0.05	0.07
	(0.05)	(0.05)	(0.08)	(0.04)	(0.04)	(0.07)	(0.09)	(0.09)	(0.16)
BS Variety		0.44***	0.62***		0.47***	0.65***		0.58***	0.73***
		(0.11)	(0.15)		(0.10)	(0.13)		(0.21)	(0.27)
BS Variety * Academic Seniority			−0.35**			−0.33**			−0.30
			(0.18)			(0.16)			(0.33)
Constant	1.84***	1.87***	1.78***	1.73***	1.75***	1.67***	1.87***	1.93***	1.87***
	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	(0.27)	(0.27)	(0.28)
Observations	2092	2092	2092	2453	2453	2453	934	934	934
R-squared	0.03	0.04	0.04	0.03	0.03	0.04	0.03	0.04	0.04
Start Year of the Project	YES	YES	YES	YES	YES	YES	YES	YES	YES

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

Table A7
Regression analyses: Effect of *BS Variety* on (a) the probability to receive at least one science-based patent citation

	(A37)	(A38)	(A39)
	Logit	Logit	Logit
	Dummy Science-Based Patents	Dummy Science-Based Patents	Dummy Science-Based Patents
Log Publications	0.46***	0.01	0.01
	(0.05)	(0.06)	(0.06)
Citations (3 Years)	0.01***	0.01***	0.01***
	(0.01)	(0.01)	(0.01)
Applied Research Institute	0.29***	0.31***	0.31***
	(0.06)	(0.06)	(0.06)
H2020	−0.56	−0.51	−0.51
	(0.55)	(0.55)	(0.55)
Physical and Engineering	1.94***	2.31***	2.31***
	(0.14)	(0.14)	(0.14)
Life Sciences	2.93***	2.80***	2.80***
	(0.14)	(0.14)	(0.14)
Project Budget	0.95***	0.68***	0.67***
	(0.09)	(0.10)	(0.10)
Regional R&D	0.11***	0.12***	0.12***
	(0.03)	(0.03)	(0.03)
Regional Employment	−0.03*	−0.01	−0.01
	(0.02)	(0.02)	(0.02)
Academic Seniority	−0.60***	−0.37***	−0.27
	(0.10)	(0.10)	(0.30)
BS Variety		7.98***	8.58***
		(0.82)	(1.14)
BS Variety Sq		−5.92***	−6.91***
		(0.98)	(1.44)
BS Variety * Academic Seniority			−0.95
			(1.56)
BS Variety Sq * Academic Seniority			1.60
			(1.93)
Constant	−4.57***	−4.93***	−4.99***
	(0.27)	(0.29)	(0.32)
Observations	6081	6081	6081
Pseudo R^2	0.24	0.27	0.27
Start Year of the Project	YES	YES	YES

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

Table A8
Regression analyses: Effect of *BS Variety* on the technological scope of science-based versus technology-based citing patent applications

	(A40)	(A41)	(A42)	(A43)	(A44)	(A45)
	OLS	OLS	OLS	OLS	OLS	OLS
	Mean WIPO Fields	Mean WIPOFields	Mean WIPO Fields	Mean WIPO Fields	Mean WIPO Fields	Mean WIPO Fields
	Science Based Patents	Science Based Patents	Science Based Patents	Technology Based Patents	Technology Based Patents	Technology Based Patents
Log Publications	0-0.041*	−0.121***	−0.120***	0.166***	0.102***	0.106***
	(0.025)	(0.030)	(0.030)	(0.032)	(0.038)	(0.038)
Citations (3 Years)	0.001***	0.001***	0.001***	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Applied Research Institute	0.035	0.044	0.044	−0.004	0.003	0.003
	(0.028)	(0.028)	(0.028)	(0.036)	(0.036)	(0.036)
H2020 Program	0.214	0.192	0.196	0.301	0.284	0.298
	(0.288)	(0.287)	(0.287)	(0.369)	(0.368)	(0.368)
Physical and Engineering	0.427***	0.514***	0.513***	0.411***	0.479***	0.475***
	(0.082)	(0.084)	(0.084)	(0.105)	(0.107)	(0.107)
Life Sciences	0.511***	0.532***	0.531***	0.120	0.137	0.133
	(0.083)	(0.083)	(0.083)	(0.107)	(0.107)	(0.107)
Project Budget	0.041	0.018	0.021	0.135**	0.117*	0.128**
	(0.048)	(0.048)	(0.048)	(0.061)	(0.062)	(0.062)
Regional R&D	0.018	0.020	0.020	0.011	0.013	0.013
	(0.013)	(0.013)	(0.013)	(0.017)	(0.017)	(0.017)
Regional Employment	−0.004	−0.002	−0.002	0.001	0.002	0.002
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)
Academic Seniority	−0.065	−0.043	0.021	−0.145**	−0.128**	0.122
	(0.048)	(0.048)	(0.083)	(0.061)	(0.061)	(0.106)
BS Variety		0.557***	0.649***		0.437***	0.796***
		(0.115)	(0.150)		(0.147)	(0.192)
BS Variety * Academic Seniority			−0.170			−0.667***
			(0.180)			(0.231)
Constant	1.346***	1.369***	1.331***	0.333*	0.351*	0.203
	(0.140)	(0.140)	(0.145)	(0.180)	(0.179)	(0.186)
Observations	2886	2886	2886	2886	2886	2886
R-squared	0.047	0.054	0.055	0.074	0.077	0.079
Start Year of the Project	YES	YES	YES	YES	YES	YES

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

Data availability

The authors do not have permission to share data.

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