



The impact of public funding on science valorisation: an analysis of the ERC Proof-of-Concept Programme

Federico Munari^{*}, Laura Toschi

Department of Management - University of Bologna, Via Capo di Lucca, 34, 40126 Bologna, Italy

ARTICLE INFO

JEL codes:

G32

G38

L52

O34

O38

Keywords:

science valorisation

impact

technology transfer

proof-of-concept

public funding

grants

ABSTRACT

Governments and public agencies are increasingly keen to support the translation of scientific discoveries into commercial and societal applications through science valorisation funding, as a way to enhance progress and inclusive growth. In this paper, we use grant-level data from the European Research Council Proof-of-Concept (PoC) programme, in order to assess the impact of public funding on a broad set of science valorisation outcomes, including licensing, spinoff formation, R&D collaborations, consulting and access to follow-on funding. We employ an instrumental variable approach to compare the valorisation outcomes of projects that obtained an ERC PoC grant to a group of projects that applied to the PoC scheme but were not funded. We find that the programme was effective in fostering the early valorisation of scientific discoveries by all measures of success that we employed. Overall, thus, our findings speak in favour of this type of policy instrument as a catalyst to accelerate the transition of scientific breakthroughs towards practical applications.

1. Introduction

Knowledge transfer between research, industry, and society represents a powerful engine of progress and inclusive growth (Bozeman and Youtie, 2017). However, several barriers limit the successful transformation of scientific breakthroughs into new products or services—and by extension, their ability to address societal challenges (Bruneel et al., 2010). One of the most significant and frequently cited hurdles is the “funding gap” that limits the possibility of turning research results into practical applications and attracting private investors in the process (Audretsch et al., 2012; Lockett and Wright, 2005; Rasmussen and Soheim, 2012). Indeed, traditional financing instruments from either private (i.e., banks, business angels, venture capitalists) or public (i.e., R&D subsidies) sources have only limited relevance for universities’ early-stage research valorisation projects, due to the latter’s immature phase of development and high levels of risks. For these reasons, many potential breakthroughs emerging from university research laboratories fall into the so-called technological “valley of death” and are never converted into new, useful applications and practices (Auerswald and

Branscomb, 2003). Several examples can be found in this respect. For instance, in the case of medical research, the process of translating early scientific discoveries into effective treatments for patients is time-consuming, costly and often unsuccessful. According to estimates of the National Institute of Health reported in Seyhan (2019), 80 to 90% of research projects fail before they ever get tested in humans and for every drug that gains FDA approval, more than 1000 were developed but failed. In the cleantech sector, several promising breakthrough technologies stemming from university laboratories - such as advanced biofuels or solar photovoltaics - proved to be too immature and too expensive to be commercialized, thus becoming unsuited for the VC funding model and leading to an investment bust in this area in the mid-2010s (Weyant et al., 2018).

To address these missed opportunities for economic and social progress, a number of public financial schemes have arisen at the national, regional, and university level in order to explicitly target science valorisation activities (Bradley et al., 2013; Munari et al., 2018; Rasmussen, 2008). Such policy instruments, branded in different ways (e.g., Proof-of-Concept, Pre-Seed, or Translational Funding), all share the

* Corresponding author.

E-mail addresses: federico.munari@unibo.it (F. Munari), laura.toschi@unibo.it (L. Toschi).

common aim of translating the scientific discoveries of universities or public research centres into beneficial applications¹.

However, despite importance of effectively transferring knowledge from research into society, we still know very little about the actual function and impact of public funding for science valorisation. The effectiveness of science valorisation funding is not straightforward and obvious for several reasons, mainly linked to the fact that valorisation activities require a different set of competences, motivations and values from those required to conduct frontier research. On the one hand, the availability of funding is only one component of a more articulate support system necessary to turn new advanced knowledge into practical applications. On the other hand, researchers might be potentially confronted with complex and seemingly contradictory indications about how to set their priorities.

As highlighted by Molas-Gallart et al. (2016), scholars still debate the ways in which science-valorisation support activities should be implemented and evaluated. Indeed, the literature still lacks systematic and robust assessments of the effects of public funding programmes on science valorisation outcomes; the few available analyses mainly adopt a descriptive or anecdotal perspective (Kochenkova et al., 2016). This gap is the result of several factors. First, the phenomenon has only recently proliferated and its implementation has varied widely across countries, agencies, institutions, universities and sectors (Munari et al., 2017; Rasmussen and Soheim, 2012). Second, there is complexity in capturing the multidimensional nature of science valorisation outcomes, which includes a diversified set of channels: commercialization of research through licensing of inventions or creation of a new venture, academic engagement through inter-organisational collaborations with industrial partners, or search for follow-on funding to further develop inventions towards commercial applications (D'Este and Patel, 2007; O'Shea et al., 2005; Perkmann et al., 2013). Third, it is difficult to access relevant data on applicants and beneficiaries, given that such initiatives typically target individual researchers and research teams, which are not as easily observable as existing (and registered) companies (Gulbranson and Audretsch, 2008). Fourth, also as a consequence of the previous point, we still know very little on the individual characteristics of researchers (and in particular of Principal Investigators) that are likely to impact on the effectiveness of public funding programmes in stimulating science valorisation outcomes. In particular, academic seniority has been often positively related to commercialisation activities in the existing literature. Previous research has generally shown a positive relationship between the progression into the academic career and engagement in commercialisation, explained by a set of reasons based on personal motivations, social capital and previous collaboration experience (D'Este and Patel, 2007; Haeussler and Colyvas, 2011; Link et al., 2007). However, to our knowledge there is almost no evidence on the differential effects of the availability of science valorisation funding in the early or late career stages of researchers. Fifth, there are methodological challenges associated with the “selection-bias” that is likely to plague any “after-the-fact” attempt to evaluate the effects of a research grant programme (Jaffe, 2002).

In this paper, we intend to provide the first comprehensive analysis of the effects of a major public funding programme in support of science valorisation activities: the Proof-of-Concept Programme of the European Research Council (ERC). Established in 2007 to improve the quality of Europe's science, the ERC is the European Union's premier funder of

frontier research. To maximise the value of the blue-sky research funded by its core programme, the ERC agency established Proof-of-Concept (PoC) Grants in 2011 as a way to fund further valorisation work to verify the innovation potential of ideas arising from previous ERC-funded projects. ERC PoC grants thus cover activities during the very early stage of turning research outputs into a commercial or socially valuable propositions, such as prototype building and testing, patent filing, market assessment, business planning, and connecting to late stage funding.

The aim of our study is to address the following research questions: *does the ERC PoC scheme contribute to the valorisation of research stemming from previous ERC projects, by facilitating the further development of their commercial and social potential? Does the impact of the ERC PoC scheme varies according to the academic seniority of the Principal Investigator?* More precisely, we employ an instrumental variable approach to compare the valorisation outcomes of projects that obtained an ERC PoC grant to a group of projects that applied to the PoC scheme but were not funded. To do so, we draw on data from an original survey distributed to all academic researchers who received ERC funding under the 7th Framework Programme (FP7), including those who received PoC grants, those who applied for PoC funding but did not receive it, and awardees of other ERC Frontier Research grants. The data used in this study refer to the 242 survey responses obtained from ERC PoC grant holders and the 204 responses from ERC PoC applicants who were not funded (and constituting our control group). Our assessment takes into account the multidimensional nature of the science valorisation process, and focuses on the project's likelihood of achieving a positive valorisation outcome (Perkmann et al., 2013) in terms of commercialisation (via a licensing agreement or the creation of a startup company) or academic engagement (via collaborative R&D/R&D contracts or consulting). It also analyses the project's likelihood of attracting follow-on funding (through additional public or private sources). Moreover, we assess whether these capabilities are influenced by specific contingencies. In particular, we focus on characteristics at the individual level and assert that the academic seniority of the PI (his/her stage of development in the academic career) may moderate the relationship between the receipt of a PoC grant and valorisation outcomes. To control for the selection into grants, we conducted instrumental variables regression analyses.

Our study thus provides several contributions that are relevant for academic scholars and policy-makers. On the side of academic contributions, it responds to the call by Martin (2016) to extend the focus of studies on R&D policies to policy instruments that either have been taken for granted or at least have not been subject to rigorous assessments, which includes individual research valorisation project grants. In extending the existing evidence on the effects of public funding for research and innovation (Beaudry and Allaoui, 2012; Dimos and Pugh, 2016; Howell, 2017; Hottentrott et al., 2017; Wallstein, 2000), our study thus provides four main contributions. First, we fill a gap in the literature on research and innovation grants, which has heretofore either assessed the impact of public funding for science (mainly in terms of scientific productivity) or the impact of R&D subsidies targeting established companies (large or small, mature or young). To our knowledge, this is the first assessment of a policy explicitly designed to tackle the “funding gap” by targeting individual research valorisation projects. Indeed, we exploit the unique characteristics of the ERC proof-of-concept scheme which is granted to the Principal Investigators and thus focuses on the individual researcher, rather than on projects or companies. Second, we contribute to the literature on the lifecycle model of science commercialisation (Levin and Stephan, 1991). To this purpose, we take advantage of the specific structure of the ERC funding schemes, which differentiate frontier research grants in terms of academic experience of their principal investigators. Based on such data, we highlight that the effectiveness of valorisation funding tends to be more pronounced in the specific case of early-stage researchers. This is an interesting result which is opposed from the previous literature that have shown that academics in the early phase of their career tend to

¹ Examples of such policy instruments include, among many others: the NIH Centers for Accelerated Innovations (NCAI) and the NIH Research Evaluation and Commercialization Hubs (REACH) programs in the United States; the Proof of Concept Funding Scheme of the European Research Council; the Exist Support Program in Germany; the proof-of-concept programmes of the SATT Technology Transfer Accelerators in France; the Itatech Funding Initiative to support technology transfer in Italy; the translational funding programmes of the Medical Research Council in the United Kingdom.

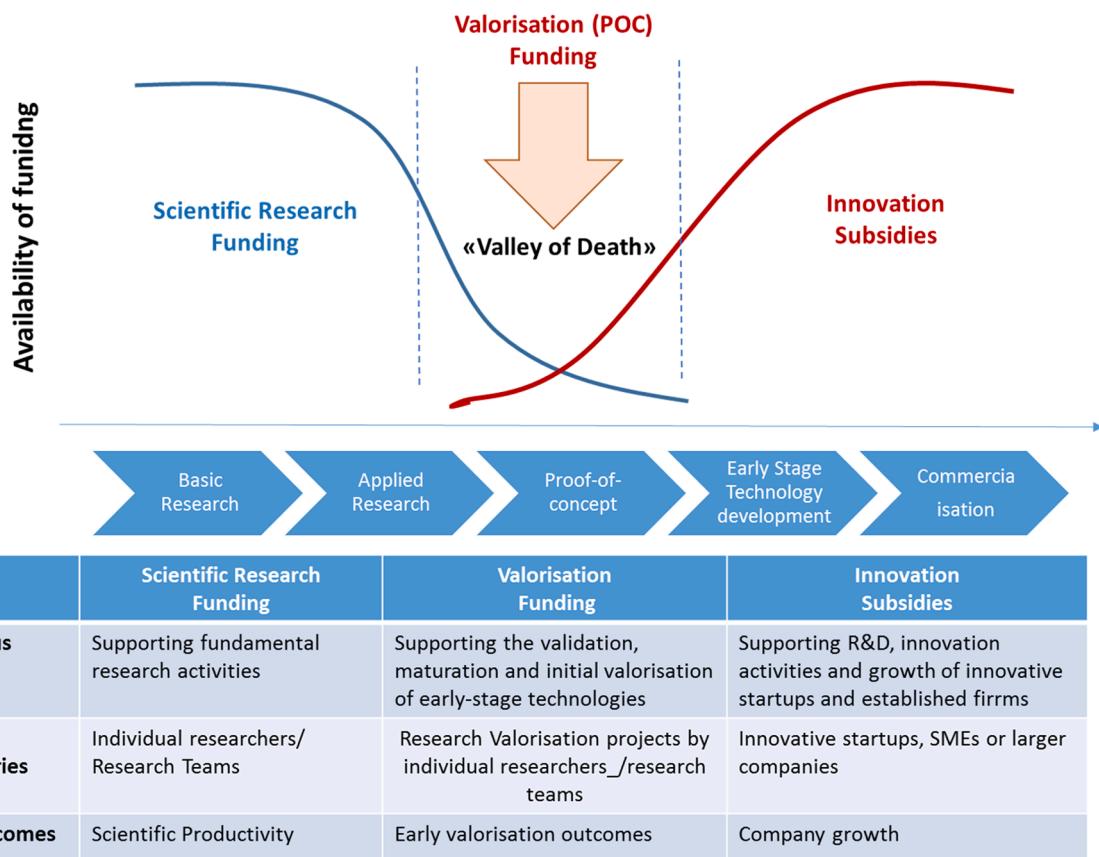


Figure 1. Distinguishing features of valorisation funding grants

experience higher barriers to valorisation as they prefer to be more focused on augmenting their scientific prestige within their direct academic audience, leaving their senior peers to undertake efforts to interact with the business audience for commercializing their research. Thus, our results suggest that PoC schemes seem to be a successful mechanism for concretely filling not only the “funding gap” faced by early-stage valorisation projects, but also the “motivational gap” of their principal investigators (PIs). Third, we adopt a broad vision of impact, given that the survey-based data from ERC grantees that we use in our empirical analyses include not only commercialisation outcomes, which have generally attracted attention from the extant academic literature and the broader policy community, but also academic engagement outcomes and the ability to attract additional developmental funding. In this way, we address a call in the literature on the commercialisation of public science, concerning a broader assessment of the multiple pathways that link university research to industry (Fini et al., 2018). Fourth, from a methodological point of view, we exploit the unique characteristics of the ERC PoC programme, using data on both grantees and non-funded applicants, thereby accounting for the selection into the programme issue, and addressing the additionality issue (Jaffe, 2000). Although other studies have exploited this approach (Howell, 2017; Wang et al., 2017), they were typically focused on startup companies rather than individual researchers or teams of researchers. Finally, to our knowledge, this is one of the first academic studies centred on the assessment of a funding programme of the ERC, the most important European Agency in support of frontier research, and thus constitutes a

novel body of evidence.

The results of our study present also important policy implications for a variety of actors, including university managers, policy makers, representatives of science funding agencies, technology transfer office professionals. They highlight the importance of PoC programs as instruments to improve the maturation and innovation potential of technologies and projects generated from university research. The availability of well-designed PoC programs emerges as a critical component in a technology transfer ecosystem, in particular in order to encourage the engagement of early-stage researchers in this area.

The rest of the paper is organised as follows. We first present the theoretical background by summarising research on the importance of public policies to address the funding gap in science valorisation. Second, we formulate our hypotheses on the effectiveness of science valorisation grants. Third, we present the context of our study (i.e., the ERC PoC programme). Fourth, we describe our data and specify the econometric strategy adopted to test our predictions. We then discuss the results and provide relevant implications for academics and practitioners.

2. Theory and hypotheses

2.1. Public policies to address the “funding gap” in science valorisation

Science valorisation broadly refers to the multiple ways in which knowledge from universities and public research institutions can be used by firms and society to generate economic and social value and industry

development (OECD, 2013)². There are many channels available to valorise science and establish links with knowledge users, which can be classified in terms of relational intensity, significance to industry, degree of knowledge finalisation, and level of formalisation. Perkmann et al. (2013) provided a useful classification for science valorisation activities, distinguishing two main components: commercialisation activities and academic engagement. The former involves the patenting and licensing of inventions as well as academic entrepreneurship (the founding of a new firm to exploit a patented invention or a body of unpatented expertise) (Lokett and Wright, 2005; Thusby and Thursby, 2002). Academic engagement, on the other hand, encompasses knowledge-related collaboration by academic researchers with companies and other non-academic organisations, including both formal (e.g., collaborative research, contract research, and consulting) and informal activities (e.g., providing ad hoc advice and networking with practitioners) (Abreu et al., 2009; D'Este and Patel, 2007; Perkmann et al., 2013). Science valorisation is thus a broad concept, including two different dimensions of commercialisation and academic engagement, which differ in terms of complexity and degree of formalization. It has attracted mounting attention from scholars, practitioners, and policymakers due to its importance in fostering economic progress and inclusive growth.

Indeed, promoting science valorisation has become a central priority for policymakers around the world. Such efforts can favour the diffusion of public research results to industry and lead to the generation of new products, processes, and services that may help address major social challenges, such as health, security, energy, climate change, and the efficient use of natural resources (OECD, 2019). To this purpose, a wide array of public policies has been implemented globally over the last three decades, including novel regulations to clarify the assignment of IPRs, grants for collaborative research, financial support for university spinoffs, mobility schemes for researchers, and financial incentives for the establishment of intermediary organizations such as Technology Transfer Offices, Science Parks, and Incubators (Kochenkova et al., 2016; OECD, 2019; Villani, 2013).

However, ample evidence speaks to the persistence of a so-called "funding gap" (or "Valley of Death") between basic research and the commercialisation of new products and services (Munari et al., 2018). This notion refers to the lack of dedicated funding sources to support the testing, validation, and maturation activities required to bring a novel idea from research to a stage where it is mature enough to attract the interest of private corporations or investors. The problem is that these types of maturation activities (e.g., prototype building, testing, IP protection, market assessment, business planning) are typically not eligible for traditional public funding programmes oriented to basic research activities. At the same time, early-stage valorisation projects or start-ups are often unable to attract the interest of traditional private funding sources - including business angels and seed investors - due to their embryonic nature, high levels of risk, and limited investability (Rasmussen and Soheim, 2012).

To solve this paradox, national governments, regional authorities, and universities have increasingly activated innovative funding sources specifically designed to help research laboratories demonstrate the

² Previous research has referred to various concepts and definitions to identify the process of turning scientific results into industrial and societal applications, including university-industry collaborations, knowledge transfer activities, and third mission activities. Although different definitions can be adopted, they share some common features: Science valorisation is a process, ultimately aiming at enhancing economic and societal value stemming from scientific results, and it can occur in several forms, including licensing, new company creation, contracting with industrial and societal partners, and consulting. Our focus on science valorisation is rooted in its multidimensional nature, encompassing both activities with a more commercial and formalised orientation (such as licensing agreements and new company formation) and academic engagement activities characterised by a lower degree of complexity and formalisation (such as R&D collaborations and consulting).

technical and commercial feasibility of their discoveries and inventions to industrial/societal partners and investors (Bradeley et al., 2013; Gulbranson and Audretsch, 2008; Rasmussen, 2008). We refer to these as "science valorisation" funding, although they may assume different names and labels in various countries or institutions (the two most frequent being "proof-of-concept funding" or "translational funding")³. Such policy instruments provide capital (and often support and training) to individual researchers or research teams in order to facilitate the implementation of a wide spectrum of valorisation activities, such as intellectual property rights protection, prototype building and testing, market analysis and business planning, entrepreneurial team formation, and networking with external partners.

Figure 1 summarises the distinguishing features - in terms of objectives, target beneficiaries, and funding stages - of science valorisation funding with respect to other public funding instruments targeting upstream (e.g., scientific research funding) or downstream (e.g., innovation and R&D subsidies) phases. Unlike traditional funding sources for basic research, science valorisation funding does not focus purely on the advancement of knowledge; rather, it encourages the early steps towards knowledge application and use. Likewise, whereas traditional innovation subsidy programmes target pre-established private companies (not only start-ups, but also small and large companies at later stages of development), science valorisation funding is typically oriented at earlier pre-company formation stages, targeting projects implemented by individual researchers and research teams.

Despite the rapid diffusion of such policy instruments for supporting university-society knowledge transfer among international institutions, central governments, regional funding agencies, and specific universities, we still have limited empirical evidence on their effectiveness and impact⁴, as discussed in the next section.

2.2. Existing empirical evidence on the effects of science valorisation funding

Any assessment of the effectiveness of policy instruments in support of science valorisation should be characterised by a focus on (i) science-based projects and (ii) valorisation outcomes. To date, these two dimensions have been analysed separately. Numerous studies have assessed the effects of grant funding for science-based projects, but focused on science productivity as the outcome variable, instead of science valorisation (Beaudry and Allaoui, 2012; Hottentrott and Lawson, 2017; Jacob and Lefgren, 2011; Wang et al., 2011; Zhang et al., 2018). Similarly, there is a vast literature on the effects of public R&D subsidies on firm productivity, as measured in different ways, but these works target in the majority of cases new and small firms instead of early-stage research projects, thus focusing on the later steps of the so-called "funding gap" (Czarnitzki and Lopes-Bento, 2013; Howells, 2017; Vanino et al., 2019; Wallsten, 2000).

Within this vast literature, there is a narrower stream of studies

³ Other synonyms used by public agencies or universities to refer to this type of funding instrument include proof-of-principle funds, translational funding, pre-seed funding, verification funding, maturation programmes, and ignition grants.

⁴ Public funding programmes for science valorisation can be implemented by international organisations (as in the case of the European Research Council Proof-of-Concept scheme), national governments or national innovation agencies (as in the case of the Exit Programme by the German Federal Ministry of Economics and Energy, the VFTI Programme implemented by the Vinnova Innovation Agency in Sweden), or by regional innovation agencies (as in the case of the Northern Ireland Spinouts Grants promoted by Invest Northern Ireland, or the Industrial Research Fund in Flanders). Many universities around the world are increasingly managing these programmes internally, often with the support of public money. For a discussion of the level of diffusion and degree of centralization/decentralization of this type of policy instrument, see Munari et al. (2016).

focused on grant-based policies more directly oriented to high-tech and science-based sectors, but again, these target new ventures as the primary beneficiaries, as in the case of the United States' Small Business Innovation Research Programme (Feldman and Kelley, 2003; Howell, 2017; Huan-Saad et al., 2018; Lerner, 2009; Lerner, 1999; Link and Scott, 2010; Siegel and Wessner, 2012; Wallsten, 2000; Wang et al., 2017; Wessner, 2008)⁵.

By contrast, to our knowledge, there is no quantitative and systematic evidence about the effects of publicly funded science valorisation grants that target individual researchers or research groups with the purpose of translating scientific discoveries into beneficial applications and practices⁶. The lack of focus on valorisation outcomes for university labs' early-stage technologies is a significant issue, especially in light of previous studies showing that the project's development phase and the beneficiary's linkages with academia are likely to impact the project's ultimate success (Siegel and Wessner, 2012; Howells, 2018). Existing studies on these policy instruments illustrate, often in purely qualitative terms, the design and experiences of specific proof-of-concept (PoC) programmes, but they present only anecdotal evidence of their effectiveness.

For instance, in one of the first studies on PoC centres, Gulbranson and Audretsch (2008) discussed the pioneering experiences of the Deshpandhe Center at MIT and of the von Liebig Center at University of California San Diego; the authors provided data on the number of projects supported, the number of spinoffs and licenses created through the programme, and the amount of capital leverage. In a similar vein, Rasmussen (2008) reviewed several policy initiatives in Canada at the federal level, where general agencies provide proof-of-concept funding to university researchers in order to foster the commercialisation of their projects. The author cited the general positive impact of these public policy measures, which target early-stage research of potential commercial value by providing different types of proof-of-concept funding, such as the Intellectual property Mobilization (IPM) program or the Proof of Principle (POP) program. Bradley et al. (2013) analysed the economic impact of the 32 Proof-of-Concept Centres associated with US universities and supported by the 2011 Startup America initiative. The authors provided exploratory evidence of an increase in university start-ups after the university became affiliated with a PoC, although this study did not present a control group as counterfactual. Molas-Gallart et al. (2016) analysed different approaches and practices adopted to develop Translational Research programmes, and from this defined subsequent evaluation approaches to test for the effectiveness of such programmes. Bozeman and Youtie (2017) discussed the socio-economic impact of four US National Science Foundation (NSF) programmes implemented to enhance the social impact of research, adopting a set of criteria related to the type of socio-economic benefit generated, the breadth and type of beneficiaries, and the timing of the benefit stream. Huang-Saad et al. (2017) investigated the NSF I-Corps program, an innovative funding programme offering researchers funding and innovation/entrepreneurship training. The authors showed, in descriptive

⁵ The SBIR programme was established in 1982 to strengthen the US high technology sector and support small firms; it has served as a benchmark of many subsidy policies around the world. Among its goals, it intends to increase university-industry technology transfer through private-sector commercialisation of innovations derived from publicly funded research. It is centred on a two-phase structure (smaller Phase I grants target companies at earlier stages of their development path), and it is implemented by various federal agencies in the United States. Numerous studies have assessed its impact, focusing on the innovation and growth rates of beneficiary companies vis-à-vis other comparable companies.

⁶ This is particularly true for academic studies. There have been assessments of POC policies implemented by the Funding Agencies or commissioned to independent third parties. However, such assessments very often present a purely descriptive approach and do not adopt rigorous methodologies based on a counterfactual logic.

terms, that teams participating in the programme had higher odds of obtaining follow-on commercialisation funding compared to similar teams.

In a survey-based study of 128 university TTO managers across 32 European countries, Munari et al. (2018) focused on different types of science valorisation funding instruments (from university-oriented translational funding to university-oriented seed funding). The authors adopted a different approach to evaluate the success of these programs: namely, directly asking to the TTOs of recipient universities to express their perceived effectiveness towards the funding schemes. Two factors emerge as particularly critical for the implementation of such funding schemes at the university level: a viable size of the TTO and the research quality of the university. A recent work by Fini et al. (2018) provides a new and interesting perspective: that societal impact and change can be the main outcomes for evaluating the success of funding schemes that support science valorisation. Although their work does not provide quantitative data, it offers a new approach that deserves further investigation. In sum, the emerging literature on science valorisation funding shows a substantial lack of systematic studies that empirically assess such policy instruments with a counterfactual logic.

2.3. Assessing the effectiveness of science valorisation grants

As highlighted in the previous section, science valorisation activities are multifaceted and occur through various channels, thus generating a variety of outcomes that are useful for capturing their impact. A set of outcomes relate to the concept of commercialisation previously mentioned, and thus include the activation of licensing agreements for the transfer of a scientific invention to an established firm, or the constitution of an academic spinoff to commercialise new products, processes, or services (Lockett and Wright, 2005; Thursby and Thursby, 2002). Other valorisation pathways, more centred on the notion of academic engagement (Perkmann et al., 2013), may lead to outcomes such as the activation of research collaborations, research contracts, or consulting agreements with industrial or societal partners (D'Este and Patel, 2007). There are thus different reasons to expect that the receipt of a public valorisation grant will have a positive impact on the ability to achieve the aforementioned valorisation outcomes. On the one hand, there is the simple effect of public funding in alleviating the financial constraints for the recipient team(s) of researchers. They could therefore implement a set of technical and business development activities to demonstrate the technology's viability and potential. Specifically, public funding should facilitate the achievement of proof-of-concept activities and the construction of prototypes, which may show feasibility and thus reduce uncertainty for potential clients, partners, and investors (Rasmussen, 2008). Howells' analysis (2017) of the effects of SBIR funding on high-tech energy start-ups is consistent with the view that grants enable the recipient team to invest in reducing technological uncertainty, which makes the project a more viable commercial and investment opportunity. In a similar vein, Audretsch et al. (2012) studied 4,122 US entrepreneurs and showed that innovative nascent ventures with patents and prototypes are indeed more likely to obtain financing from external investors. In addition to facilitating the development of prototypes, science valorisation grants may serve to construct or reinforce the establishment of business development competences that are often lacking with teams of scientists. For instance, thanks to market assessment activities, early interactions with stakeholders may lead to users or prospective customers, or business plan redactions (Lockett and Wright, 2005). They can thus serve to build new skills, learn new languages, and gain self-confidence in the application potential—steps that are critical to reducing the competence and communication gaps that often plague technology transfer endeavours (Salmenkaita and Salo, 2002).

For these reasons, we advance the following hypothesis:

Hp1: Projects supported by public science valorisation grants have a higher likelihood of reaching positive valorisation outcomes than similar

projects that did not obtain such funding.

An additional key indicator of success for a valorisation grant is the ability to attract additional and subsequent funding, from either public or private sources, for the further development of an idea/technology related to the project (Munari et al., 2017). Indeed, given the early-stage nature of discoveries generated from frontier research projects, it is unlikely that the receipt of a valorisation grant will spur the maturity level needed for commercial or societal applications. Indeed, even after the completion of the grant-funded project, reaching the final market often requires further efforts to mature and de-risk the technologies through additional funding stages. Thus, it is often necessary to tap into subsequent funding sources, either provided by private investors (such as business angels, venture capital or, increasingly, crowdfunding platforms) or by other specialised public funding agencies. For such reasons, public policies centred on valorisation grants often include the mobilization of private investments among their objectives, including those of business angels and venture capital firms (Wessner, 2008). Coherently with this aim, the literature typically uses the ability to attract follow-on funding as a way to assess the effects of public funding on innovation and start-ups (Audretsch et al., 2012; Howells, 2017; Siegel and Wessner, 2012).

In this respect, valorisation grants provided by reputable institutions or agencies may serve an important certification role (Lanahan and Armanios, 2018; Lerner, 1999). According to Sine et al. (2007), certification represents "a process in which a central institutional actor with authority or status formally acknowledges that a venture meets a particular standard" (p. 578). In this context, the receipt of a valorisation grant can act as a signal of quality for external investors, conveying positive information about the value and prospects of the underlying technology⁷. Consistently with this view, several studies on the effects of the US SBIR programme have shown the higher capacity of SBIR grantees - in particular, of Phase I grantees - to attract subsequent VC funding, as compared to a control group of similar ventures (Howells, 2017; Lerner, 1999)⁸. Regarding the effectiveness of certification mechanisms, the literature has also highlighted that the grant effect might weaken and become less precise over time because the availability of additional information may reduce or displace the initial informational benefits provided by the grant (Lanahan and Armanios, 2018). Under this view, certification could be particularly effective in the early phases of valorisation paths, which are typically covered by proof-of-concept and translational funding.

For these reasons, we hypothesize that:

Hp2: Projects supported by public science valorisation grants have a higher likelihood of obtaining follow-on funding from external sources (i.e., business angels, venture capitalists) than similar projects that did not obtain such grants.

2.4. The moderating effect of researcher's academic seniority

In the previous sections, we have suggested that the underlying

⁷ Although we are aware that private and public investors may be different along several dimensions (i.e., goals, governance mode, decision process, network, time-horizon, searched impact, amount of funding offered), for the objective of our paper, we suggest that the certification effect derived by the achievement of a valorisation grant provided by reputable institutions is positively evaluated by both private and public investors. However, in our analyses, we will separate the effect of the signal for private and public investors in order to capture differences in magnitude (not in sign).

⁸ Howells (2017) and Lanahan and Armanios (2018) showed the absence of an SBIR Phase 2 effect on VC financing, suggesting that this second phase does not add value as a signal. Lanahan and Armanios (2018) explained this finding in terms of certification redundancy, meaning that when start-ups receive follow-on certification from the same institution, this certification not only reveals similar information, but may also imply that the firm's value potential is less widely shared.

mechanisms for the positive effect of science valorisation grants on valorisation outcomes are the following: increasing the researchers' generation confidence in the potential of their technology; creating new and business-oriented competences, and supporting the development of prototypes. The magnitude of this positive effect, however, will depend on the researchers' motivation and capacity to engage in valorisation activities. We conceptualise this dimension using the notion of the PI's *academic seniority*, which is already used in the extant literature (Bozeman and Gaughan, 2007; D'Este and Perkmann, 2011; Levin and Stephan, 1991). We define seniority in terms of stage of development of the PI's into the academic career.

The PI's experience has been widely and coherently defined with a lifecycle model of science commercialisation (Levin and Stephan, 1991), generally suggesting a positive relationship between the progression into the academic career and engagement in commercialization activities (D'Este and Patel, 2007). This model suggests that, in the first stages of their career, scientists tend to be more focused on strengthening their academic reputation through scientific publications. In the early phases, they should have more incentives to invest in generating public knowledge, as a way to enhance their scientific prestige and academic career prospects. In addition, they might face fewer opportunities to interact closely with potential business and societal partners, partly due to limited visibility and credibility, or to a less developed network of relationships. Only in a second phase, once they mature and consolidate their positioning in their institutional context, do they become more likely to engage in the commercialisation of their research. Under this view, academic seniority seems to produce a higher ability to establish links with industry or societal partners, more variety and frequency of interactions with industry, and more pronounced incentives towards commercialisation (Bercovitz and Feldman, 2008; D'Este and Patel, 2007; Ding and Stuart, 2006; Stephan et al., 2007).

However, existing empirical evidence does not always support such predictions; indeed, some studies show opposite or neutral results (Colyvas and Powell, 2007; Stuart and Ding, 2006)⁹. Ultimately, the link between academic seniority and research commercialization is still an open question (Aldridge and Audretsch, 2011; Haeussler and Colyvas, 2011), particularly with regard to the potential impact of science valorisation funding.

If we adopt the perspective of the lifecycle model of science commercialisation, we can argue that the importance of science valorisation funding should be particularly pronounced for early stage researchers, as they should experience more severe barriers in undertaking the valorisation path. On the one hand, since valorisation grants may work as quality certification signals towards external business partners (Bozeman and Gaughan, 2007), they might be relatively more important for early-stage scientists who are characterised by lower visibility levels. In addition, this dedicated funding could also be relatively more useful as social capital for early stage researchers (as compared to more tenured ones), allowing them to bolster and solidify their networks. For instance, they could use such funding to participate in trade fairs, conferences or workshops with practitioners, business meetings, and thereby grow their personal networks and contacts. As a consequence, especially in the case of early stage researchers, science valorisation funding could help them find potential business or societal partners to further develop their ideas and discoveries.

Accordingly, we formulate the following hypothesis:

Hp3a: The positive effect of the support of public science valorisation grants on the likelihood of reaching positive valorisation outcomes is higher if the principal investigator is in the earlier stages of his/her academic career.

⁹ Theoretically, some studies advance opposite explanations for the effects of academic seniority on valorisation outcomes. Scientists in the early stages of their careers might be more active in valorisation activities, compared to more tenured researchers, due to lower levels of risk aversion and lower institutional constraints (Colyvas and Powell, 2007; Stuart and Ding, 2006).

Receiving science valorisation funding is not only relevant for young researchers in order to improve their number and variety of business and societal partners. It can also play a pivotal role in attracting the attention of external financial investors. It is well known that financing new technological projects with high potential is a risky activity due to the lack of track records of the company and the presence of high levels of uncertainty. External investors, thus, tend to rely on observable cues to infer the value of their potential investments (Stuart et al., 1999). Among others, a team with experience is recognized being a desirable characteristic evaluated by financial actors in their investment decisions (Beckman et al., 2007; Burton et al., 2002; Gompers et al., 2010; Hsu, 2007). Accordingly, the extant literature suggests that the bias of venture capitalists and other private investors tends to be stronger against young people (Hoening et al., 2015), as they have fewer track records, weak professional experiences and limited relationships with industrial partners. Therefore, obtaining a PoC funding may be particularly important for researchers in the early stages of their career as it would compensate for the lack of experience and act as a valuable signal of quality to financial partners. We, thus, suggest also the following hypothesis:

Hp3b: The positive effect of the support of public science valorisation grants on the likelihood of obtaining follow-on funding from external sources is higher if the principal investigator is in the earlier stages of his/her academic career.

3. CONTEXT OF THE STUDY: THE ERC PROOF-OF-CONCEPT PROGRAMME

The European Research Council (ERC) was established in 2007 with the aim of supporting the highest-quality frontier research in Europe across all fields. Through competitive funding, it provides individual long-term grants for ground-breaking, high-risk/high-gain research. The Council offers four main types of grants that represent the core of its activities: Starting Grants, Advanced Grants, Consolidator Grants and Synergy Grants (in the rest of the paper, we refer to these main funding schemes as "Frontier Research grants"). The selection of projects in such schemes is based on a high-quality, international peer-review process, with the sole selection criterion being scientific excellence. During the period under investigation in our study (2007-2016), the ERC funded more than 6,900 projects in these categories.

In 2011, the ERC introduced a new funding scheme, the Proof of Concept programme (PoC), with the aim of encouraging researchers, who previously won an ERC grant, to further investigate the commercial and societal potential of their innovative ideas stemming from ERC-funded projects (Wessner and Munari, 2017). Accordingly, PoC funding covers activities at the very early stage of development, so as to drive ERC-funded ideas to a pre-demonstration phase where opportunities for application have been identified. For instance, PoC funding may be used to conduct technical feasibility studies; to develop prototypes; to undertake technical tests; to develop intellectual property rights protection strategies; to assess market demand and identify user needs; to cover initial expenses for the creation of a new company; and/or to search for additional funding sources. PoC Grants are up to €150,000 for a period of 18 months.

The PoC calls are published once a year and each PI can apply only one project per year. As far as the evaluation process, an independent reviewers' panel, composed of five members, evaluates each project based on three criteria. The first one – "Excellence in innovation potential" - measures the extent to which the proposed project will significantly contribute in reaching the initial steps of pre-commercialisation or social innovation. The second one – "Impact" – assesses the types of benefits that the proposed project is expected to generate for the economy, society, culture, public policy or services. Finally, the third one – "Quality and efficiency of the implementation" – evaluates whether the proposed project is structured around a robust approach that shows its technical and application feasibility. Each

reviewer independently evaluates the assigned proposals along the three aforementioned criteria, assigning a value of 1 (i.e., pass) and 0 (i.e., fail) for each criterion. In order to be considered for funding, proposals will have to obtain a pass mark by a majority of independent experts on each of the three evaluation criteria. With five reviewers on the panel, projects need to cross a 9-point minimum threshold to be eligible for funding. Once the project proposals have been evaluated by all reviewers, they are ranked based on total scores and then funded based on such ranking. If there is not enough budget to fund all projects above the threshold, proposals are sorted through a priority ranking based on the highest value for the criteria of quality, then impact, and finally implementation.

Since its launch in 2011, the PoC programme has attracted significant interest from ERC beneficiaries, with a total of 1,695 project proposals submitted over the period 2011-2016 (the focus of our analyses). These originated from about 12% of the ERC Frontier Research grantees¹⁰. Over the same period, the programme budget increased from 10 million Euro per year in the period 2011 – 2013, to 15 million Euro in 2014 and then to 20 million Euro in 2015 and 2016 (Wessner and Munari, 2017). As a consequence of the increased funding, the number of grants tripled during this period, with 618 PoC projects funded by the end of 2016, originating from around 5% of all ERC Frontier Research grantees. The average success rate of the ERC PoC programme (assessed as the ratio of the total number of grants over the total number of applications) was 36% over the 2011-2016 period.

4. DATA AND METHODS

4.1. Sample

The data used in this study were gathered through a survey¹¹, developed by an independent expert group under the direction of the European Research Council Executive Agency and Scientific Council, to assess the results derived from the ERC PoC programme. The survey was distributed, from July 2016 to December 2017, to all 7th Framework Programme (FP7) ERC grantees (including PoC awardees, PoC applicants who did not receive an award, and other ERC Frontier Research grant awardees)¹², who represented the population of eligible applicants for the ERC-PoC funding. The general aim of the survey was to understand how well the ERC PoC programme achieved the goals of maximising the value of previous ERC-funded research, through the further development of its commercial and social innovation potential. Along its seven sections, the survey gathered information on the awareness of the PoC's existence and reasons for applying (or not) to it; on the valorisation activities performed, with a focus on key objectives of PoC projects and their achievement; outcomes and impact of PoC grants in terms of generating licensing agreements, new venture creation, collaborative R&D contracts, consulting activity and access to additional funding; creation of new skills and an increase of awareness for valorisation activities by the PI and his/her team; and recommendations for improving the PoC programme.

¹⁰ This percentage accounts for all re-applications from the same Principal Investigator.

¹¹ The survey was based on an ad-hoc questionnaire, implemented on the SurveyMonkey web-platform. A pilot test of the questionnaire was conducted in January 2017, with a selected group of PIs of ERC PoC projects. The feedback received was taken into consideration to finalize the questionnaire. For additional information on the survey, see Wessner and Munari (2017).

¹² The 7th Framework Programme was implemented by the European Union/European Commission over the period 2007-2013 to support and foster research in the European Research Area. It was followed by the Horizon 2020 Programme running from 2014 to 2020. For the survey, it was decided to target the recipients of FP7 ERC Frontier Research Grants in order to focus on projects already completed (or almost completed), considering the typical duration of frontier research projects.

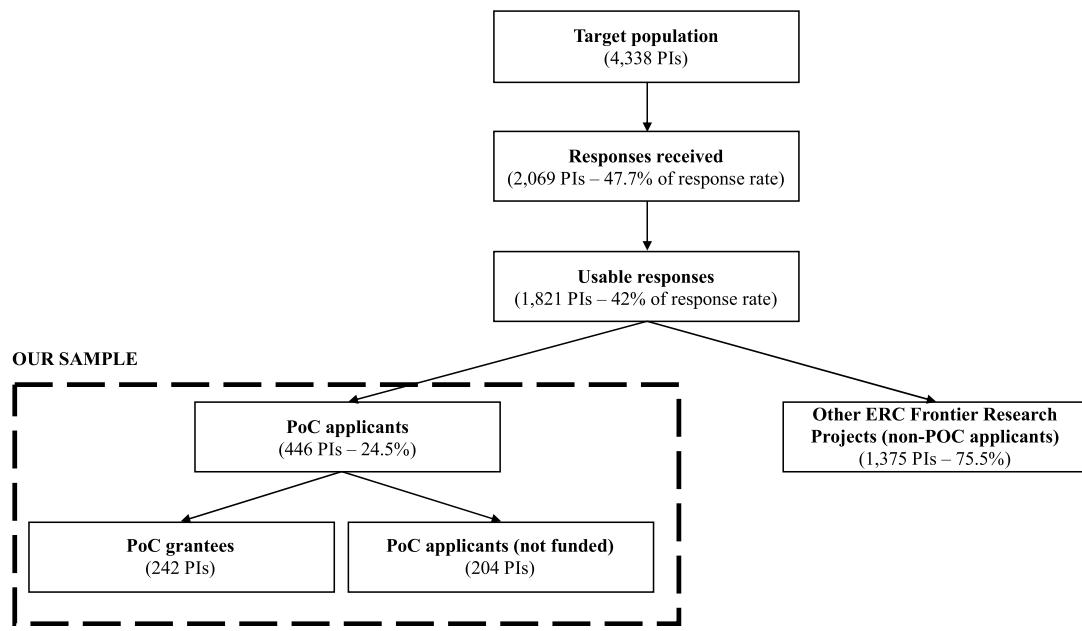


Figure 2. Sample selection process

The survey was sent to all 4,338 PIs of FP7 ERC Frontier Research Projects (those awarded over the period 2007–2013), corresponding to 4,378 ERC projects, as they represent all the potential applicants to the ERC PoC funding scheme since its foundation¹³. Three different rounds of recall were implemented via email in order to solicit responses to the survey. Following such recalls, we received 2,069 responses (corresponding to a response rate of 47.7%). However, as some PIs did not give consent to use the data and some responses were incomplete, the final sample only included 1,821 responses (representing a response rate of 42%). Of these, we limited our analysis to 446 responses that came from PIs who applied to the ERC PoC programme, including 242 responses from ERC PoC grantees and 204 responses from ERC PoC applicants who had not been funded (the remaining 1,375 responses derived from other ERC Frontier Research grantees who had not applied to the ERC PoC programme). See Figure 2 for a synthesis of the sample selection process. From a methodological perspective, the possibility of comparing approved applicants with refused ones allowed us to overcome some of the selection and endogeneity issues that are generally associated with similar studies. We will detail this topic later in the section describing our econometric approach.

The survey responses obtained from ERC PoC grantees represent 39.2% of the population of all ERC PoC grantees up to the end of 2016 (242 out of 618). On a similar vein, the survey responses obtained from ERC PoC applicants represent around 25% of the population of all ERC PoC applications up to the end of 2016 (446 out of 1804). The Table reported in Annex I1 of the paper reports the distribution by sector,

application year, gender of the PI and European region of the observations included in our sample, and it compares them to the similar distributions of all PoC applications received by the ERC during the 2011–2016 period. The distribution of survey responses from ERC PoC applicants closely resembles the distribution of the target population, along most analytical dimensions, given that no statistically significant differences emerged in the respective distributions¹⁴. Therefore, the survey achieved a very high level of representativeness of the ERC PoC population, enabling robust conclusions from the analysis of the responses. See Annex 1 for more detailed analyses on the representativeness of the sample used for this study.

4.2. Variables

A summary of the variables used in our analyses are shown in Table 1.

4.2.1. Dependent variable

As discussed in the theoretical section, science valorisation is a broad and multidimensional concept that includes two main dimensions: commercialisation and academic engagement (Perkmann et al., 2013). These two groups can be further unpacked: The commercialisation dimension includes licensing agreements and new venture creation as valorisation paths. The academic engagement dimension, instead, includes collaborative R&D agreements/contracts and consulting as additional paths. In the survey, we asked respondents to choose among the four aforementioned categories in order to provide a faceted description of the valorisation outcomes resulting from their project as of February 2017. Next, we adopted a two-level hierarchical structure and measured our dependent variable in three different ways, that were subsequently adopted in our regression analyses. We started with the highest-level classification, which assesses the overall ability to reach a

¹³ Although the number of projects is larger than the number of PIs (which implies that some of the respondents got funded for more than one ERC Frontier project), the survey specified that, in case of multiple projects submitted by the same PI, the answers had to be provided by considering the most recent project submitted. Accordingly, the sample reflects the structure of one project for each PI, without multiple PIs represented.

¹⁴ The only dimension where a statistically significant difference emerged is represented by the distribution by application year, given that the survey responses tend to be, on average, more recent as compared to the overall PoC applications. This distribution, therefore, is likely to render our findings on valorisation outcomes rather conservative, given that the projects included in our sample had, on average, a shorter time period for achieving valorisation outcomes.

Table 1

List of variables

Variable name	Description	Datasource	Datasource
Science valorisation	Dummy equal to 1 if the project leads at least to one of the following valorisation outcomes (zero otherwise): licensing agreements, new venture creation, R/D contracts or consulting	Survey	Survey
Commercialisation	Dummy equal to 1 if the project leads at least to one of the following commercialisation outcomes (zero otherwise): licensing agreements or new venture creation	Survey	Survey
Academic engagement	Dummy equal to 1 if the project leads at least to one of the following academic engagement outcomes (zero otherwise): R&D agreements/contracts or consulting	Survey	Survey
Follow-on funding	Dummy equal to 1 if the project obtains follow-on funding, private or public (zero otherwise)	Survey	Survey
Private follow-on funding	Dummy equal to 1 if the project obtains follow-on private funding (zero otherwise)	Survey	Survey
Public follow-on funding	Dummy equal to 1 if the project obtains follow-on public funding (zero otherwise)	Survey	
PoC grant	Dummy equal to 1 if the project is granted	Survey	Survey
PI male	Dummy equal to 1 if the project's principal investigator is a male (zero otherwise)	PoC application form	PoC application form
Starting Grant	Dummy equal to 1 if the ERC frontier research grant was a Starting Grant	PoC application form	PoC application form
Consolidator Grant	Dummy equal to 1 if the ERC frontier research grant was a Consolidator Grant	PoC application form	
Advanced Grant	Dummy equal to 1 if the ERC frontier research grant was a Advanced Grant	PoC application form	
Life Sciences	Dummy equal to 1 if the PoC scientific domain is life sciences (zero otherwise).	PoC application form	PoC application form
Physical Sciences & Engineering	Dummy equal to 1 if the PoC scientific domain is physical sciences and engineering (zero otherwise)	PoC application form	PoC application form
Social Sciences & Humanities	Dummy equal to 1 if the PoC scientific domain is social sciences and humanities (zero otherwise)	PoC application form	PoC application form
Team size	Number of members for the project's team	Survey	Survey
TTO involvement	Dummy equal to 1 if the TTO of the host institution provided support in the preparation of the proposal (zero otherwise)	Survey	Survey
Past number of patents	Number of patent applications filed by the research team before the submission of the PoC proposal	Survey	Survey
Past number of project publications	Number of publications generated by the original ERC frontier research up to one year after the closure of the project and before the submission of the PoC proposal	CORDIS	CORDIS

valorisation outcome in a broad sense, without disentangling its sub-components. Accordingly, our first dummy, *Science valorisation*, took the value 1 when the project led to at least one of the following outcomes: the creation of licensing agreements, a new venture, collaborative R&D agreements/contracts, or consulting activities, and 0 otherwise¹⁵. Then, we moved down to the next level, which offers two more fine-grained dimensions that capture two different nuances of the valorisation process. In accordance with Perkmann et al. (2013), who suggested that the drivers and outcomes of commercialisation activities partially differ from engagement, we created two different additional measures: *Commercialisation* and *Academic engagement*. The former focuses on more complex and formalised valorisation activities, taking the value 1 when the project has led to a licensing agreement or the creation of a new venture, and 0 otherwise. The latter reflects the creation of inter-organisational collaborations, taking the value 1 when the project has led to collaborative R&D agreements/contracts or to consulting, and 0 otherwise. These two dimensions, as explained in the theoretical section, mirror two different logics: “commercialisation means an academic invention is exploited with the objective to reap financial rewards; by contrast, academic engagement is broader and is pursued for varying objectives” (Perkmann et al., 2013: 424)

The ability to attract follow-on funding, from either public or private sources, in order to further develop an idea/technology towards commercial or societal applications is an additional and important measure of success for a valorisation grant, as indicated by previous research (Howells, 2017; Toschi and Munari, 2015). In this respect, we also assessed the research team's ability to attract additional funding using three dummy variables. The first variable *Follow-on funding* is a dummy

variable taking the value 1 for ERC projects where the PI declared in the survey that they were able to obtain follow-on funding from other sources, both private and public (i.e., other EU-level, national or regional public funding, or private funding such as VC firms, business angels, private foundations, industrial corporations, crowdfunding, banks), in order to further support the exploitation path¹⁶. The other two dummy variables, *Private follow-on funding* and *Public follow-on funding*, are based on survey data as well, but are more narrowly defined in order to treat them separately. Accordingly, *Private follow-on funding* takes the value 1 for projects that obtained follow-on funding from private funding sources (such as private VC firms, business angels, private foundations, industrial corporations, crowdfunding, banks, etc.), while *Public follow-on funding* takes the value 1 for projects that obtained follow-on funding from public funding sources (such as national public funds, host institution funding or regional public funds)¹⁷.

4.2.2. Independent variables

Our Hypotheses 1 and 2 suggest that obtaining science valorisation grants affects the likelihood of the research team achieving positive outcomes in terms of valorisation. We thus modelled the receipt of the ERC PoC grant with a dummy variable *PoC Grant* equal to 1 if a project received ERC PoC financial support (as in the case of PoC grantees), and 0 otherwise (that is, for projects included in our sample that applied for an ERC PoC grant but were not funded). We used information provided

¹⁵ In order to build such variable, we used the responses to a set of close-ended questions included in the section “Valorisation Outcomes” of the survey, such as the following question related to “Licensing Agreements”: “Has the valorisation project resulted so far in a licensing agreement with private or public parties, concerning the idea/technology (at least in part)?”. Similar questions were included in the survey respectively in the case of: “Collaborative R&D agreements and R&D contracts”, “Consulting”, “Creation of a new company”.

¹⁶ In order to build such variable, we used the responses to a set of close-ended questions included in the section “Access to additional developmental funding” of the survey, and in particular to the following question: “Was any additional developmental funding obtained from other private or public sources to support (at least in part) the development and valorisation of your idea/technology?”. In case of positive answer to such question, the survey also asked the respondent to specify the type of funding sources (private or public).

¹⁷ It is important to note that in the answers gathered through the survey, public and private sources of funding are not mutually exclusive, but complementary, so that some projects were jointly funded by both private and public sources.

by the PIs in order to construct this variable.

To test Hypotheses 3a and 3b, regarding the moderating role of PIs' academic seniority, we used dummy variables to capture the different types of originating ERC frontier research grants at the basis of PoC applications, exploiting the distinction of ERC frontier research grants based on the academic seniority of the PI. The ERC provides three major types of frontier research grants: Starting Grants are assigned to researchers at an early stage of their academic careers (they are limited to PIs with 2-7 years of experience since the completion of PhD) with the goal of encouraging them to become independent leaders of high-quality research. Consolidator Grants are assigned to more experienced PIs, with 7-12 years of experience after the PhD, as a way to consolidate their scientific trajectory. Advanced Grants support outstanding researchers who are already established leaders in their fields, and thus typically target PIs with more advanced seniority levels¹⁸. We exploited such differences in order to create two dummy variables capturing the level of academic seniority of the PI, and used Starting Grants as the baseline case: the dummy *Consolidator Grant* takes the value 1 if the PI was awarded a previous ERC Consolidator grant (and he/she is consequently in an intermediate phase of academic career), and 0 otherwise; the dummy *Advanced Grant* takes the value 1 if the PI was awarded a previous ERC Advanced grant (and he/she is consequently in a more advanced phase of academic career).

4.2.3. Control variables

Following previous studies on the effects of research and innovation grants, we control for a set of factors likely to influence valorisation outcomes. Concerning the personal characteristics of the PI, we consider the possible existence of gender disparities in the exploitation of innovation, as the literature indicates the existence of a gender gap in technology transfer activities (Giuri et al., 2018; Murray and Graham, 2007). It appears that female scientists might be less likely to engage in commercial and entrepreneurial activities for reasons related to the existence of structural barriers (Ding et al., 2006, 2013; Frietsch et al., 2009; Meng 2016; Murray and Graham, 2007; Tartari and Salter, 2015). We accounted for this possibility through a dummy variable *PI male*, equal to 1 if the PI is a man and 0 otherwise.

Team size is a variable counting the number of researchers involved in the project team, based on survey information. This variable accounts for differences in team size because, in managerial and entrepreneurial studies, larger teams have been shown to outperform in entrepreneurial and commercialisation activities due to exploiting a broader range of skills (Eesley et al., 2013; Eisenhardt and Schoonhoven, 1990; Kirchberger and Pohl, 2016).

Given the important role of TTOs in knowledge transfer from academia to organizations going to market, we propose that the involvement of TTOs in the preparation of PoC project proposals may impact the subsequent ability of researchers to achieve valorisation outcomes (Debackere and Veugelers, 2005; Giuri et al., 2019; O'Shea et al., 2005). TTOs may indeed help to develop a broader perspective that is focused on not only scientific and technical aspects, but also on commercial and societal aspects, thereby increasing the impact of university research. We thus included a dummy variable equal to 1 if research teams were supported by the TTO of their host institution in the preparation of the ERC PoC proposal, and 0 otherwise (*TTO involvement*). We referred to a specific question of the survey in order to construct this variable.

¹⁸ The ERC also provides Synergy Grants for frontier research projects with a strong multi-disciplinary orientation. In our survey, only four observations belonged to this category. We decided to convert these observations into one of the remaining categories. Thus, we compared the age of the PI in the Synergy Grants with the average PI's age of the other categories, finding the one where the age was more similar. For our four observations, this overlap occurred with the Consolidator category.

Patenting experience may increase a team's or firm's likelihood of developing licensing agreements, new venture creation, R&D collaborations, or other forms of academic engagement activities. Numerous studies have shown that patents not only serve an important appropriability function (clarifying the existence of proprietary rights on an invention), but also signal to external parties the quality of a technology and its future exploitation prospects (Hall, 2004; Hsu and Ziedonis, 2013; Long, 2002; Munari and Toschi, 2015; Stuart et al., 1999). To capture this effect, we included a count variable, measuring the number of patent applications generated by the research team in the previous ERC Frontier Research project leading to the ERC PoC application (*Past number of patents*).

Similar to the previous variable, the achievement of scientific outcomes may also be relevant in our context (Arora and Gambardella, 1998; Jaffe, 2002). Projects with more publications give the researcher a larger portfolio of findings to commercialise, and thereby generate more visibility and reputation with which to attract industry and financial capital (Azoulay et al., 2007; Ding and Stuart, 2006; Zucker et al., 2002). In order to control for this dimension, we included the variable *Past number of project publications*, which count the number of publications generated through the original ERC frontier research grant up to one year after the completion of the project¹⁹. To create this variable, we used the CORDIS website (Community Research and Development Information Service), which the European Commission²⁰ promotes in order to identify the FP7 ERC frontier research projects and their related publications.

Finally, we included three sets of dummy variables to control for sectorial, national, and time differences. We first considered the heterogeneity in the valorisation opportunities across scientific domains, creating three dummies for projects in the three major research domains categorised by the ERC: *Life Sciences, Physical Sciences & Engineering, and Social Sciences & Humanities*²¹. We also included a set of dummy variables based on the countries of the PIs' host institutions, so as to account for the uneven evolution of the technology transfer infrastructure in Europe and the different levels of national economic development, both of which influence the opportunities for valorisation (Munari et al., 2016). Time dummies (years), corresponding to the year of application to the PoC funding, were included to capture the time window available to engage in valorisation activities.

4.3. Empirical strategy

A significant challenge in assessing the relationship between the receipt of a valorisation grant and the subsequent valorisation outcomes is the possibility of endogeneity bias (Bascle, 2008). Indeed, the capacity to obtain a PoC grant is not an exogenous and randomised treatment, but rather, the result of a selection process implemented by the ERC through expert evaluators who consider the underlying quality and potential of the proposal. This selectivity problem (public funding going to proposals judged in advance as likely to succeed) is well-known in the literature on the effectiveness of innovation grants because it may lead to biased regression estimates (Jaffe, 2002). Previous studies have adopted a variety of empirical strategies to address this issue, ranging from

¹⁹ For PoC proposals submitted after less than one year from the ending of the original ERC frontier research grant, we considered the publications up to the date of the PoC proposal submission.

²⁰ CORDIS is the publicly and freely accessible repository of the results obtained by the projects funded by the EU's framework programmes for research and innovation (from FP1 to Horizon 2020). For more information: <https://cordis.europa.eu/about/en>

²¹ In our survey, only four observations belong to the Synergy category. We decided to convert these observations into one of the remaining three major sectorial categories by searching the web for the scientific background and Department affiliation of the PI.

propensity score matching to comparing matched samples of treated and untreated entities (Scandura, 2016; Vanino et al., 2019), difference-in-difference approaches (Branstetter and Sakakibara, 2000), regression discontinuity design (Howell, 2017; Wang et al., 2017), and instrumental variable approach models (Hottenrott et al., 2017; Wallsten, 2000).

To address this issue, we employed a two-stage least squares (2SLS) instrumental variable (IV) approach. Our econometric model is characterised by a binary endogenous regressor (*PoC grant*) with a binary outcome (corresponding to our different measures of valorisation activities). The analysis of such limited dependent variables seems to call for nonlinear models. However, in Probit or Tobit models, the subsequent second-stage estimate results are inconsistent (Angrist, 2001). For this reason, we used a linear probability model for this estimate instead of a Probit model, as suggested by Angrist (2001). Regarding the instruments for the reception of a valorisation grant (i.e., variables not correlated with the error term of the outcome equation, but correlated with the predictor suspected of being endogenous), we used: (i) the total budget available for PoC grants in a given year and (ii) the PI's past applications for PoC grants.

Instrument (i) is based on the notion that variations in the available amount of research financing create an exogenous "shock" affecting the total number of potentially awardable projects, but do not impact the expected valorisation outcome (Lichtenberg, 1988; Wallsten, 2000; Jaffe, 2002). Wallsten (2000), analysing the SBIR grants, used the available budget in each year as an instrument and showed that adopting this variable significantly reduces the impact of SBIR on performance. Lichtenberg (1988) applied a similar instrument for defence procurement funding. In the specific context of the ERC-PoC scheme, grants that are awarded exclusively take the form of a standard lump sum pre-fixed at 150,000 euro by a European Commission decision. This amount does not change over time. Each project knows in advance the maximum amount of funding that can be obtained by the PoC and, thus, defines a financial plan that aligns with this threshold. Therefore, an increase in the overall budget available for the research funding programme will affect the ERC's decision about how many projects will receive the grant, but will not impact the project plan itself. The choice (and ability) to perform any type of valorisation activities remains an independent decision of the PI and his/her team. In order to construct this variable, we exploited a discontinuity in the availability of financial resources for the ERC PoC scheme. Indeed, over the period 2011–2016, the ERC PoC programme budget increased from 10 million Euro per year (in the first three years of the programme) to 15 million Euro in 2014 to 20 million Euro in 2015 and 2016. Accordingly, we assessed the variable *PoC yearly available budget* based on this increase of the annual budget over the period of analysis.

Instrument (ii) reflects the rationale that PIs who have past familiarity with the selection procedures of the ERC-PoC scheme are more likely to obtain a grant due to learning effects that improve the chances of success (Hottenrott et al., 2017). According to Hottenrott et al. (2017), firms that have past experience with a certain scheme are more likely to be granted a subsidy in that scheme. In the case of previously rejected project submissions, having applied for the same programme in the past allows the PI to better understand the evaluation process and address potential issues that emerged from previous reviews of the project, in terms of structure, content and storytelling. This variable allows us to consider the PIs' personal level of familiarity with the requirements of the PoC funding submission and evaluation process. Programmes for research valorisation have a common goal, but the submission and evaluation procedure could significantly differ among them. Being able to meet the expectations of a specific scheme's evaluators is thus a relevant factor for obtaining the grant. Granted, this familiarity with the application process is not correlated with any of the valorisation outcomes used in the second-stage equation. Indeed, the decision to provide PoC funding to a PI for his/her proposal is based on the intrinsic quality and potential of the project, while the PI's choice

Table 2
Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Science valorisation	408	0.31	0.46	0	1
Commercialization	407	0.18	0.39	0	1
Academic engagement	405	0.23	0.42	0	1
Follow-on funding	397	0.31	0.46	0	1
Private follow-on funding	397	0.10	0.30	0	1
Public follow-on funding	397	0.25	0.44	0	1
PoC grant	446	0.54	0.50	0	1
PI male	446	0.81	0.39	0	1
Starting Grant	446	0.56	0.50	0	1
Consolidator Grant	446	0.03	0.17	0	1
Advanced Grant	446	0.41	0.49	0	1
Life Sciences	446	0.34	0.47	0	1
Physical Sciences & Engineering	446	0.52	0.50	0	1
Social Sciences & Humanities	446	0.14	0.35	0	1
Team size	446	7.08	4.13	1	47
TTO involvement	446	0.60	0.47	0	1
Past number of patents	445	1.06	1.25	0	14
Past number of project publications	446	26.42	23.09	1	100

(and ability) of valorising his/her research is a matter of execution and does not depend on his familiarity with the application process. The variable *Past experience with PoC application* exploits data provided by the ERC on all the applications received for the PoC scheme. For each PI responsible for a project, this variable assumes value 1 if the PI submitted at least one previous application to the ERC PoC programme (before the project application object of the survey), and 0 otherwise. Our data show that 20% of our observations had previous experience with the ERC PoC evaluation process.

To test for the validity of our procedure, we assessed whether the instrumental variables pass the commonly applied statistical requirements. We checked for the instruments' assumption of relevance (i.e., the instruments were strongly correlated with the likelihood of receiving a grant) through the Cragg-Donald F-statistic (Stock and Yogo, 2002; Stock et al., 2002). The values ranged from 21.454 to 22.335, which are above the critical value for instrument strength (19.93 at 10% bias); thus, we can assert that our instruments are strong because it is possible to reject the null hypothesis that the coefficients on the instruments are equal to zero in the structural equation. We also tested for the validity of overidentifying restrictions in 2SLS models with the Sargan's statistic (Basile, 2008). The joint null hypothesis of the Sargan's test is that the instruments are consistent (i.e., not correlated with the error term of the structural equation). The values of the test ranged from 0.11 to 0.65, which confirm the exogeneity of the two instruments. In our specific research design, this implies that the PoC yearly available budget and past experience with PoC application do not affect valorisation activities²².

5. Analyses and results

Tables 2 and 3 show the summary statistics and pairwise correlations for the variables included in our main specifications. Most variables exhibited reasonably small correlation coefficients. The mean variance

²² Only the models with *Commercialization* as dependent variable show results for the Sargan test which reject the null hypothesis, suggesting a potential endogeneity of the instruments. In order to better investigate this issue, a difference-in-Sargan statistic was run on each instrument to test whether they violated the exogeneity condition. The statistic shows that each instrument can be considered as exogenous (p-value of the C statistic equal to 0.427 for the total budget available for PoC grants in a given year and 0.3422 for the PI's past applications for PoC grants). In addition, we also controlled for the endogeneity of *PoC grant*, finding that the null hypothesis that the variable can be treated as exogenous cannot be rejected. Accordingly, we estimated a model in which *PoC grant* is treated as exogenous, through an OLS regression. The results, that we do not report for the sake of brevity, confirm our previous expectations.

inflation factors of the regression models were below the value of 3.04, excluding any problem of multicollinearity. Over the period 2011-2016, 54% of ERC PoC applications included in our sample (corresponding to 242 projects) were awarded a PoC grant. On average, only 19% of ERC PoC grants were held by female researchers and the average size of the research team was 7. ERC PoC applications mostly originated from ERC Starting Grants (56%) and Advanced Grants (41%), with only a few stemming from Consolidator Grants (3%). In terms of scientific domain, the Physical Sciences & Engineering domain was the most represented (52%), followed by the Life Sciences domain (34%) and the Social Sciences & Humanities domain (14%). The applicant's host institution provided support in preparing the proposal for 60% of the applications. Finally, ERC PoC grant applicants reported an average of one patent application and 26 publications before submitting the project for the ERC PoC scheme.

Turning to our dependent variables, 31% of the overall sample reported the achievement of valorisation outcomes in terms of R&D contracts/R&D collaborations, consulting agreements, licensing agreements and new company formations at the time of the survey. When interpreting such findings, it is important to keep in mind the relatively short time that elapsed between the PoC awards and the survey distribution. By focusing only on commercialisation (i.e., licensing and spinoff creation) or academic engagement outcomes (i.e., R&D contracts and consulting agreements), the percentage became 18% and 23%, respectively. Meanwhile, our data show that 31% of ERC PoC applicants were successful in obtaining additional (non-ERC) funding.

In order to address our hypotheses, we also performed additional analyses to compare the treated group with the control group. Annex 2 compares the proportion tests between treated (i.e., granted) and not treated (i.e., not granted) groups for the outcome variables of interest. In our empirical setting, the latter group represents the control group. On average, granted projects showed greater engagement in valorisation activities and a greater ability to obtain additional funding, and these differences were statistically significant. More precisely, the likelihood of positive valorisation outcome was significantly higher in the group of PoC grantees compared to the control group (around 46% in the treated group, compared to around 14% of cases in the control group). Similarly, the likelihood of commercialisation through licensing or spinoff formation was significantly higher in the group of PoC holders, as compared to the control group (27% vs 8%). In a similar vein, PoC grantees showed higher average values for the probability of academic engagement (33% vs. 11%), as well as better performance in terms of follow-on funding attraction (38.7% vs. 21.1%). The same scenario arises if we consider the sources of funding separately: 15% (versus 5%) for private follow-on funding and 34% (versus 15%) for public follow-on funding. Such significant differences between the two groups also reflect the fact that a high share of respondents in the control group indicated that they stopped valorisation activities for the technology after submitting to the PoC programme. These responses underline the triggering role of the ERC PoC grant in actually undertaking valorisation activities.

5.1. Regression analyses controlling for endogeneity

Table 4a and **Table 4b** shows the full sample results of our regressions when correcting for endogeneity issues through an instrumental variable procedure. For each limited dependent variable, we performed three different analyses: one for testing the effect of only control variables; one to assess the impact of receiving the ERC PoC funding; and one for testing the interaction effects of PIs' seniority. As far as the outcomes considered, Models 1-3 predict the probability of any type of valorisation, ignoring the distinction between different avenues of valorisation; Models 4-6 estimate probabilities of commercialisation activity (i.e., licensing agreements or new venture creation); Models 7-9 are focused on academic engagement activity (i.e., R&D contracts or consulting). The last nine models examine the ability to attract follow-on

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Science valorisation	1.00																	
(2) Commercialization	0.70*	1.00																
(3) Academic engagement	0.82*	0.38*	1.00															
(4) Follow-on funding	0.39*	0.31*	0.34*	1.00														
(5) Private follow-on funding	0.37*	0.34*	0.37*	0.51*	1.00													
(6) Public follow-on funding	0.34*	0.35*	0.34*	0.87*	0.58*	1.00												
(7) PoC grant	0.34*	0.25*	0.26*	0.19*	0.16*	0.22*	1.00											
(8) PI male	0.02	0.07	-0.03	0.06	-0.00	0.05	0.08	1.00										
(9) Starting Grant	0.01	-0.03	0.01	-0.00	-0.01	-0.01	0.13*	-0.14*	1.00									
(10) Consolidator Grant	0.03	0.06	0.00	0.09	0.08	0.12*	-0.09	-0.10*	-0.01	1.00								
(11) Advanced Grant	-0.02	0.01	-0.02	-0.03	-0.02	-0.04	-0.10*	-0.14*	-0.04	-0.15*	1.00							
(12) Life Sciences	0.04	0.06	-0.02	0.13*	0.08	0.12*	0.00	0.05	-0.04	0.03	0.03	1.00						
(13) Physical Sciences & Engineering	0.09	0.06	0.10*	-0.05	-0.03	-0.03	0.18*	0.07	0.07	-0.01	-0.06	-0.75*	1.00					
(14) Social Sciences & Humanities	-0.18*	-0.17*	-0.12*	-0.11*	-0.06	-0.12*	-0.26*	-0.17*	-0.05	-0.04	0.06	-0.29*	-0.42*	1.00				
(15) Team size	0.07	-0.00	0.09	0.10*	0.10*	0.06	-0.08	-0.03	-0.02	0.04	0.00	-0.06	-0.09	0.09	1.00			
(16) TTO involvement	0.00	-0.02	0.03	0.07	0.03	0.07	0.07	0.07	0.01	-0.04	0.08	0.04	-0.16*	0.07	0.07	1.00		
(17) Past number of patents	0.22*	0.25*	0.20*	0.14*	0.22*	0.13*	0.09	0.06	-0.02	-0.04	0.03	0.05	0.04	-0.13*	0.03	-0.02	1.00	
(18) Past number of project publications	0.02	-0.01	0.08	-0.10*	-0.09	-0.10	0.02	0.02	-0.17*	-0.09*	0.21*	-0.22*	0.18*	0.05	0.01	-0.03	-0.03	1.00

* shows significance at the 0.05 level

Table 4aRegressions with instrumental variables for *Science valorisation, Commercialisation and Academic engagement*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Science valorisation	Science valorisation	Science valorisation	Commercialisation	Commercialisation	Commercialisation	Academic engagement	Academic engagement	Academic engagement
PI male	0.006 (0.058)	-0.033 (0.060)	-0.026 (0.058)	0.047 (0.048)	0.023 (0.050)	0.028 (0.048)	-0.034 (0.053)	-0.060 (0.055)	-0.058 (0.057)
Team size	0.037** (0.015)	0.016 (0.016)	0.029* (0.017)	0.024* (0.013)	0.011 (0.014)	0.017 (0.014)	0.039*** (0.014)	0.024 (0.015)	0.039** (0.016)
TTO involvement	-0.032 (0.048)	-0.058 (0.050)	-0.054 (0.049)	-0.048 (0.040)	-0.064 (0.041)	-0.062 (0.040)	-0.051 (0.044)	-0.070 (0.045)	-0.059 (0.048)
Past number of patents	0.066*** (0.017)	0.049*** (0.018)	0.062*** (0.018)	0.065*** (0.014)	0.054*** (0.015)	0.060*** (0.015)	0.058*** (0.016)	0.046*** (0.016)	0.062*** (0.018)
Past number of project publications	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.002* (0.001)	0.001 (0.001)	0.002* (0.001)
Consolidator Grant (CoG)	0.088 (0.133)	0.250* (0.142)	0.323 (0.238)	0.155 (0.111)	0.256** (0.117)	0.307 (0.197)	0.026 (0.122)	0.138 (0.129)	0.007 (0.231)
Advanced Grant (AdG)	-0.028 (0.047)	0.051 (0.051)	0.244* (0.134)	-0.000 (0.039)	0.049 (0.042)	0.117 (0.110)	-0.032 (0.043)	0.023 (0.047)	0.318** (0.130)
PoC grant	0.638*** (0.149)	0.676*** (0.147)	0.399*** (0.123)	0.399*** (0.123)	0.370*** (0.121)	0.370*** (0.121)	0.448*** (0.136)	0.640*** (0.144)	0.640*** (0.144)
PoC grant # CoG		-0.178 (0.558)			-0.172 (0.462)			0.566 (0.544)	
PoC grant # AdG		-0.396* (0.240)			-0.151 (0.198)			-0.575** (0.235)	
Constant	-0.038 (0.163)	-0.144 (0.169)	-0.248 (0.179)	-0.114 (0.135)	-0.180 (0.140)	-0.212 (0.148)	-0.091 (0.149)	-0.163 (0.154)	-0.349** (0.175)
Number of observations	407	407	407	406	406	406	404	404	404
PoC scientific domain dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
HI country dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors are in parenthesis

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

Table 4bRegressions with instrumental variables for *Follow-on funding* and *Private follow-on funding*

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Follow-on funding	Follow-on funding	Follow-on funding	Private follow-on funding	Private follow-on funding	Private follow-on funding	Public follow-on funding	Public follow-on funding	Public follow-on funding
PI male	0.052 (0.060)	0.023 (0.062)	0.026 (0.068)	0.006 (0.039)	-0.007 (0.040)	-0.010 (0.041)	0.052 (0.057)	0.023 (0.058)	0.022 (0.062)
Team size	0.016 (0.016)	0.003 (0.017)	0.028 (0.019)	0.029*** (0.010)	0.023** (0.011)	0.030** (0.012)	0.034** (0.015)	0.020 (0.016)	0.039** (0.018)
TTO involvement	0.034 (0.050)	0.017 (0.051)	0.019 (0.056)	0.002 (0.032)	-0.006 (0.032)	-0.008 (0.034)	0.029 (0.047)	0.011 (0.048)	0.011 (0.052)
Past number of patents	0.042** (0.017)	0.031* (0.018)	0.057*** (0.021)	0.050*** (0.011)	0.045*** (0.012)	0.053*** (0.013)	0.038** (0.016)	0.027 (0.017)	0.048** (0.019)
Past number of project publications	-0.001 (0.001)	-0.002* (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002 (0.001)	-0.001 (0.001)
Consolidator Grant (CoG)	0.269** (0.136)	0.373*** (0.143)	0.579** (0.273)	0.128 (0.088)	0.173* (0.091)	0.279* (0.165)	0.325** (0.127)	0.431*** (0.134)	0.612** (0.249)
Advanced Grant (AdG)	-0.014 (0.048)	0.037 (0.052)	0.570*** (0.155)	-0.012 (0.031)	0.010 (0.033)	0.201** (0.094)	-0.014 (0.045)	0.038 (0.049)	0.476*** (0.142)
PoC grant		0.401*** (0.153)	0.767*** (0.171)		0.173* (0.098)	0.354*** (0.103)		0.411*** (0.143)	0.748*** (0.156)
PoC grant # CoG			-0.297 (0.640)		-0.167 (0.387)				-0.250 (0.584)
PoC grant # AdG			-1.030*** (0.279)		-0.356** (0.169)				-0.838*** (0.255)
Constant	-0.041 (0.166)	-0.108 (0.171)	-0.447** (0.209)	-0.086 (0.108)	-0.115 (0.109)	-0.241* (0.127)	-0.062 (0.156)	-0.131 (0.160)	-0.413** (0.191)
Number of observations	396	396	396	396	396	396	396	396	396
PoC scientific domain dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
HI country dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES

external funding: Models 10-12 show the results for the mix of public and private sources of additional financing; Models 13-15 limit the analyses to only private sources, whereas Models 16-18 focus on public sources.

As far as the influence of our control variables, it is interesting to highlight the importance of some factors on valorisation outcomes. First, team size is positive and statistically significant, suggesting that an increase in the number of people involved in the project increases valorisation outcomes. Indeed, the implementation of a PoC valorisation plan typically requires a broad knowledge set and some kind of support for the research team to deal with the various challenges on the innovation path. The second important factor to consider is the generation of patents in the previous ERC Frontier Research project. As expected, the existence of technologies that had started the process of legal protection through patent applications is a positive determinant for subsequent valorisation outcomes. This trend is stronger with a higher the number of patent applications submitted in the past. Regarding the scientific domain from which the project originated, our analyses show that the probability of advancing their projects towards valorisation is relatively higher in the fields of Life Sciences and Physical/Engineering Sciences.

Now, we discuss the results of the main effect analyses that were implemented to test our first two hypotheses. In line with Hypothesis 1, Model 2 suggests that projects that received support from the ERC PoC grant were more likely to achieve valorisation outcomes ($p < .001$). As previously explained, this model uses broad measure of valorisation as the dependent variable, which includes both commercial and academic engagement activities. The results of our regression analyses continue to support our predictions even if we split our outcome variable into its two components. Specifically, Model 5 shows the results for the commercial aspect of valorisation ($p < .001$) whereas Model 8 presents the academic engagement component ($p < .001$). In both cases, the dummy capturing the acquisition of an ERC PoC grant was positively and significantly associated with achieving commercialisation outcomes (Model 5) or academic engagement outcomes (Model 8).

Hypothesis 2 suggested that, in general, PoC projects are more likely

to receive follow-on funding compared to the control group. The positive and significant value of *PoC grant* ($p < .001$) in Model 11 supports our prediction. In this model, we considered a joint form of financing from both private and public sources. Among public sources, we can cite national public funds, host institution funding, and regional public funds. Among private sources, we can cite industrial or business private corporations, private VC funds, and foundations. Like with the previous hypothesis, we included two more fine-grained and conservative measures for the dependent variable (source of funding). The early-stage nature of ERC PoC projects implies a strong need to further de-risk the technologies before they are likely to receive additional funding. Studies on financial provision suggest that private source involvement is less likely to occur in cases of high uncertainty. With Model 14, we are thus interested in understanding whether the impact of ERC PoC support is strong even if we consider the ability to only attract additional private funding. The positive and significant coefficient for *PoC grant* ($p < .001$) in this model supports our prediction. Similarly, Model 17 suggests that PoC grantees are more able to obtain funding from public sources ($p < .001$).

The final step of our analyses involves analysing the moderating role of the PI's academic seniority, as suggested in Hypothesis 3. Our results suggest a statistically significant and negative effect of the PI's academic seniority on the probability of engaging in valorisation outcomes. The positive relationship between *PoC grant* and science valorisation outcomes and follow-on funding (as postulated in Hypotheses 1 and 2) was attenuated for researchers in the more advanced stages of their academic career. This result suggests that researchers in the later stages of their academic career may benefit relatively less from the support of PoC funding compared to those at the earlier stages of their academic career (such as those captured by the dummy Starting Grants used as baseline). The additionality effect of the PoC grant is relatively more pronounced for this class of advanced researchers, who can already benefit from their high prestige and stronger networks in the pursuit of valorisation paths, as predicted by Hypothesis 3. Interestingly, we could not confirm this finding in the models using *Commercialisation* as the dependent variable,

which showed a different dynamic in respect to the other models. For the most complex paths of licensing and spinoff formation, our results do not support the idea that PIs' academic seniority levels shape the impact of the PoC grant.

5.2. Robustness checks

We conducted further tests to check that our results are robust to changes in specifications. First, we worked on our dependent variables. In the theoretical part of this work, we highlighted that the distinction between commercialisation and academic engagement is well rooted in the extant literature (Perkmann et al., 2013). However, in order to support this theoretical differentiation among valorisation activities with our data, we also performed a factor analysis, based on the principal component method and with the four original items (licensing, new venture creation, R&D contracts and consulting). Our aim was to identify the major factors that would allow us to classify the possible pathways of science valorisation. The analysis revealed two main factors that explained 68% of the variation in the original four items. The first factor drives items "Licensing" and "New venture creation"; the second factor underpins items "R&D agreements/contracts" and "Consulting activity". The retained factors resemble the two possible types of research valorisation, as suggested by Perkmann et al. (2013). Factor 1 is linked to the commercialisation orientation, while Factor 2 corresponds to academic engagement-oriented objectives.²³ In addition, in order to test the effect of PoC funding on each single type of valorisation activity, we also considered all four possible forms of valorisation outcomes (i.e., licensing agreements, new venture creation, consulting, and R&D contracts) independently. These analyses (see Appendix 3) confirm our previous findings: *PoC grant* is positive and statistically significant in all the models. Meanwhile, the interaction of *PoC grant* with the PI's academic seniority is negative and statistically significant only for R&D contracts and consulting (but not for licensing and new venture creation), which aligns with our previous results for the variable *Commercialisation*.

Second, we changed our explanatory variables. We used the amount of funding received by the PoC in substitution to our dummy *PoC grant*. More precisely, we used the log (funding amount + 1), so that not-granted projects assumed a value of 1. However, it is important to note that there was very little variation in the distribution of the amount of funding: In the vast majority of cases, PoC projects received the maximum amount of 150.000 Euro (with a few projects receiving a slightly lower amount). Also, we used the age of the PI during the PoC application year (or its logarithmic transformations) as an alternative operationalization of seniority. Due to the high correlation with our measures of academic seniority, we used one or the other separately. Moreover, we changed the moderator variable of academic seniority. Projects belonging to the Consolidator Grant group are represented only by the 3% of the total sample. This small number of observations is due to the fact that Consolidator Grants started in 2013, which was also the last year of the FP7 program. As the survey was submitted to the winners of an FP7 grant, the size of this category was naturally lower with respect to the others. In order to make our results more robust, we dropped the few observations of Consolidator Grant. Our results were confirmed.

Third, we changed some control variables. As far as team size, instead of counting the total number of team members, we also considered the team composition to assess the effect of a heterogeneous team where members with different experience contribute to the development of the project. In particular, we considered the number of external members like business and industry partners, consultants and similar profiles with commercial skills included in the team. Involving members who are external to the research context is extremely valuable

for achieving all phases of the valorisation process. Meanwhile, as an alternative measure to control for geographical effects, we created four dummy variables to aggregate countries into European areas - *Eastern Europe*, *Northern Europe*, *Southern Europe*, and *Western Europe*.²⁴ Although we do not report the analyses for brevity reasons, the results were again confirmed in all cases.

Finally, in addition to the instrumental variable approach adopted, we perform an approach similar to the Regression Discontinuity Design (RDD), exploiting the evaluation scores obtained by a subset of PoC proposals during the evaluation process. Since we were only able to use this information for a limited number of proposals (only 119 proposals from 2011 to 2015, with no observations for the year 2016), decreasing considerably our sample size, we were not able to undertake a complete RDD research design on the whole sample. However, we adopted this procedure on the subsample of projects to integrate the results from the instrumental variable procedure²⁵. In all the specifications adopted following this procedure, and despite a limited number of observations, we obtained results in line with those previously reported from the 2SLS instrumental variable procedure.

5.3. Additional analyses

The main purpose of our paper was to investigate the effect that public science valorisation grants have on the likelihood of reaching positive valorisation outcomes and obtaining follow-on funding.

To test our hypotheses, we utilised tangible measures of performance that determine a project's progression along its life cycle until the full exploitation of its commercialisation potential. However, according to the theory of reasoned action (Ajzen and Fishbein, 1980), people consider the implications of their action before deciding to engage (or not engage) in a certain behaviour. In the context of research valorisation, this means that, before pursuing valorisation activities, researchers have to be aware of the benefits deriving from such efforts. For these reasons, applying (or not) for the PoC scheme implies another pool of outcomes, which refers more specifically to the PI behaviour towards valorisation (instead of to project progression). We refer to this different type of outcome as intangible or "soft" benefits, as they are mainly related to learning, awareness and confidence in valorisation. This positive impact in terms of the award recipients' mindset is potentially one of the more enduring impacts of the awards, contributing to a cultural change among the research teams. For this reason, it deserves stand-alone analyses. In this section, we focus on this latter aspect and assess the PIs' perceived improvement in the valorisation skills, awareness and confidence of project members as a result of the valorisation project.

In order to address this topic, we exploited a set of survey questions asking the respondents to rate (in a Likert-scale from 1 to 5) to what extent the valorisation project improved the commercial and business

²⁴ Eastern Europe includes Bulgaria, Czech Republic, Estonia, Greece, Poland, and Slovenia; Northern Europe includes Denmark, Finland, Iceland, Ireland, Norway, Sweden, and the United Kingdom; Southern Europe includes Cyprus, Italy, Portugal, Spain, and Turkey; and Western Europe includes Austria, Belgium, France, Germany, Hungary, Netherlands, and Switzerland

²⁵ More precisely, this is the procedure we followed: We first centred the variable *Project score* at the funding threshold of 9 points over a total of 15 points and we ran a fuzzy RDD based on two-stage least squares, instrumenting for grant receipt (Jacob and Lefgren, 2011; Wand et al., 2017). The fuzzy model is appropriate (in contrast to the sharp model), as 12 PoC proposals were rejected although with score above the threshold due to budget constraints. In order to define the optimal bandwidth, we employed the procedure by Calonico et al. (2014) and weighted the observations in the RD window based on a triangular kernel. As suggested by Gelman and Imbens (2019), we considered a local linear model. To further confirm our findings, we ran the same analyses with quadratic polynomial function and applied different bandwidths (as suggested by Imbens-Kalyanaraman, 2012).

²³ We thank one of the Reviewer for this suggestion.

Table 5
Regressions on perceived effectiveness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PI male	Business skills	Business skills	Business skills	Valorisation awareness	Valorisation awareness	Valorisation awareness	Valorisation confidence	Valorisation confidence	Valorisation confidence
Team size	0.044 (0.211)	0.084 (0.212)	0.078 (0.212)	-0.081 (0.212)	-0.065 (0.213)	-0.043 (0.215)	0.012 (0.204)	0.034 (0.205)	0.041 (0.206)
TTO involvement	0.123*** (0.044)	0.130*** (0.044)	0.126*** (0.045)	0.191*** (0.052)	0.173*** (0.050)	0.184*** (0.051)	0.112*** (0.042)	0.113*** (0.043)	0.119*** (0.044)
Past number of patents	0.214 (0.158)	0.265* (0.160)	0.262 (0.160)	0.058 (0.159)	0.110 (0.160)	0.142 (0.161)	0.147 (0.156)	0.219 (0.158)	0.230 (0.159)
Past number of project publications	0.064 (0.045)	0.046 (0.045)	0.043 (0.046)	0.076* (0.046)	0.053 (0.046)	0.064 (0.046)	0.066 (0.045)	0.043 (0.046)	0.049 (0.046)
Consolidator Grant (CoG)	0.037 (0.463)	0.114 (0.460)	0.254 (0.852)	-0.250 (0.437)	-0.077 (0.447)	-0.866 (0.699)	0.431 (0.474)	0.572 (0.484)	0.241 (0.803)
Advanced Grant (AdG)	-0.154 (0.153)	-0.076 (0.155)	-0.220 (0.334)	-0.143 (0.154)	-0.056 (0.156)	0.148 (0.335)	-0.038 (0.152)	0.036 (0.154)	0.196 (0.337)
PoC grant	0.789*** (0.186)	0.705*** (0.269)			0.813*** (0.191)	0.890*** (0.274)		0.877*** (0.189)	0.959*** (0.267)
PoC grant # CoG		-0.215 (1.013)				1.513 (0.951)			0.569 (1.022)
PoC grant # AdG		0.188 (0.381)				-0.277 (0.380)			-0.209 (0.381)
/cut1	-0.560 (0.631)	-0.013 (0.648)	-0.143 (0.695)	-0.851 (0.606)	-0.546 (0.616)	-0.379 (0.664)	-0.712 (0.602)	-0.304 (0.614)	-0.178 (0.659)
/cut2	0.053 (0.624)	0.623 (0.641)	0.497 (0.688)	-0.632 (0.601)	-0.297 (0.610)	-0.123 (0.659)	-0.265 (0.595)	0.195 (0.607)	0.322 (0.655)
/cut3	0.743 (0.627)	1.357** (0.647)	1.230* (0.693)	0.348 (0.601)	0.769 (0.613)	0.953 (0.662)	0.735 (0.596)	1.263** (0.612)	1.388** (0.659)
/cut4	1.701*** (0.633)	2.365*** (0.656)	2.239*** (0.701)	1.642*** (0.607)	2.119*** (0.622)	2.314*** (0.671)	1.917*** (0.603)	2.502*** (0.621)	2.630*** (0.667)
Number of observations	228	228	228	239	239	239	237	237	237
Pseudo R ²	0.031	0.059	0.059	0.044	0.075	0.082	0.031	0.067	0.068
PoC scientific domain dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
HI country dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors are in parenthesis

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

development skills of the project members and made them more aware of and confident about valorisation. Given the nature of our dependent variable, we used an Ordered Probit specification. The new analyses were run on a limited sample of observations, as the answers to the aforementioned questions were only provided by respondents who applied for the ERC PoC Programme and proceeded with valorisation activities, either through a PoC (in case of grantees) or through other sources (in case of PoC applicants that were not funded). Respondents in our sample who did not continue with the valorisation project were not included in this set of analyses, thus reducing the number of observations²⁶.

While we do not report our descriptive statistics here for the sake of brevity, they show that, on average, the scores obtained for the three dimensions of indirect performance are 3.77, 4.02 and 3.87 for commercial and business development skills, valorisation awareness and valorisation confidence, respectively. Furthermore, these perceived improvements are significantly ($p<.001$) higher for respondents who received the grant compared to the control group who did not (3.9 versus 3.1 for commercial and business development skills improvement; 4.1 versus 3.4 for valorisation awareness; and 4.0 versus 3.2 for

valorisation confidence).

We also assessed the relationship of such intangible outcomes with our main explicative variable (*PoC grant*) using a regression framework. Table 5 shows our main regression results. We can assert that the effect of public science valorisation grants on changes in competences and mindset is positive and significant for all the three measures ($p<.001$). In general, these results show a positive impact in terms of changing grant recipients' mindset towards valorisation. However, this set of analyses did not find confirm our hypotheses on perceived effectiveness; thus, this aspect deserves more investigation from future research.

6. Discussion and conclusions

Public policies that provide financial support for science valorisation are an increasingly important and diffuse type of policy instrument, but their assessment remains relatively unexplored in the academic literature. Our goal was to assess the effectiveness of a relevant international public support programme for science valorisation, the Proof-of-Concept Scheme of the European Research Council. To do so, we exploited unique survey-based data that allowed us to compare a group of projects receiving PoC grants from this scheme with a control group of projects that applied to the programme but were not funded. The novelty of our effort derives from its unique context, the novel type of policy instrument, the research design, the multidimensional levels of analysis, and the associated insights, which derive from our ability to leverage internal administrative and survey data.

Our access to ERC survey data allowed us to estimate both the project characteristics associated with winning PoC grants and the impact of those grants on several measures of valorisation outcomes. Moreover,

²⁶ For this set of additional analyses, our final sample comprised 242 granted projects and 115 not-granted projects that continued with valorisation activities. However, due to missing information for some of the respondents, we were able to perform the analyses on 231 observations concerning the improvement in commercial and business development skills, 242 observations for the analyses concerning the level of valorisation awareness, and 239 observations for the analyses concerning the valorisation confidence.

the unique features of the ERC PoC measures allowed us to consider a set of highly heterogeneous projects from different PIs, universities, scientific fields, and countries. Our evaluation of the PoC programme of the ERC, which is based on an instrumental variable approach, finds that the programme has been effective in fostering the early valorisation of scientific discoveries. By all measures of valorisation success that we employed – licensing, start-up creation, research contracts, and consulting, as well as access to follow-on funding – projects that had received the grant performed significantly better than those that had not. Overall, our findings support this type of policy instrument as a catalyst to accelerate the transition of scientific results towards commercial and societal applications. Second, our analyses suggest a negative moderating effect of the PI's academic seniority on the relationship between receiving PoC funding and attracting follow-on funding—as well as the probability of engaging in valorisation outcomes (albeit in a less strong way). This finding confirms the relevant role of PoC in addressing the funding gap that limits the transformation of research into practical and commercial applications, especially for junior researchers who, in the extant literature, have been considered less active in these types of activities.

Our study therefore presents relevant implications for policymaking. Our results suggest the importance of activating these types of instruments as a complement to traditional funding sources for basic research. Such efforts can create the adequate conditions to effectively transfer scientific knowledge from universities and public research centres into practical applications. However, a potential issue which may arise in this respect is whether such funding schemes may generate some kinds of side effects. It could be questioned that an excessive emphasis towards valorisation activities may come at the expense of the attention and effort devoted to basic research activities, an issue which is amply debated in the previous literature (Perkmann et al., 2013). In this sense, there is ample evidence that significant valorisation outcomes are more likely to be pursued by researchers that are more scientifically productive than their colleagues (Azoulay et al., 2007; Van Looy et al., 2006). In addition to that, it has been shown that the quality of the research base at the basis of gap funding instruments is a fundamental prerequisite for their success (Munari et al., 2018). Therefore, the availability of valorisation funding should not be interpreted as a substitute for funding streams oriented towards basic research activities, but rather as an additional component of a more holistic innovation framework. Broadly speaking, research and development can be seen as the creation of new knowledge available to the whole society in different and complementary ways.

The successful experience of the ERC Proof-of-Concept programme should thus encourage the replication of PoC-type programmes among EU member states and other countries, including developing countries. For example, in recent years, France, Germany, and Poland have undertaken this type of initiative with their SATT, Exist, and Tango national PoC programmes, respectively. However, despite the importance of PoC policy schemes, their diffusion across countries and individual universities (Munari et al., 2018) is still limited. Therefore, there is ample space for experimentation in this field. Policymakers interested in the design and implementation of new funding programmes for science valorisation should carefully consider the national contextual contingencies and, in particular, the degree to which technology transfer practices are implemented at the national level, as this factor significantly impacts the optimal level of centralisation/decentralisation (Munari et al., 2017). University administrators interested in the application of PoC funding measures within their institutions, on the other hand, should carefully consider the critical preconditions illustrated by previous literature (Bradley et al., 2013; Munari et al., 2017): namely, the size and excellence of university scientific production, and the size and expertise of the university TTO. Moreover, our study highlights the importance of thoroughly evaluating the impact of public policies centred on science valorisation funding in order to develop a better understanding of likely trajectories and beneficiary needs. In this

respect, our results provide guidelines as to how to design an evaluation approach and adopt a multidimensional set of outcome metrics.

Although our findings highlight clear policy conclusions, further research is needed to address the limitations of our study and assess the generalizability of our findings. Our focus on a single policy action (while covering multiple countries and institutions) presents unique advantages, but it warrants some reflections on the possibility of extending the results to other contexts. In this sense, it should be noted that ERC PoC grants build on previous generous ERC Frontier Research grants, thereby targeting some of the most successful and productive scientists in Europe. Moreover, the amount of PoC funding provided per project is significant when compared to the average funding levels that characterize university-level PoC programmes in Europe²⁷. For these reasons, further studies on other programmes (ideally with a cross-country design) would illuminate whether impact varies depending on institutional contexts.

Moreover, due to the relatively recent activation of the ERC PoC programme, a major constraint of our analysis is the relatively short period between the granting of the award and the assessment of the valorisation outcomes. It is well-known that the translation of scientific discoveries into useful novel applications in the market or society requires a long gestation period. Therefore, the relatively recent activation of the ERC PoC programme means the bulk of the awardees have not yet reached a stage where the broader impact (in terms of market penetration, job creation, and wider societal benefits) can be fully determined. Thus, this programme should be assessed on a regular basis to ascertain awardees' progress. In this sense, further research is also needed on other policy programmes that cover a longer time span and adopt a broader view of impact (Fini et al., 2018). Finally, we were not able to exploit data on evaluation scores for all the project applications to the ERC PoC grant because wanted to resolve the selection problem in grant evaluation with a regression discontinuity approach, as done by recent studies (Howell, 2017; Wang et al., 2017). Instead, we adopted the instrumental variable approach, as suggested by Jaffe (2002). Nonetheless, the fair and effective selection process for science valorisation projects is an important issue—one deserving studies dedicated to the specific set of competences that are required for evaluating valorisation projects. Despite these limitations, we believe that our study sheds new light on an innovative policy instrument that contributes to reaping additional benefits from public investments in scientific research.

CRediT authorship contribution statement

Federico Munari: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Writing - review & editing. **Laura Toschi:** Conceptualization, Methodology, Software, Data curation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

No.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Acknowledgments

We are grateful to Prof Charles Wessner, Prof Klaus Bock, Prof Reinhilde Veugelers, Laura Pontiggia, Veronica Beneitez-Pinero and Gian Franco Casula for valuable comments during the preparation of this article. The analyses and findings of this article are the responsibility of

²⁷ The mapping exercise of POC programmes activated by European universities, by Munari et al. (2018), reported an average level of funding provided per POC project equal to approximately 55,000 Euro.

the Authors.

Annexes

[Annex 1](#), [Annex 2](#), [Annex 3a](#), [Annex 3b](#).

Annex 1

Distribution of PoC applications and survey responses: T-test on proportion differences to assess the representativeness of our sample

Panel A	ERC PoC data (2011-2016)		Our survey data (2011-2016)		Comparison of proportion test	Sign
SCIENTIFIC DOMAIN	Total # of ERC PoC applications	Proportion of ERC PoC applications by scientific domain	Total # of ERC PoC applications in our sample	Proportion of projects in our sample by scientific domain		
Life Sciences	657	0.37	154	0.34	1.32	*
Physical Sciences & Engineering	890	0.50	234	0.52	-0.69	
Social Sciences & Humanities	218	0.12	64	0.14	-0.88	
Total	1,765*	1.00	446	1.00		
Panel B	ERC PoC data (2011-2016)		Our survey data (2011-2016)		Comparison of proportion test	Sign
PI GENDER	Total # of ERC PoC applications	Proportion of ERC PoC applications by PI's gender	Total # of ERC PoC applications in our sample	Proportion of projects in our sample by PI's gender		
Male	1,481	0.82	361	0.81	0.54	
Female	323	0.18	85	0.19	-0.54	
Total	1,804	1.00	446	1.00		
Panel C	ERC PoC data (2011-2016)		Our survey data (2011-2016)		Comparison of proportion test	Sign
APPLICATION YEAR	Total # of ERC PoC applications	Proportion of ERC PoC applications by year	Total # of ERC PoC applications in our data	Proportion of projects in our sample by year		
2011	151	0.08	36	0.08	0.20	
2012	143	0.08	30	0.07	0.85	
2013	292	0.16	48	0.11	2.86	***
2014	442	0.25	99	0.22	1.02	
2015	339	0.19	102	0.23	-1.94	**
2016	437	0.24	131	0.29	-2.24	**
Total	1,804	1.00	446	1.00		
Panel D	ERC PoC data (2011-2016)		Our data (2011-2016)		Comparison of proportion test	Sign
EUROPEAN AREA	Total # of ERC PoC applications	Proportion of ERC PoC applications by European area	Total # of ERC PoC applications in our sample	Proportion of projects in our sample by European area		
Eastern Europe	37	0.02	13	0.03	-1.04	
Northern Europe	504	0.29	120	0.27	0.69	
Southern Europe	487	0.28	123	0.29	0.01	
Western Europe	737	0.42	190	0.42	-0.32	
Total	1,765*	1.00	446	1.00		

* In the case of Panel A and Panel D there were missing values on the sectors and countries of 39 PoC applications.

Annex 2

T-test on proportion difference of the outcome variables by treatment group

	PoC grant			No PoC grant			Difference-test	
	Obs.	Mean	SE	Obs.	Mean	SE	t-test	p-value
Science valorisation	224	0.455	0.033	184	0.136	0.025	-6.935	***
Commercialisation	223	0.269	0.030	184	0.076	0.020	-5.024	***
Academic engagement	221	0.330	0.032	184	0.109	0.023	-5.280	***
Follow-on funding	217	0.387	0.033	180	0.211	0.030	-3.784	***
Private follow-on funding	217	0.147	0.024	180	0.050	0.016	-3.177	**
Public follow-on funding	217	0.341	0.032	180	0.150	0.027	-4.350	***

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

Annex 3aRegressions with instrumental variables for *Licensing*, and *New venture creation*

	(1)	(2)	(3)	(4)	(5)	(6)
PI male	Licensing 0.018 (0.040)	Licensing 0.001 (0.042)	Licensing 0.005 (0.041)	New venture creation 0.075* (0.041)	New venture creation 0.058 (0.041)	New venture creation 0.060 (0.041)
Team size	0.018* (0.011)	0.009 (0.011)	0.017 (0.012)	0.012 (0.011)	0.003 (0.011)	0.003 (0.012)
TTO involvement	-0.013 (0.033)	-0.024 (0.034)	-0.023 (0.034)	-0.072** (0.034)	-0.084** (0.034)	-0.084** (0.034)
Past number of patents	0.072*** (0.012)	0.065*** (0.012)	0.073*** (0.013)	0.054*** (0.012)	0.047*** (0.012)	0.047*** (0.013)
Past number of project publications	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)
Consolidator Grant (CoG)	-0.124 (0.092)	-0.052 (0.099)	0.049 (0.166)	0.236** (0.094)	0.307*** (0.096)	0.334** (0.165)
Advanced Grant (AdG)	0.001 (0.032)	0.036 (0.036)	0.151 (0.093)	0.010 (0.033)	0.045 (0.035)	0.032 (0.093)
PoC grant		0.281*** (0.103)	0.295*** (0.102)		0.284*** (0.102)	0.251** (0.102)
PoC grant # CoG			-0.287 (0.390)			-0.107 (0.388)
PoC grant # AdG			-0.240 (0.168)			0.018 (0.168)
Constant	-0.138 (0.112)	-0.186 (0.117)	-0.246* (0.126)	-0.089 (0.115)	-0.134 (0.114)	-0.123 (0.125)
Number of observations	410	410	410	404	404	404
PoC scientific domain dummy	YES	YES	YES	YES	YES	YES
HI country dummy	YES	YES	YES	YES	YES	YES
Year dummy	YES	YES	YES	YES	YES	YES

Standard errors are in parenthesis

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

Annex 3bRegressions with instrumental variables for *R&D collaboration and contracts*, and *Consulting*

	(7)	(8)	(9)	(10)	(11)	(12)
PI male	R&D collaboration/contracts -0.002 (0.049)	R&D collaboration/ contracts -0.023 (0.051)	R&D collaboration/ contracts -0.021 (0.053)	Consulting -0.036 (0.038)	Consulting -0.044 (0.038)	Consulting -0.046 (0.039)
Team size	0.031** (0.013)	0.019 (0.014)	0.034** (0.015)	0.026*** (0.010)	0.021** (0.010)	0.027** (0.011)
TTO involvement	-0.024 (0.040)	-0.040 (0.042)	-0.030 (0.045)	-0.019 (0.032)	-0.025 (0.032)	-0.025 (0.032)
Past number of patents	0.055*** (0.014)	0.045*** (0.015)	0.062*** (0.017)	0.019* (0.011)	0.015 (0.011)	0.022* (0.012)
Past number of project publications	0.001* (0.001)	0.001 (0.001)	0.002* (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Consolidator Grant (CoG)	-0.089 (0.112)	0.005 (0.120)	-0.083 (0.217)	0.070 (0.087)	0.106 (0.090)	0.150 (0.158)
Advanced Grant (AdG)	-0.026 (0.039)	0.020 (0.044)	0.333*** (0.122)	-0.002 (0.031)	0.015 (0.033)	0.162* (0.089)
PoC grant		0.378*** (0.127)	0.581*** (0.134)		0.143* (0.095)	0.281*** (0.098)
PoC grant # CoG			0.443 (0.510)			-0.020 (0.371)
PoC grant # AdG			-0.612*** (0.221)			-0.274* (0.161)
Constant	-0.026 (0.137)	-0.088 (0.143)	-0.285* (0.164)	-0.083 (0.107)	-0.106 (0.107)	-0.199* (0.120)
Number of observations	406	406	406	404	404	404
PoC scientific domain dummy	YES	YES	YES	YES	YES	YES
HI country dummy	YES	YES	YES	YES	YES	YES
Year dummy	YES	YES	YES	YES	YES	YES

Standard errors are in parenthesis

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

References

- Ajzen, I., Fishbein, M., 1980. Understanding attitudes and predicting social behaviour. Prentice-hall, Englewood Cliffs, NJ.
- Aldridge, T.T., Audretsch, D., 2011. The Bayh-Dole Act and scientist entrepreneurship. Research Policy 40, 1058–1067.
- Arora, A., Gambardella, A., 1998. The Impact of NSF Support for Basic Research in Economics. Carnegie-Mellon University, mimeo.
- Audretsch, D.B., Bönte, W., Mahagaonkar, P., 2012. Financial signaling by innovative nascent ventures: The relevance of patents and prototypes. Research Policy 41 (8), 1407–1421.
- Auerswald, P.E., Branscomb, L.M., 2003. Valleys of death and Darwinian seas: financing the invention to innovation transition in the United States. Journal of Technology Transfer 28 (3), 227–239.
- Angrist, J., 2001. Estimation of limited dependent variable models with dummy endogenous regressors: Simple strategies for empirical practice. Journal of Business & Economic Statistics 19, 2–16.

- Azoulay, P., Ding, W., Stuart, T., 2007. The determinants of faculty patenting behavior: demographics or opportunities? *Journal of Economic Behavior & Organizations* 63 (4), 599–623.
- Bascle, G., 2008. Controlling for endogeneity with instrumental variables in strategic management. *Strategic Organization* 6, 285–327.
- Beaudry, C., Allaoui, S., 2012. Impact of public and private research funding on scientific production: The case of nanotechnology. *Research Policy* 41 (9), 1589–1606.
- Beckman, C.M., Burton, M.D., O'Reilly, C., 2007. Early teams: The impact of team demography on VC financing and going public. *Journal of Business Venturing* 22 (2), 147–173.
- Bercovitz, J., Feldman, M., 2008. Academic entrepreneurs: Organizational change at the individual level. *Organization Science* 19 (1), 69–89.
- Bozeman, B., Gaughan, M., 2007. Impacts of Grants and Contracts on Academic Researchers' Interactions with Industry. *Research Policy* 36 (5), 694–707.
- Bozeman, B., Youtie, J., 2017. Socio-economic impacts and public value of government-funded research: Lessons from four US National Science Foundation initiatives. *Research Policy* 46, 1387–1396.
- Burton, M.D., Sorensen, J.B., Beckman, C.M., 2002. Coming from good stock: careerhistories and new venture formation. In: Lounsbury, M., Ventresca, M. (Eds.), *Research in the Sociology of Organizations—Social Structure and Organizations Revisited*, 19. JAI Press, Greenwich, CT, pp. 229–262.
- Bradley, S.R., Hayter, C.S., Link, A.N., 2013. Proof of concept centers in the United States: an exploratory look. *J. Technol. Transfer* 38 (4), 349–381.
- Calonico, S., Cattaneo, M.D., Vazquez-Bare, G., 2014. Robust data-driven inference in the regression-discontinuity design. *Stata Journal* 14 (4), 909–946.
- Colyvas, J.A., Powell, W.W., 2007. From vulnerable to venerated: the institutionalization of academic entrepreneurship in the life sciences. *Research in the Sociology of Organizations* 25, 219–259.
- Czarnitzki, D., Lopes-Bento, C., 2013. Value for money? New microeconometric evidence on public R & D grants in Flanders. *Research Policy* 42 (1), 76–89.
- Debackere, K., Veugelers, R., 2005. The role of academic technology transfer organizations in improving industry science links. *Research Policy* 34, 321–342.
- D'Este, P., Patel, P., 2007. University-industry linkages in the UK: What are the factors underlying the variety of interactions with industry? *Research Policy* 36 (9), 1295–1313.
- Ding, W.W., Murray, F., Stuart, T.E., 2013. From bench to board: Gender differences in university scientists' participation in corporate scientific advisory boards. *Academy of Management Journal* 56 (5), 1443–1464.
- Ding, W.W., Stuart, T.E., 2006. When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences. *American Journal of Sociology* 112 (1), 97–144.
- Eisenhardt, K.M., Schoonhoven, C.B., 1990. Organizational growth: linking founding team, strategy, environment, and growth among U.S. semiconductor ventures, 1978–1988. *Administrative Science Quarterly* 35 (3), 504–529.
- Feldman, M.P., Kelley, M.R., 2003. Leveraging research and development: Assessing the impact of the U.S. Advanced Technology Program. *Small Business Economics* 20, 153–165.
- Fini, R., Rasmussen, E., Siegel, D., Wiklund, J., 2018. Rethinking the Commercialisation of Public Science: From Entrepreneurial Outcomes to Societal Impacts. *Academy of Management Perspectives* 32 (1), 4–20.
- Frietsch, R., Haller, I., Funken-Vrohlings, M., Gruppa, H., 2009. Gender-specific patterns in patenting and publishing. *Research Policy* 38, 590–599.
- Gelman, A., Imbens, G., 2019. Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business and Economic Statistics* 37 (3), 447–456.
- Giuri, P., Grimaldi, R., Kochenkova, A., Munari, F., Toschi, L., 2018. The effects of university-level policies on women's participation in academic patenting in Italy. *Journal of Technology Transfer* forthcoming.
- Giuri, P., Munari, F., Scandura, A., Toschi, L., 2019. The strategic orientation of universities in knowledge transfer activities. *Technological Forecasting and Social Change* 138, 261–278.
- Gompers, P., Kovner, A., Lerner, J., Scharfstein, D., 2010. Performance persistence in entrepreneurship. *Journal of Financial Economics* 96 (1), 18–32.
- Gulbranson, C.A., Audretsch, D.B., 2008. Proof of concept centers: accelerating the commercialisation of university innovation. *Journal of Technology Transfer* 33 (2), 249–258.
- Haeussler, C., Colyvas, J.A., 2011. Breaking the Ivory Tower: Academic Entrepreneurship in the Life Sciences in UK and Germany. *Research Policy* 40, 41–54.
- Hottenrott, H., Lopes-Bento, C., Veugelers, R., 2017. Direct and cross scheme effects in a research and development subsidy program. *Research Policy* 46, 1118–1132.
- Hottenrott, H., Lawson, C., 2017. Fishing for complementarities. *Research Grants and research productivity*. *International Journal of Industrial Organization* 51, 1–38.
- Howell, S.T., 2017. Financing innovation: Evidence from R&D grants. *American Economic Review* 107, 1136–1164.
- Hsu, D.H., 2007. Experienced entrepreneurial founders, organizational capital, and venture capital funding. *Research Policy* 36 (5), 722–741.
- Imbens, G., Kalyanaraman, K., 2012. Optimal bandwidth choice for the regression discontinuity estimator. *Rev. Econ. Stud.* 79 (3), 933–959.
- Jacob, B.A., Lefgren, L., 2011. The impact of NIH postdoctoral training grants on scientific productivity. *Research Policy* 40, 864–874.
- Jaffe, A., 2002. Building programme evaluation into the design of public research-support programmes. *Oxford Review of Economic Policy* 18 (1), 22–34.
- Kochenkova, A., Grimaldi, R., Munari, F., 2016. Public policy measures in support of knowledge transfer activities: a review of academic literature. *The Journal of Technology Transfer* 41 (3), 407–429.
- Lanahan, L., Aramanios, D., 2018. Does More Certification Always Benefit a Venture? *Organization Science* 29, 931–947.
- Lerner, J., 1999. The government as venture capitalist: The long-run effects of the SBIR program. *Journal of Business* 72, 285–318.
- Levin, S.G., Stephan, P.E., 1991. Research productivity over the life cycle: Evidence for academic scientists. *The American Economic Review* 81 (1), 114–132.
- Lockett, A., Wright, M., 2005. Resources, capabilities, risk capital and the creation of university spin-out companies. *Research Policy* 34 (7), 1043–1057.
- Martin, B., 2016. R&D policy instruments – a critical review of what we do and don't know. *Industry and Innovation* 23 (2), 157–176.
- Meng, Y., 2016. Collaboration patterns and patenting: Exploring gender distinctions. *Research Policy* 45, 56–67.
- Molas-Gallart, J., D'Este, P., Llopis, O., Rafols, I., 2016. Towards an alternative framework for the evaluation of translational research initiatives. *Research Evaluation* 25 (3), 235–243.
- Munari, F., Rasmussen, E., Toschi, L., Villani, E., 2016. Determinants of the university technology transfer policy-mix: a cross-national analysis of gap-funding instruments. *Journal of Technology Transfer* 41 (6), 1377–1405.
- Munari, F., Sobrero, M., Toschi, L., 2017. Financing technology transfer: assessment of university-oriented proof-of-concept programmes. *Technology Analysis & Strategic Management* 29 (2), 233–248.
- Munari, F., Sobrero, M., Toschi, L., 2018. The university as a venture capitalist? Gap funding instruments for technology transfer. *Technological Forecasting and Social Change* 127, 70–84.
- Murray, F., Graham, L., 2007. Buying science and selling science: Gender differences in the market for commercial science. *Industrial and Corporate Change* 16 (4), 657–689.
- OECD, 2013. *Commercialising Public Research: New Trends and Strategies*. OECD Publishing, Paris.
- OECD, 2019. Science-industry knowledge exchange: a mapping of policy instruments and their interactions, 66. *OECD Science, Technology and Industry Policy Papers*, Paris. April 2019.
- O'Shea, R.P., Allen, T.J., Chevalier, A., Roche, F., 2005. Entrepreneurial orientation, technology transfer and spinoff performance of US universities. *Res. Policy* 34 (7), 994–1009.
- Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Brostrom, A., D'Este, P., Fini, R., Geuna, A., Grimaldi, R., Hughes, A., Krabel, S., Kitson, M., Llerena, P., Lissoni, F., Salter, A., Sobrero, M., 2013. Academic engagement and commercialisation: a review of the literature on university-industry relations. *Research Policy* 42, 423–442.
- Rasmussen, E., 2008. Government instruments to support the commercialisation of university research: Lessons from Canada. *Technovation* 28, 506–517.
- Rasmussen, E., Sørheim, R., 2012. How governments seek to bridge the financing gap for university spin-offs: proof-of-concept, pre-seed, and seed funding. *Technology Analysis and Strategic Management*. 24 (7), 663–678.
- Salmenkaita, J.P., Salo, A., 2002. Rationales for government intervention in the commercialisation of new technologies. *Technology Analysis & Strategic Management* 14 (2), 183–200.
- Seyhan, A.A., 2019. Lost in translation: the valley of death across preclinical and clinical divide – identification of problems and overcoming obstacles. *Translational Medicine Communications* 4 (18).
- Siegel, D., Wessner, C., 2012. Universities and the success of entrepreneurial ventures: evidence from the small business innovation research program. *The Journal of Technology Transfer* 37 (4), 404–415.
- Stephan, P., Gurmu, S., Sumell, A., Black, G., 2007. Who's patenting in the university? Evidence from the survey of doctorate recipients. *Economics of Innovation and New Technology* 16 (2), 71–99.
- Stock, J.J., Yogo, M., 2002. Testing for weak instruments in linear IV regression (NBER Working Paper No. 824). Cambridge, MA. Available at: <http://www.nber.org/papers/t0284.pdf>.
- Stock, J.H., Wright, J.H., Yogo, M., 2002. A survey of weak instruments and weak identification in generalized method of moments. *J. Bus. Econ. Stat.* 20 (4), 518–529.
- Stuart, T.E., Huang, H., Hybels, R.C., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly* 44 (2), 315–349.
- Stuart, T., Ding, W., 2006. When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences. *American Journal of Sociology* 112 (1), 97–144.
- Tartari, V., Salter, A., 2015. The engagement gap: Exploring gender differences in University-Industry collaboration activities. *Research Policy* 44 (6), 1176–1191.
- Thursby, J.G., Thursby, M.C., 2002. Who Is Selling the Ivory Tower? Sources of Growth in University Licensing. *Management Science* 48 (1), 90–104.
- Van Looy, B., Callaert, J., Debackere, K., 2006. Publication and patent behavior of academic researchers: conflicting, reinforcing or merely co-existing? *Research Policy* 35 (4), 596–608.
- Vanino, E., Roper, S., Becker, B., 2019. Knowledge to money: Assessing the business performance effects of publicly-funded R&D grants. *Research Policy* 48 (7), 1714–1737.
- Wallsten, S., 2000. The effects of government-industry R&D programs on private R&D: The case of the Small Business Innovation Research Program. *RAND Journal of Economics*.
- Wang, Y., Li, J., Furman, J.L., 2017. Firm performance and state innovation funding: Evidence from China's Innofund program. *Research Policy* 46 (6), 1142–1161.
- Wessner, C., 2008. An Assessment of the Small Business Innovation Research Program (Editor). National Academies Press, (US), Washington (DC).

- Wessner, C., Munari, F., 2017. An Empirical Assessment of the ERC Proof-of-Concept Programme. Final Technical Report prepared for the European Research Council Executive Agency. Bruxelles. December 2017.
- Weyant, J., Fu, E., Bowersock, J., 2018. Renewed Energy: Insights for Clean Energy's Future. Kauffman Fellows Press.
- Zhang, F., Yan, E., Niu, X., 2018. Joint modelling of the association between NIH funding and its three primary outcomes: patents, publications and citation impact. *Scientometrics* 117, 591–602.
- Zucker, L.G., Darby, M.R., Armstrong, J.S., 2002. Commercializing knowledge: university science, knowledge capture, and firm performance in biotechnology. *Management Science* 48 (1), 138–153.