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Corinna Ghirelli
Banco de España

Enkelejda Havari
IESEG School of Management, LEM and IZA

Elena Meroni
European Commission, Joint Research Centre

Stefano Verzillo
European Commission, Joint Research Centre

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ABSTRACT

The Long-Term Causal Effects of Winning an ERC Grant*

This paper investigates the long-term causal effects of receiving an ERC grant on researcher productivity, excellence and the ability to obtain additional research funding up to nine years after grant assignment. We use data on the universe of ERC applicants between 2007-2013 and information on their complete publication histories from the Scopus database. For identification, we first exploit the assignment rule based on rankings, comparing the outcomes of the winning and non-winning applicants in a regression discontinuity design (RDD). We fail to find any statistically significant effect on research productivity and quality, which suggests that receiving an ERC grant does not make a difference in terms of scientific impact for researchers with a ranking position close enough to the threshold. Since RDDs help identify a local effect, we also conduct a difference-in-differences (DID) analysis using the time series of bibliometric indicators available, which allows us to estimate the effect on a wider population of winning and non-winning applicants. Differently from the RDD results, DID estimates show that obtaining an ERC grant leads to positive long-term effects on scientific productivity, impact and the capacity to attract other EU funds in the fields of Chemistry, Universe and Earth Sciences, Institutions and Behaviours, Human Mind Studies and Medicine. Further analysis of heterogeneous effects leads us conclude that the positive results obtained with DID seem to be driven by the top-ranked applicants in these fields.

JEL Classification: I23, D04, O3

Keywords: research grants, ERC, regression discontinuity design, difference in differences, EU funds, policy evaluation

Corresponding author:
Enkelejda Havari
IESEG School of Management
3 rue de la Digue
59000 Lille
France

E-mail: e.havari@ieseg.fr

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1 Introduction

Governments allocate a considerable portion of their budget to supporting basic research in a variety of disciplines (Jacob and Lefgren, 2011). Following the American tradition, several European countries are now distributing research funds through competitive grants (Carayol and Lanoë, 2017), which evaluate both the principal investigators' profiles and the potential impact and quality of the proposed project. Despite the variety of programs and grant-assignment mechanisms, the evidence of their impact on scientific output or other related dimensions generally remains limited (Ganguli, 2017).

In this paper, we provide novel evidence from the European Research Council (ERC) grants, which represent the largest competitive scheme in Europe. The main goal of the ERC is to stimulate scientific excellence by funding the very best, creative researchers of any nationality and age and supporting their innovative ideas.[1] Importantly, it encourages the development of ground-breaking and high-risk/high-gain research.

The ERC has built a reputation for excellence, as demonstrated by numerous grantees winning prestigious international awards, including 7 Nobel Prizes, 4 Fields Medals, and 5 Wolf Prizes. In addition, 6,100 of the 150,000 articles produced with these grants have been published in journals ranked in the top 1%. However, there is limited evidence on the causal impact of these grants on scientific productivity and excellence in the medium and long term, despite the significant amount of public money invested in the programme (the ERC represents 17% of the overall Horizon 2020 budget, i.e. 13.1 billion euros over the 2014–2020 period).

The available studies documenting the impact of ERC grants are limited to reports that do not compare the career trajectories of ERC beneficiaries with those of the unsuccessful applicants. As a result, it becomes challenging to make any causal claim on the obtained findings. Moreover, they study the career of ERC winners between two and five years after grant assignment, when they are still using the grant.[2] The aim of this paper is to present new evidence on the causal impact of receiving a competitive grant, such as the ERC grant, on researchers' scientific productivity, excellence, and their ability to secure other funding in the medium to long term (up to 9 years after the grant was assigned). To obtain credible results on the impact of ERC grants, it is crucial to collect data over an extended period and beyond the typical 5-year grant duration.

[1] Researchers from anywhere in the world are free to apply for these grants provided that their research project is carried out in an EU member state or associated country.

[2] Every year, the ERC publishes a qualitative evaluation of recently completed projects. You can find the most recent evaluation for 2021 projects funded at this link.

Each year, there is an open call for ERC grants of different types (e.g. Starting, Consolidator and Advanced Grants) and in three main domains (Life Sciences, LS; Physical Sciences and Engineering, PE; and Social Sciences and Humanities, SH). Applicants are evaluated and ranked by panels of experts. Selection occurs in two steps. In step 1, proposals are evaluated by selected international peer reviewers on the basis of excellence as the sole criterion. It is applied to the evaluation of both the research project and the Principal Investigator in conjunction. Peer reviewers are in charge of assessing and scoring the proposals. Those who pass the quality threshold are ranked in step 2, after a more in-depth assessment of the research proposal. Depending on the budget available, a cut-off applies to the ranking list and only the highest-ranked proposals are offered an ERC grant until the call's budget has been exhausted (the amount of funding may vary each year).[3] This setting makes it ideal to use a regression discontinuity design (RDD) to estimate the impact of an ERC grant by comparing the outcomes of winning and non-winning applicants around the cut-off, in this way accounting for any form of selection due to either observed or unobserved characteristics. RDD estimates help identify a local effect, often in small samples. Since we can observe publications between 5 years before and up to 9 years after grant assignment, we complement the RDD analysis by also performing a difference-in-differences (DID) analysis, testing for the common trend assumption.

The estimated parameters obtained using these two methods are very different in nature as the identification occurs under different assumptions. The RDD helps estimate the effect of the grants only for scholars who are sufficiently close to the cut-off point, whereas DID estimates the effect including all observations (i.e. including also scholars who are at the top of the final ranking).

We use data on the universe of ERC grant applications submitted in the 2007–2013 period and match these with data on applicants' full publication histories from the Scopus bibliometric database. Specifically, we extract the publications of all winning and non-winning ERC applicants from their first publication ever until April 2021. In terms of research productivity and excellence, we consider the number of published articles, the number of articles published in journals ranked among the top 1% and top 10%, the h-index, and the field-weighted citation impact (FWCI). In addition, we consider the number of distinct funds received (by the network of co-authors) in order to study the well-known Matthew effect, i.e. the hypothesis that receiving a grant increases the probability of

[3] See for example the full description of the Advanced Grant procedure at this link.

receiving other grants in the near future. We could not identify a credible bibliometric indicator in our data that would allow us to examine whether receiving an ERC grant encourages the development of groundbreaking and high-risk/high-gain research. As such, this aspect remains unexplored in our paper.

Overall, RDD results do not show significant effects of grants on productivity and quality. However, we do find strong evidence in favour of the Matthew effect, for what regards EU funding meaning that ERC winners in the 9 years after receiving the ERC are recognised also from other EU funding bodies as high-quality researchers, with already strong experience in managing large research funds being able to produce high-quality research. On the other side, we don't find any effect on the total number of funding, suggesting that rejected applicants are able to access alternative funding sources.

By contrast, the DID results show that obtaining an ERC grant yields positive long-term effects on scientific productivity, impact and the capacity to attract other EU funds in the field of Chemistry, Universe and Earth Sciences, Institutions and Behaviours, Human Mind Studies and Medicine. Further analysis of heterogeneous effects leads us to conclude that the positive results obtained with DID seem to be driven by the top-ranked applicants in these fields.

This paper contributes to the literature on competitive-based grants and their effects in different ways. To the best of our knowledge, this is the first comprehensive study to analyse the causal effect of receiving an ERC grant on scientific productivity, excellence and research networks using a quasi-experimental setting based on rankings. A recent paper that uses micro-level data on ERC grants by Veugelers et al. (2022) examines whether the ERC selects researchers with a track record for conducting risky research, addressing a different research question from ours and using different data and methodology (they only have a random sample of non-winning applicants), which has different implications for policy. Second, compared to previous studies on competitive grants, our analysis offers a longer time perspective by following both winning and non-winning applicants up to 9 years after their grant application. Having a long time span available after the assignment of an ERC grant (which lasts for 5 years) is **crucial**, considering the time needed for producing research papers from the grantee's research activity and the often considerable publication lag, especially in some fields. Third, given that the ERC funding scheme targets researchers at different stages of their careers (young and senior ones) and concerns different disciplines, this is one of the first studies to investigate different types of grants (Starting and Advanced) as well as different disciplines spanning from Biology to Economics.

The remainder of the paper is organized as follows: Section 2 briefly reviews the literature, while Section 3 describes the ERC programme in detail and the assignment mechanisms for the grants. In Section 4, we present the data used in the analysis and the selected outcomes of interest. Section 5 explains the empirical framework, and results are presented in Section 6. Section 7 discusses policy implications and Section 8 offers some concluding remarks.

2 Related literature

The question of whether receiving grants improves scientific productivity has been widely investigated. The literature focuses on two main units of analysis: universities and individual researchers. Studies focusing on universities usually find a positive relationship between funding and publication outcomes, whereas those looking at individual researchers tend to find mixed results.[4] In this section, we focus on the second strain of literature since it is the most relevant to the purposes of this paper. Overall, the results of this literature offer mixed findings, depending on the country studied, the seniority of the researchers and the outcomes considered.

The first studies to use data on all applicants (successful and unsuccessful) focus on US grants (Jacob and Lefgren, 2011; Wang et al., 2019). Jacob and Lefgren (2011) investigate the impact of National Institutes of Health (NIH) grants on researchers' publications and citations in the 5 years after receiving the grant and on the probability of receiving future grants. Using an instrumental variable approach, they do not find a significant effect of receiving a grant on total publications or citations but do find a positive effect on the probability of receiving funding in the future. The explanation provided is that in a competitive market for research funding, non-successful researchers may have access to other sources of funding which offsets any effect of productivity. Similar conclusions are reached by Arora and Gambardella (2005), who focus on National Science Foundation (NSF) grants for US economists. They match successful and non-successful applicants based on age, publications (considering indicators of quality and quantity) and the score received for their research proposals. They find no effect of receiving a grant on future publications, with the exception of young economists, who benefit slightly from the grant. Again, the claim is that experienced researchers can easily find alternative sources of funding or can carry out their research anyway. Similarly, Wang et al. (2019) examine

[4] See, among others, Whalley and Hicks (2014); Rosenbloom et al. (2015); Popp (2016).

junior scientists applying for NIH grants over the 1990–2005 period. They compare near misses to near winners using the evaluation score in a fuzzy RDD. No effect is found on the number of published papers, but they find a negative effect of receiving the grant on the quality of publications in the 9 years after the application (measured using citations). The effect remains even after taking into account different attrition rates in the two groups (using an indicator for being active in the NIH system). They claim that this effect can be explained by the concept of "What doesn't kill you makes you stronger": scientists who do not get a grant have a higher probability of leaving the academic field, but those who remain actually perform better than the winners in terms of producing higher quality papers. Other papers have also investigated the effect of different typologies of grants: the paper by Azoulay et al. (2011) compares two different types of grants: the Howard Hughes Medical Institute (HHMI), which tolerates early failure, rewards long-term success, and gives its appointees great freedom to experiment, and the National Institutes of Health (NIH), whose grantees are subject to short review cycles, predefined deliverables, and renewal policies unforgiving of failure. It finds that winners of the former grants perform better than winners of the second one, suggesting that rewarding long-term success, encouraging intellectual experimentation, and providing rich feedback to its appointees may improve the outcomes.

A second set of studies has focused on European national grants, i.e. from the Danish and Norwegian open mode grant schemes (Langfeldt et al., 2015), the Swiss National Foundation (SNSF) (Heyard and Hottenrott, 2021; Baruffaldi et al., 2020), the Agence Nationale de la Recherche (ANR) in France (Carayol and Lanoë, 2017) and the Luxembourg National Research Fund (FNR) (Hussinger and Carvalho, 2022), among others. Hussinger and Carvalho (2022) conduct a difference-in-differences analysis that shows that research grants from the Luxembourg National Research Fund (FNR), the central research funding agency in Luxembourg, increase the scientific output of university professors by 31% (which corresponds to one additional publication). They further show that scientific output drops again around five years after receiving the grant. However, the authors find that university professors who realize a quality increase in their journal publications in the years following the grant benefit from a long-lasting publication quality effect.

Based on data on applicants to Danish and Norwegian open-mode grant schemes-research projects as well as on postdoc fellowships, Langfeldt et al. (2015) apply a DID approach to study the extent to which research grants are likely to affect the publication and citation rates of principle investigators (PIs), focusing on grants assigned between 2001 and 2010 in Norway and between 2001 and 2008 in Denmark. Results show how the grants seem to have only increased productivity (measured as the number of publications per year) in Norway, the explanation being that the grant helped PIs add staff to their research teams, leading to more output, but no effect is found for the normalized citation score. In Norway, there is also a positive effect on the number of highly cited articles, measured as articles with citations above the global average and more than twice the global average.[5] No effect is found for Danish researchers, but positive effects are detected for post-doctoral students, who seem to receive a higher number of citations (top publications).

Heyard and Hottenrott (2021) investigate whether receiving a grant from the Swiss National Foundation (SNSF) impacts researchers' publication outputs. They find that receiving this grant facilitates the publication and dissemination of additional research in the short term (about one additional article in each of the three years following the grant). In addition, they find positive effects on citation metrics and altmetrics of publications, which suggests that the impact of the grant goes beyond quantity and that it also fosters quality and impact. Similarly, Baruffaldi et al. (2020) study whether receiving a grant from the Swiss National Foundation promotes the international mobility of researchers and boosts their scientific production and career. The authors collect detailed data on all applicants (winners and non-winners) and implement a regression discontinuity design analysis. They do not find any significant effect of the grant on output quantity and career progress, a result that is in line with what we find for ERC grants in this paper. In a recent study, Ayoubi et al. (2021) evaluate a Swiss funding programme sponsoring interdisciplinary collaboration. Based on DID results, they report that researchers who apply for the programme experience an increase of 43% in publications and that their average impact factor increases by 7%. Interestingly, whether the researcher receives the grant or not seems to have no additional effect on individual researcher scientific productivity.

Carayol and Lanoë (2017) consider competitive research grants (both thematic and non-thematic) awarded by the Agence Nationale de la Recherche (ANR) in France in the first 5 years since its creation (2005–2009) and quantify the impact of these grants on scientific production and research collaborations. Similarly to the ERC, the ANR

[5] However, no effect is detected when looking at the percentage of publications with citations above and twice above the global average.

aimed to finance projects from all disciplines.[6] Using DID combined with propensity score matching, they find that receiving an ANR grant increases publications by 3.5% (or even 8.5% if the impact factor of the journals in which articles are published is taken into account). Regarding research collaborations, they find a large and significant effect on the total number of co-authors. This effect could be explained by two factors: hiring more young researchers (PhD and post-docs) or becoming more attractive as research partners. Unfortunately, the authors cannot separate the two effects due to data limitations.

Finally, there is another group of papers that concentrates on countries where alternative sources of funding are limited. Ganguli (2017) focuses on a grant for scientists in the former Soviet Union. The author examines the impact of an individual cash grant, claiming that at that time in that area, no other alternative sources of funding were available. The analysis relies on a fuzzy RDD, exploiting the discontinuity in the eligibility criteria, and the results show that receiving the grant leads to a large positive effect on the number of publications and citations in the three years following the programme (2 additional publications), inducing scientists to stay longer in the science sector and reducing the likelihood of migration abroad. A similar effect is found in two papers investigating the effect of research funding in two Southern American countries, Argentina and Chile, where alternative sources of funding are also quite limited. The paper by Benavente et al. (2012) estimates the effect of receiving a Chilean National Science and Technology Research Fund (FONDECYT) grant in Chile between 1988 and 1999. The authors claim that the grant was practically the only national source of funding for scientific research in the country at that time. Implementing an RDD approach and using the score assigned during the application phase as a running variable, they find a positive effect on the number of publications (2 additional peer-reviewed articles) but no effect on quality (citations per article). Similarly, Chudnovsky et al. (2008) estimate the effect of the Fund for Scientific and Technological Research (FONCyT) in Argentina. They focus on grants assigned in 1998–1999 and, using a DID approach, find that successful applicants produce 1 more publication in the 5 years following the grant. They also find that the effect is stronger for younger scientists.

[6] According to the authors, nearly 2.5 billion euros were awarded to research projects, the total cost of which amounts to about 10 billion euros.

3 Institutional background: ERC selection process

Every year, the ERC publishes a call for proposals for each of three programmes: Starting Grants (SG), Consolidator Grants (CG) and Advanced Grants (AG). Proposals are selected by highly recognized scholars who participate in different panels and evaluate the quality of the projects and the profile of the principal investigators (PIs) at the same time.

For each of the three programmes, SG, CG and AG, there are 25 *panels*[7] covering several subfields in three large *domains*: Life Sciences (LS), Physical and Engineering Sciences (PE), and Social Sciences and Humanities (SH).

Grants are awarded as a result of a two-step selection process. In the first step, panel members evaluate a short version of the proposal as well as the research career of the PI, using excellence as a sole criterion. In our data, focusing on the period 2007-2013, on average, about 30% of proposals reach the second phase. In the second step, more attention is given to the project itself, and a second more in-depth evaluation is carried out. Besides the members of the panel, projects are also evaluated by external reviewers selected by the panels based on their expertise in each specific subfield. In our data, on average, 50% of proposals that pass the first step is funded. The budget allocated to each *domain* is established ex-ante[8], but the budget allocated to each *panel*, within a domain depends proportionally on the budgetary demand of its assigned proposals in order to equalise the success rate across panels.[9]

This mechanism implies that the number of grants awarded by each panel is a function of the number of applications received. In terms of organization, each ERC panel consists of a chair and 10-16 members. The panel chair and panel members are selected by the ERC Scientific Council on the basis of their scientific reputation. As mentioned above, in addition to the panel members (who act as 'generalists'), the ERC evaluations rely on input from experts external to the panel, called referees, who can provide input remotely. Panel members instead make the final decision during face-to-face meetings. The names

[7]For the most recent ERC programmes there are 27 panels.

[8]Details are reported in the ERC work programme for each call. Overall, each year around 40% of the budget is allocated to the PE domain, 34% to the LS domain, 14% to the SH domain, and 13 % to the interdisciplinary domain. Indicative budgets may permit a variation of the budget for each domain by a maximum of 10% of the total budget for the call.

[9]An indicative budget will be allocated to each panel, in proportion to the budgetary demand of its assigned proposals. This indicative budget is calculated as the cumulative grant request of all proposals to the panel divided by the cumulative grant request of all proposals to the domain of the call, multiplied by the total indicative budget of the domain. See for example the work programme for 2010, explanation provided in Annex 2.

of the panel chairs are published on the ERC website before the deadline for the call, whereas the names of the members of the panel are published after the evaluation process is completed.

In our data, we have information about the ranking assigned to each candidate by the panel of experts. Based on the envelope (budget assigned), a selected number of researchers receive an ERC grant (known as beneficiaries). The candidates remaining are referred to as non-beneficiaries. The evaluation procedure and assignment mechanism followed by the ERC make it ideal for applying a sharp regression discontinuity design, where the winner of the last available grant (in each type of ERC programme, panel and year) determines the cut-off score. In our analysis, we compare the outcomes of beneficiaries (scholars who were awarded a grant) and non-beneficiaries who did not obtain a grant but passed the first-step of the evaluation, both in an RDD and a DID framework. We do not include non-beneficiaries who did not pass the first step in the potential control group as they are most likely different in terms of observable characteristics.

4 Data

First, data on applicants for the European Research Council (ERC) grant were drawn from CORDA, a database managed by the European Commission's Directorate-General for Research and Innovation (DG-RTD). In particular, we rely on data from the FP7 programme running over the 2007—2013 period. We keep all applications that reached the second step of the selection process. We do not consider applicants to H2020 or Horizon Europe for two main reasons: i) we would like to observe researchers outcomes also after the end of the 5-years grant period and not only during it; ii) we would allow enough time for the bibliometric outcomes to materialize consindering both the time needed to carry out the ERC research project and the time needed to get a research paper published in a scientific journal (publication lag). The original sample consists of 9,057 applications, considering both winners and non-winners reaching at least stage two of the selection process.

The final sample of applicants was then matched with the Scopus Elsevier bibliometric database on the basis of the surname, first name and affiliation of applicants at the time of the ERC application. We used the Scopus Elsevier database to gather all documents (articles, book chapters, editorial letters and reviews) published in international scientific outlets up to April 2021, allowing us to cover a maximum of 15 years after the first funding year (when cohort 2007 is considered) and at least 8 years for the most recent cohort considered (2013). For all applicants, we aimed to retrieve their personal Scopus profiles, allowing us to download all their published documents from before and after the application year.[10]

Identifying the correct Scopus author profile for a given ERC applicant is not an easy task and involves a relevant homonymy problem due to the absence of a reliable unique identifier for the FP7 pool of researchers.

A disambiguation algorithm was thus developed, which basically works as follows: first of all, the algorithm retrieves all Scopus author profiles of ERC grant applicants for which only one profile exactly matches in Scopus (along with their published papers). This means that when imposing as matching parameters the surname, name and institution of affiliation, there is only one Scopus author profile that is exactly matched to an applicant.

Second, for those ERC applicants for which the algorithm identifies more than one Scopus author profile, it selects the most reliable one by imposing additional conditions based mainly on the field of study. Basically, the algorithm selects the Scopus author profile with all of its publications published in journals belonging to the Scopus disciplines that are closest to the disciplines where already matched applicants (in the exact matching step described above) to the same ERC panel have published.[11]

Finally, a manual check was performed for applicants for which the disambiguation procedure did not produce a satisfying result.[12]

In this way, we collected more than 1 million documents published by the ERC applicants identified on Scopus. From this database, we were able to compute yearly cumulative outcomes for both ERC beneficiaries and non-beneficiaries by measuring their research productivity during their careers (before and after applying for the ERC grant). There were a number of authors that we could not find in Scopus. The original sample size was 9,057, and we found a specific match for 8,524 authors.[13]

For the sample of individuals found in Scopus, we made the further following selections:

[10] We accessed Scopus via the Elsevier Developer Portal, which includes a dedicated Research Product API Service (Available at `https://dev.elsevier.com`). We also retrieved data needed to construct the FWCI indicator and the funding information variables during a period of secondment spent by SV at DG-RTD in February–March 2023.

[11] More details on the disambiguation algorithm used are available upon specific request to the authors. We gratefully acknowledge the help of Stefano Montanelli (University of Milan) in testing and developing with us the adopted algorithm.

[12] We are indebted to Francesca Verga, Isadora Mathevet and Alice Calandra for the valuable research assistance provided on this project as part of their traineeship activities at the European Commission, Joint Research Centre in 2021, 2022 and early 2023.

[13] To be more precise, we were not able to find 5 PIs applying for the LS AdG, 89 applicants to the PE AdG, 91 applicants to the SH AdG, 120 applicants to the LS StG, 121 applicants to the PE StG, and 102 applicants to the SH StG; the remaining unmatched PIs were applicants to the CoG or Interdisciplinary panel.

we did not consider applicants for the Consolidator Grant as this typology was introduced in 2013 and the sample size is limited (689 applicants), and we did not consider the Interdisciplinary panel, as its selection process follows a different pattern and the sample size is particularly limited (131 winners).

Table 1 shows the distribution of applications passing the first step and reaching phase two by year and type of grant. This sample is composed of 7,704 researchers and includes all applicants, without taking into account that some of those rejected could be successful in a future application.

This could negatively affect our results as we included in the sample of unsuccessful applicants those who might be awarded the grant later on, and their outcomes might be affected as well. Therefore, we removed them from the sample of the rejected and kept them only if they were awarded the grant. Thus, if a PI applied in 2008 and was rejected and then applied again in 2009 and was successful, he was included in the sample only in 2009 and was not used as a control in the 2008 call. Removing these individuals meant dropping 720 observations from the sample. We also dropped the panels for which there were only winners in a given call year.[14] This leaves us with 6,777 observations in total, divided between the two types and by winner status as reported in Table 2.

To explore differences by discipline we further disaggregated the 3 domains into 11 smaller groups.[15] We introduced a new micro-field classification based on a simple procedure.[16] We first perform a mapping of the ERC panels to Scopus' main subject categories (the 31 ASJC areas), using the publications of the ERC winners (who were funded in certain panels). Each publication is assigned by Scopus to one main subject category based on the publication venue (e.g. journal).[17] Using this information, we built a matrix with 25 ERC panels as rows, 30 Scopus categories as columns, and numbers of publications in the matrix cells. We excluded the 'multidisciplinary' category, which is not specific enough to allow precise mapping. The matrix values were then normalized considering row/column percentages.

Based on this matrix, we observed how publications of certain ERC panels overlap in certain Scopus categories and we then grouped together those exhibiting similar profiles. Finally, a few panels (e.g. SH5 and SH6) are scarcely covered by Scopus (i.e. their pro-

[14] After these selection choices, we rebuilt the final ranking within each panel and call year.

[15] Using the original 25 panels would not offer a large enough sample size to perform the analyses.

[16] We would like to thank Elena-Simona Toma and her colleagues at ERCEA for suggesting the approach.

[17] The main category was identified restricting the ASJC code to its first two digits to avoid duplicates (e.g. a paper being counted twice because it belongs to two different categories).

duction indexed in Scopus is very small), so we decided to directly exclude them from this classification. The obtained classification is reported in Table A.1. The sample sizes of these groups are reported in Table 3.

Table 1: Distribution of applicants by year and type of grant

Year	StG	AdG	Total
2007	0	426	426
2008	599	0	599
2009	530	427	957
2010	638	748	1,386
2011	675	917	1,592
2012	615	762	1,377
2013	684	683	1,367
Total	3,741	3,963	7,704

Table 2: Distribution of winning and rejected applicants by type of grant

Type	Rejected	Winner	Total
Advanced Grants (AdG)	1,690	1,566	3,256
Starting Grants (StG)	1,404	2,117	3,521
Total	3,094	3,683	6,777

Table 3: Distribution of winners and rejected applicants by grant type and derived field

				Rejected	Winners	Total
LS	Biology and Chemistry	AdG	1	245	250	495
		StG	2	231	371	602
	Medicine	AdG	3	235	236	471
		StG	4	173	282	455
	Applied LS	AdG	5	146	106	252
		StG	6	96	123	219
PE	Math	AdG	7	93	96	189
		StG	8	72	122	194
	Physics	AdG	9	176	174	350
		StG	10	152	244	396
	Chemistry	AdG	11	141	149	290
		StG	12	117	196	313
	Engineering	AdG	13	201	194	395
		StG	14	193	284	477
	Universe and earth science	AdG	15	138	109	247
		StG	16	98	131	229
SH	Individuals and Institutions	AdG	17	70	54	124
		StG	18	45	78	123
	Institutions and behaviour	AdG	19	88	61	149
		StG	20	87	113	200
	Human mind	AdG	21	68	68	136
		StG	22	70	89	159
		Total		2,935	3,530	6,465

4.1 Outcomes of interest

We used the database of publications downloaded from Scopus to construct the following outcomes:

1. Total number of published articles, cumulative over time;
2. Number of articles published in the top-ranked 1% of journals, where journals are ranked according to the Scopus ranking list, cumulative over time;
3. Number of articles published in the top-ranked 10% of journals, where journals are ranked according to the Scopus ranking list, cumulative over time;
4. h-index[18];
5. FWCI: field weighted citation impact[19];

[18]h-index is built including also self-citations, as done in the index built in the Scopus or SciVal, following this definition:“h-index gives information about the performance of Researchers and Research Areas. h-index of an entity is 9 if the top 9 most-cited publications have each received at least 9 citations; it is 13 if an entity’s top 13 most-cited publications have each received at least 13 citations; and so on.”

[19]Field-Weighted Citation Impact (FWCI) is also built following SciVal approach: it indicates how the number of citations received by a researcher’s publications compares with the average number of citations received by all other similar publications in the data universe.

6. Number of EU funds received, cumulative over time as *EU funds* (ERC, Marie Curie, Horizon, FP7);[20]

7. Number of all funds received, cumulative over time as *Total funds*;

The last two outcomes are built from the funding sections of the Scopus papers,[21] which implies that the funds considered may have been received by the applicant's co-authors as well. Thus, this measures whether researchers receiving a grant have more chances to apply and win other grants or to write with co-authors who have received other types of funds. This phenomenon is commonly referred to as the Matthew effect in the literature for which early successes in obtaining research grants increase future success chances (Bol et al., 2018). Descriptive statistics of the outcomes measured in the year before the call are reported in Tables 1 and 2 of the Online Appendix.

5 Empirical analysis

To investigate the causal effects of receiving ERC grants on subsequent outcomes, we rely on two alternative empirical strategies, regression discontinuity design (RDD) and difference-in-differences (DID) estimations, which hinge upon different identifying assumptions but are both valid in our setting. They deliver consistent results that strengthen our findings.

5.1 Regression Discontinuity Design

First, we consider an RDD methodology, which seems the most natural choice given the ERC assignment mechanism in place. The identifying assumption is that there is no precise control over the received score, i.e. 'no manipulation'. Under this assumption, assignment to the ERC grant can be said to be as good as random. This requirement is likely to be verified in our framework, given that ERC proposals are evaluated by selected international peer reviewers who assess them on the basis of excellence as the sole criterion. These rules apply to any type of ERC grant, whether the Starting Grant (StG), Consolidator Grant (CG) or Advanced Grant (AdG).

Given that the process takes place over a year and involves multiple stages, the rank assigned to each proposal may not fully *a priori* determine grant assignment. At least three sources of randomness intervene during the process. First, the final number of

[20]Note, these grants are all funded by the European Commission. Importantly, they can be accumulated.

[21]For additional details, see Section B of the Appendix.

grants selected and funded by the ERC in each panel is proportional to the number of applications received by that panel in each particular year, which is not known *ex ante*. Second, the number of proposals awarded a grant also depends on the total budget available, which can be slightly modified by DG-RTD along the process. In fact, there could be a top-up to the approved budget, which may slightly change—at any point in time during the process—the number of proposals funded according to the final ranking. Third, given that the ranking is year- and panel-specific, the probability of getting a grant for a specific proposal depends on its scientific quality (assessed by the panel and hopefully reflected in the final ranking) as well as on the amount of money requested and granted by the proposals ranked higher than the proposal in question, which is again not known *ex-ante* by the applicants. These conditions make the final list of granted proposals particularly difficult to predict, and this is especially true with regard to the cut-off value for the final ranking (given by the rank of the last funded proposal). From the available data, we only see the final rankings, and this should be enough to implement a sharp RDD.

For these reasons, we rely on a sharp regression discontinuity design. In our analysis, the running variable is the ranking normalized to the ranking position of the last assigned grant (cut-off point) within each panel (depending on the type of ERC grant) for every year of data. As such, the running variable represents the difference between all the applicants' ranking positions and the cut-off one in each year's panel-specific ranking.

Our setting is thus comparable to the setting described by Fort et al. (2022): there are multiple sites, which in our case correspond to multiple panel-year calls, the applicants are ranked using a score and slots are filled starting from the highest-scoring applicants, until exhaustion. The only difference is that in our setting, the number of available slots is not totally pre-determined as it depends on the budget available; nevertheless, slots are filled until the budget is exhausted. Thus, we are faced with a multi-cut-off design, in which each cut-off is the value of the ranking for the marginal subject receiving the grant, so that there is one observation located exactly at each threshold.

As the sample size in each year-panel call is relatively small, we cannot run a series of individual RDDs. Therefore, we pool all observations around the unique zero-normalized cut-off (normalizing and pooling). Thus, all years are pooled together and panels belonging to the same domain are pooled together. We run two sets of analyses: first, we group all panels together and run the analysis by grant type (Advanced and Starting Grant); second, we consider the micro-field (and the type of grant) and run the analysis by type of grant and micro-field, obtaining 22 different sets of estimations.

Normalizing and pooling can lead to biased estimates, hence we follow the solution proposed by Fort et al. (2022) and include 'site'-specific fixed effects, which in our case correspond to panel and year fixed effects.

Formally, Y_i is the outcome variable of interest for researcher i, T_i denotes the treatment status, i.e. receiving the grant, and X_i represents the rank of the researcher, which determines treatment assignment. $T_i = 1(X_i >= c)$, treatment equals 1 when the rank X_i is greater than the eligibility threshold c (which is year- and panel-specific but has been normalised to 0). Within the potential outcomes framework, Y_i is defined as $Y_i = Y_i(0) * (1 - T_i) + Y_i(1) * T_i$, where $Y_i(1)$ and $Y_i(0)$ are the potential outcomes of interest with and without the grant. In a sharp RDD, the average treatment effect, i.e. the average effect of the grant, can be written as

$$E[Y_i(1) - Y_i(0)|X_i = c] = \lim_{x \downarrow c} E[Y_i|X_i = x] - \lim_{x \uparrow c} E[Y_i|X_i = x]. \quad (1)$$

We estimate Equation 1 non-parametrically,[22] selecting the optimal bandwidth (Calonico et al., 2014, 2020) based on one common MSE-optimal bandwidth selector and a triangular kernel (Cattaneo et al., 2019). In addition, we check for the presence of mass points in the running variable and account for them accordingly as in Calonico et al. (2014). We estimate the confidence intervals relying on the bias-corrected RD estimates with a robust variance estimator, which provides valid inference when the MSE-optimal bandwidth is used.

5.2 Difference-in-Differences

While the RDD approach works well in identifying the effects of the grant for those who are locally close to the threshold, one might also be interested in understanding whether the grant has any impact on those who are far away from the ranking threshold, i.e. the top ranked scholars in each field. To shed light on this, we rely on a difference-in-differences approach, comparing outcomes before and after the grant for recipients and non-recipients.

In particular, we estimate the following equation, where y_{itf} represents the outcomes

[22] While parametric estimation basically uses all observations to find an effect, non-parametric methods provide estimates based on data closer to the cut-off, reducing bias that may otherwise result from using data further away from the cut-off to estimate local treatment effects. Non-parametric methods are by now the standard framework for empirical regression discontinuity (RD) analyses because they offer a good compromise between flexibility and simplicity.

for individual i applying to panel f in year c, measured in year t:

$$Y_{itcf} = \alpha_i + \beta_1 \sum_{k=10}^{2} T_{itcf} * (c - k) + \beta_2 \sum_{k=0}^{9} T_{itcf} * (c + k) + \gamma_t + \epsilon_{itcf}. \tag{2}$$

β_1 is a vector of coefficients capturing the effect of the grant in each year *before* the call year c. This set of coefficients should be equal to 0 in order to guarantee the validity of the common trend assumption. The reference year is $c - 1$, the year prior to the call. β_2 is a vector of coefficients capturing the effect of the grant in each year *after* the call year c. These are our main coefficients of interest, which inform us about the effectiveness of the grant. We control for α_i, individual fixed effects (which also capture call year c and panel f fixed effects). Finally, γ_t are calendar year fixed effects and ϵ_{itcf} is a random error.

The econometrics literature on event-study and difference-in-differences approaches has developed enormously in recent years and has produced a number of alternative algorithms that enable correct estimations in complicated frameworks, e.g. staggered treatment adoption, heterogeneous causal effects, multiple groups, variation in treatment timing (see Callaway and Sant'Anna, 2021; Borusyak et al., 2021; Sun and Abraham, 2021; Arkhangelsky and Imbens, 2022; de Chaisemartin and D'Haultfoeuille, 2022). We follow the procedure proposed by Callaway and Sant'Anna (2021) for two main reasons. First, it allows us to deal with multiple time periods and takes into account the fact that treatment effects may vary with the length of exposure to the treatment. Second, it allows us to condition on covariates when the parallel trend assumption potentially holds only after conditioning on observed pre-treatment characteristics (see Ham and Miratrix 2022).

In practice, this algorithm runs a series of 2×2 comparisons between periods in the future and the last period before treatment, using two-way fixed-effects models and adjusting confidence intervals to avoid multiple-testing issues. This is estimated using the doubly robust DID estimator proposed by Sant'Anna and Zhao (2020) based on stabilized inverse probability weighting and ordinary least squares. To deal with multiple testing, standard errors are computed by means of a multiplicative wild bootstrap procedure (with 999 repetitions, using the Mammen approach), clustering standard errors at the individual level.

6 Results

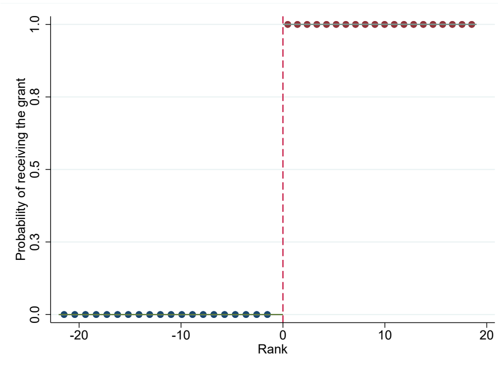
6.1 Regression Discontinuity Design

Figure 1 plots grants assigned as a function of standardized panel-specific ranks. Plotted points are conditional probabilities for each applicant in each specific bin. In both figures, the probability of receiving the grant is zero below the threshold and jumps to 1 right at the threshold value. This confirms the sharpness of the assignment in all panels and for all types of grants, which means that there is full compliance with the assignment rule in our setting. In Figure 2, we instead plot the distribution of the running variable: the rank of each applicant. We see that around the eligibility threshold, there are no particular jumps, which validates the continuity assumption needed to perform the RDD. Finally, we also perform the density tests proposed by Cattaneo et al. (2018), and in both types, there is no evidence of discontinuity[23]. Under the RDD identifying assumptions, treated and control units are identical ex-ante, i.e. they should show, on average, the same characteristics before receiving the grant so that any difference showing up after treatment is due to the grant itself. To further confirm that the RDD identification strategy is reliable in our case, we estimate the impact of receiving the grant on pre-determined outcomes, that is, outcomes measured the year before the application. Estimates on these sets of outcomes should be zero. This is reported in Table 4 by type of grant. Since the outcomes are time-varying, they are computed at the last available year before applying for the grant, which means considering all past publications up to that year. Results are overall non-significant, and this holds across types of grants. This confirms that the identifying assumptions of the RDD design are valid[24].

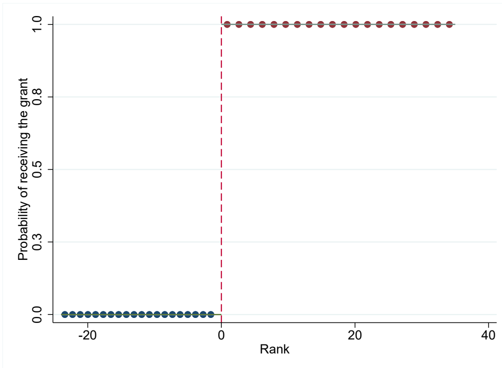
[23]The final manipulation test is T= -0.389, with a p-value of 0.698, for the Starting Grant, and T= 0.044, with a p-value of 0.965 for the Advanced Grant.

[24]There is only one exception: significant (at 5%) difference in the year of publication of the first paper for StG, which may be considered as an imperfect proxy for applicant's age. However, given its imperfect nature we cannot fully grasp the dynamic behind this result. It simply means that beneficiaries of StG on average published their first paper 1.8 years before than non-beneficiaries. This could be because they were of the same age but on average the ERC beneficiaries started publishing a couple of years earlier if compared to non-beneficiaries or because they were on average younger, or even a mix of the two.

Figure 1: Probability of receiving the grant conditional on ranking



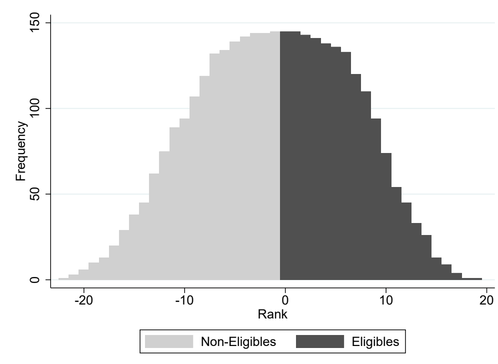
(a) Advanced Grants



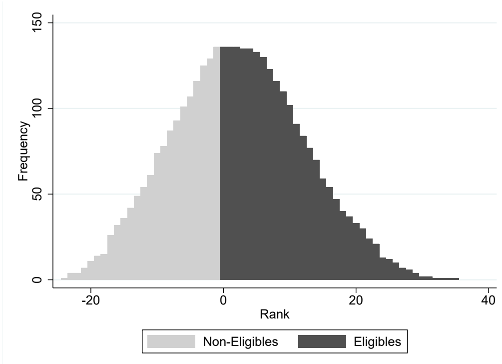
(b) Starting Grants

Note: Plotted points are conditional probabilities for all applicants in a one-unit bin width along with a conditional mean function smoothed using local linear regression (LLR). Starting and Advanced Grants.

Figure 2: Distribution of the running variable



(a) Advanced Grants



(b) Starting Grants

Table 4: Effect on predetermined outcomes

	(3)	(4)	(5)	(6)	(7)	(8)	(10)	(11)	(12)
Advanced	Year first paper	Female	#publications	# top1	# top10	h-index	fwci	Funds -all	Funds- EU
Robust	-0.799	-0.013	-20.461	0.418	-5.766	2.467	-1.307	-3.148	0.061
	(1.193)	(0.051)	(15.311)	(2.012)	(7.576)	(3.083)	(1.124)	(2.057)	(0.093)
Observations	[1676:1560]	[1691:1565]	[1691:1565]	[1691:1565]	[1691:1565]	[1691:1565]	[1691:1565]	[1691:1565]	[1691:1565]
Bandwidth	[4:4]	[4:4]	[5:5]	[4:4]	[5:5]	[3:3]	[6:6]	[5:5]	[5:5]
Effect. Obs	[570:709]	[575:712]	[714:848]	[433:574]	[575:712]	[289:433]	[848:981]	[714:848]	[714:848]
	(13)	(14)	(15)	(16)	(17)	(18)	(20)	(21)	(22)
Starting	Year first paper	Female	#publications	# top1	# top10	h-index	fwci	Funds -all	Funds- EU
Robust	-1.811**	0.007	0.780	0.147	1.301	0.504	0.784	0.544	0.197
	(0.681)	(0.046)	(2.294)	(0.354)	(1.365)	(0.706)	(0.523)	(0.934)	(0.101)
Observations	[1392:2108]	[1402:2119]	[1402:2119]	[1402:2119]	[1402:2119]	[1402:2119]	[1402:2119]	[1402:2119]	[1402:2119]
Bandwidth	[3:3]	[8:8]	[5:5]	[6:6]	[5:5]	[5:5]	[6:6]	[5:5]	[3:3]
Effect. Obs	[388:538]	[807:1064]	[506:678]	[714:941]	[506:678]	[613:811]	[714:941]	[506:678]	[390:543]

Next, we estimate the impact of the grant in the period after the application. It may take time before the grant shows any effect; therefore, we explore whether it has positive effects on outcomes in the long term (up to 9 years since the grant), as our data allow us to do so. That is, we estimate our RDD regressions year by year and separately by type of grant. To better visualize the results, we plot the RDD coefficients (along with their 95% confidence intervals) over the horizontal axis representing the years since the application to the grant.

The full set of results is shown in Section C.1 of the Appendix (see Figures C.1-C.7). Results on researcher productivity (we consider h-index, number of publications, the number of publications in top 1% and top 10% ranked journals, and the FWCI) are always not statistically different from zero: at the threshold, ERC grant recipients do not perform better than non-recipients.

With regard to EU funds, since the outcome counts the number of distinct European funds that appear in the acknowledgments of published papers and the ERC grant is one of these, a coefficient at least equal to one is *a priori* expected due to the mechanical acknowledgment of ERC grants received by treated researchers. In contrast, a coefficient above one suggests that the researchers who obtained the ERC grant tend to accumulate other European funds, i.e. either (i) collaborating with co-authors who have received additional European funds or (ii) applying for and receiving other European funds themselves. We observe that researchers receiving both types of grants acknowledge on average more EU funds than their counterparts (See Figure C.7). This is known in the literature as the "Matthew effect", i.e. researchers who obtain a grant become more likely to receive other grants (Bol et al., 2018). However, when we look at the total number of funds acknowledged (both EU and all others) there are no significant differences (See Figure C.6).

6.1.1 RDD: heterogeneity by field

We replicate the analysis of productivity outcomes—h-index, FWCI, number of publications in top 1% and top 10 % ranked journals and number of publications— for the different scientific subfields. The full set of results is reported in Section A of the Online Appendix. We do not find any effect in none of the fields associated with the SH and LS domains. For the PE domain, we find a positive impact of receiving the Starting Grant on the h-index and on the number of publications in the Physics field Figures A.10.a and A.10.d in the Online Appendix).

When we replicate the sub-field analysis for the outcomes related to funding, we observed that there is no effect on the number of funds received in the future (neither focusing only on the EU ones, nor on the total) for the fields in the LS domain. For the PE domain, we see a positive impact on the number of EU funds received, for the Starting Grants for Math, and Physics, and for the Advanced Grant for Engineering and Chemistry. For the SH domain, we find a positive impact for Starting Grants in Individuals and Institutions and Institutions and Behavior. But when we look at the total number of distinct funds, again there are no differences in any of the fields.

6.1.2 Summary of RDD estimates

Overall, the RDD findings regarding productivity show significant effects only in one particular field: Physics in the StG. That is, researchers who received the ERC grant and have a score just above the threshold value do not improve their production thanks to the grant when compared with infra-marginal non-beneficiaries in both StG and AdG. This is valid in all fields but Physics for StG. Moreover, researchers who receive an ERC grant are more likely to obtain other EU grants by themselves or through their coauthors, even if the total number of funds they receive is similar. This suggests that receiving an ERC grant early in one's career increases the chances of receiving other EU funds in the future. However, rejected ERC applicants often compensate by seeking other types of funds and can receive almost the same overall number of funds in the 9 years after applying for the ERC. It is worth noting that the information available on Scopus concerns the number of distinct funds received and not the amount of funding, for which reliable information is not available.

6.2 Difference-in-Differences

This section presents and discusses the results of estimating Eq. 2 for the main outcomes separately by type of grant and field of research. In the DID setting, we test the validity of the common trend assumption by considering observations in the pre-treatment period. To ensure sufficient coverage for all applicants, we analyse the 5 years before applying for the grant, which is especially relevant for early career researchers who apply for the Starting Grants (i.e. given their relatively young age we observe them in the Scopus database only for a few years before receiving the grant). The DID coefficient captures the difference in outcomes between treated and control groups measured in a given year, compared to the same difference in outcomes one year before the treatment (the reference year). The common trend assumption ensures that the evolution of the outcomes of treated individuals and controls follows a similar trend before the treatment, implying that the DID coefficients have to be zero in the pre-treatment period. If this holds, one can claim that any difference in trends between treated and control groups after the treatment is indeed due to the treatment itself (obtaining the ERC grant) and not to other unobserved factors.

To improve comparability between non-winners and winners, we consider all winning applicants and the best non-winning applicants.[25] The subsample of non-winning applicants is divided into two parts. The first part, defined as the 'top rank' sample, consists of the highest-ranking non-winners, usually those closest to the selection threshold. The second part, named the 'bottom rank' sample, consists of the remaining non-winners. For example, if there are 10 non-winners, the first 5 are placed in the top-rank sample while the remaining 5 are placed in the bottom-rank sample.[26] We then exclude the bottom-rank unsuccessful applicants from our analysis and only consider the top-rank unsuccessful applicants.

6.2.1 DID: heterogeneity by type of grant

We first discuss results distinguishing by type of grant—Advanced and Starting—which gives us an overview of the impact of the grants on young vs more established scholars. In Figure 3, we plot the event study coefficients of a unique regression performed for the outcomes of interest in the 9^{th} year after grant assignment. For comparison and illustration purposes, we standardize the outcome variables to have zero mean and unit variance.[27] The figure on the left shows results for the Advanced Grants and that on the right for the Starting Grants. Note that we use the DID approach proposed by Callaway and Sant'Anna (2021), which also allows for covariate conditioning, and we adjust for pre-treatment covariates in order to improve the parallel trend assumption.[28] In the figures, we report in grey the point estimate that refers to a regression in which we believe that

[25] Results are robust to using the overall sample of all winning and non-winning applicants, although in some cases the parallel trend assumption is harder to satisfy. These results are not shown but are available upon request.

[26] For further heterogeneity, we also divide the winning applicants themselves into top- and bottom-rank samples.

[27] The complete results for all years after grant assignment are shown in Appendix D In this case, we use original variables and do not standardize them.

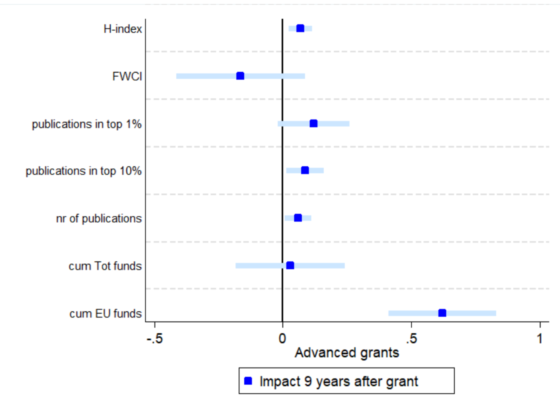
[28] We control for the following covariates: the h-index in the call year; the average number of articles per year in the 5 years before the grant; the total number of publications before the grant; total number of publications (not only articles) in top 1% journals before the grant; total number of articles in top 10% journals before the grant.

the parallel trend does not hold despite controlling for pre-treatment covariates. This happens only in one case.

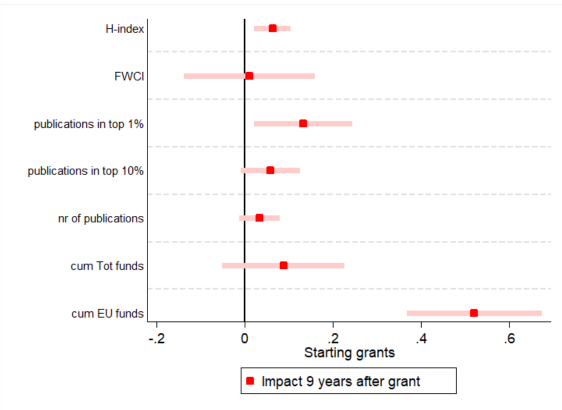
First, in terms of productivity, we find a positive and significant effect for Advanced and Starting Grants 9 years after grant assignment. For Advanced Grants, this holds for the total number of publications and the number of articles published in top 10% journals (when we condition on covariates), whereas for Starting Grants it holds for the number of articles published in top 1% journals and for the h-index.

Second, the grant helps applicants receive other EU grants. This holds for both Advanced and Starting Grants. This effect, which is known in the literature as the Matthew effect (Bol et al., 2018), is evident in the short-term, becoming significant already 3 years after the grant[29].

Figure 3: DID estimated coefficients by grant type. 9-year outcome



(a) AdG: all outcomes



(b) SG: all outcomes

Note: Estimated DID coefficients for the following outcomes: number of published articles, number of articles in top 1% journals, articles in top 10% journals, h-index, total funds obtained, EU funding obtained; measured 9 years after grant assignment. For comparison and illustration purposes, the outcome variables are standardized, so that they have all mean 0 and standard deviation equal to one.

However, when we estimate the impact on the total number of distinct funds received, we find no significant differences between ERC winners and non-winners. Our analysis suggests that non-winners may compensate for the lack of EU funding by accessing a relatively larger proportion of non-EU funds at the regional, national, or university level. As previously discussed, we do not have official data on the amount of money received from these non-EU grants, hindering our ability to investigate any existing differences in the total amount of research funds available to the two groups.

[29]See complete results in the Appendix D.

6.2.2 DID: heterogeneity by field

We now dig into heterogeneity by field. In the previous section, we saw that if there is a significant effect of the grant, it tends to show up in the long term (after 7 or more years from grant assignment). For clarity, we report in Figures 4 - 6 the estimated DID coefficients separately by type of grant (Advanced and Starting) and micro-field, where each observed indicator on research productivity (number of publications, publications in top 1% journals, publications in top 10% journals), impact (h-index, FWCI) and total funds and cumulative EU funds are measured in the 9^{th} year after winning the grant. As in the previous section, we add pre-treatment covariates as additional control variables in order to improve the parallel trend assumption (Callaway and Sant'Anna, 2021).[30] To better compare the estimates across fields we standardize the outcome variables to have zero mean and unit variance in a given micro-field.[31]

In terms of research productivity (Figure 4), we find a positive and significant effect using different indicators for both Advanced and Starting Grants in the field of Chemistry, Universe and Earth Sciences, Institutions and Behaviours, Human Mind Studies and Medicine. These are all cost-intensive fields, in which large research funding is needed to either build laboratories or run fieldwork in order to develop new research projects. A classical example is the field of Universe and Earth Sciences, characterized by large investments in the exploration of the universe.

For scientific impact, we do not find positive statistically significant effects with the exception of Chemistry when looking at the Starting Grants. Nevertheless, in line with the previous results on research productivity, we observe a positive effect (albeit non-significant) for the fields of Medicine, Physics, Universe and Earth Sciences, Institutions and Behaviours).

As for the ability to receive additional funding (the Matthew effect), we find significant evidence for many fields and especially for Starting Grants. Interestingly, it emerges across fields where ERC grants led to significant improvements in scientific productivity such as Medicine, Physics, Universe and Earth Sciences, Institutions and Behaviours, Chemistry, and Human Mind Studies, and to some extent Biological Sciences, Applied Life Sciences, Math and Engineering.

[30] H-index in the call year; average number of articles per year in the 5 years before the grant; total number of publications before the grant; total number of publications (not only articles) in top 1% journals before the grant; total number of articles in top 10% journals before the grant.

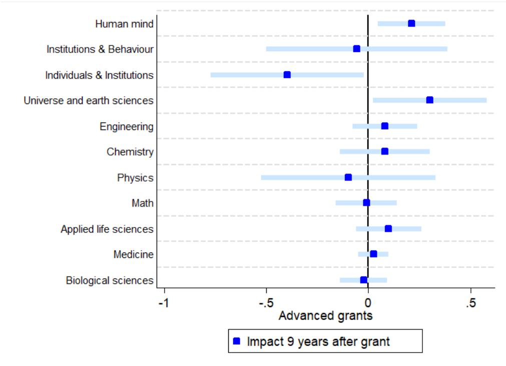
[31] The complete results for all years after grant assignment are shown in Section C of the Online Appendix. In this case, we use original variables and do not standardize them by field.

Notably, we found positive and significant effects on the total amount of funding received by the PI and their research network in Medicine, Applied Life Sciences, and Chemistry (for Starting Grants), indicating the presence of a proper Matthew effect. In other words, obtaining an ERC grant increases the overall probability of securing additional funding. In most other fields the impacts on total funding were positive but not statistically significant.

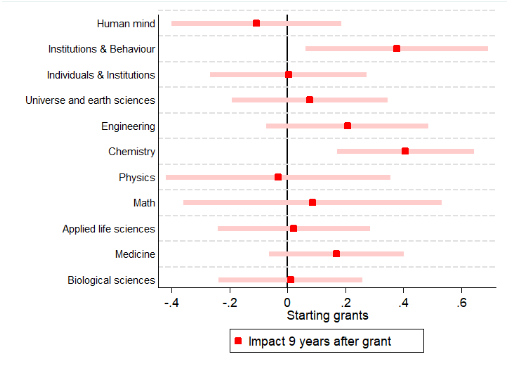
Chemistry stands out as the field where the effects of winning an ERC Starting grant are particularly pronounced and with the largest Matthew effect. Furthermore, researchers in this field demonstrate outstanding research performance, as evidenced by a higher H-index and a greater number of publications, including more publications in the top 10% and 1% of journals. One possible explanation is that Chemistry plays a critical role in advancing many other fields and has benefited substantially from technological progress. Rosenbloom et al. (2015) document for the case of academic chemistry in the US a positive causal effect of federal funding on knowledge production measured by the research productivity of academic chemists. Their research suggests that technological change may have shifted the production function, increasing the federal government's return on investment. Similarly, Chemistry consistently ranks as one of the top fields for ERC Starting grants, with a significant number of grants awarded in the past years.

To ease the readings of these figures, we summarized the results in Table 5, in which we highlight the fields in which we find positive effects in each set of outcomes: scientific productivity, impact, and research funding. We only list the fields for which we find significant effects. Blue colour refers to significant effect, while grey means suggestive effects - positive but not significant).

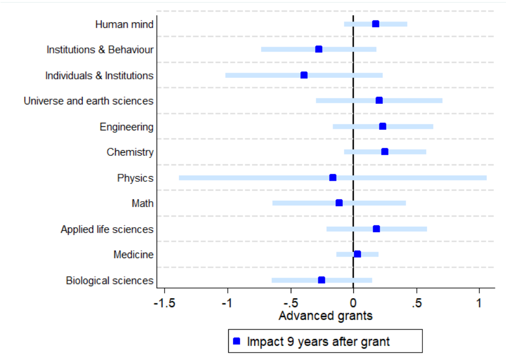
Figure 4: DID estimated coefficients by grant type and micro-field. 9-year outcomes for research productivity. Top losers versus All winners.



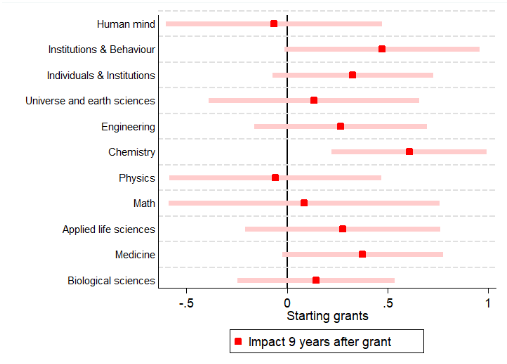
(a) AdG: no. of publications



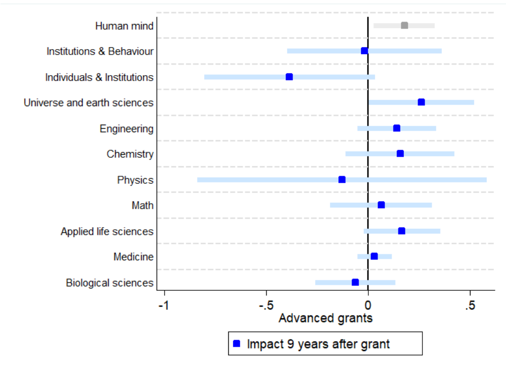
(b) SG: no. of publications



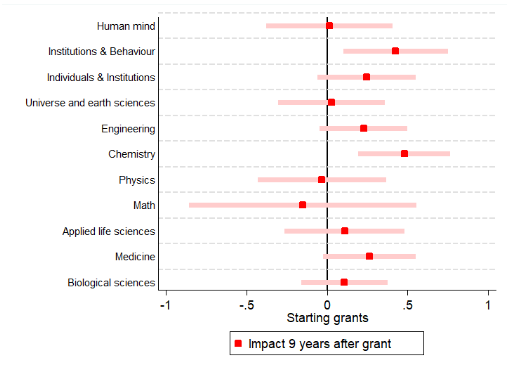
(c) AdG: publications in top 1% journals



(d) SG: publications in top 1% journals



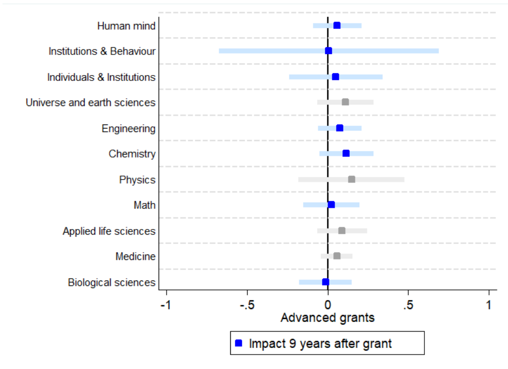
(e) AdG: publications in top 10% journals



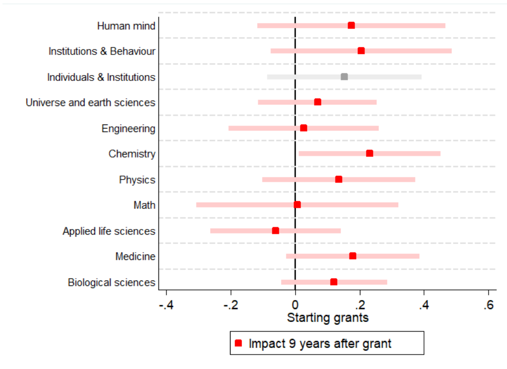
(f) SG: publications in top 10% journals

Note: Estimated DID coefficients for the following outcomes: number of published articles, number of articles in top 1% journals, articles in top 10% journals. Grey coefficients refer to estimations for which the trends between treated and controls before treatment are not parallel, despite controlling for pre-treatment covariates in the estimation. For comparison and illustration purposes, the outcome variables are standardized with respect to mean and standard deviation in each micro-field, so that they have all mean 0 and standard deviation equal to one.

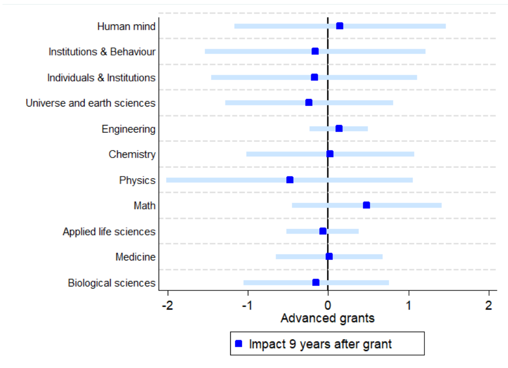
Figure 5: DID estimated coefficients by grant type and micro-field. 9-year outcomes for scientific impact. Top losers versus All winners.



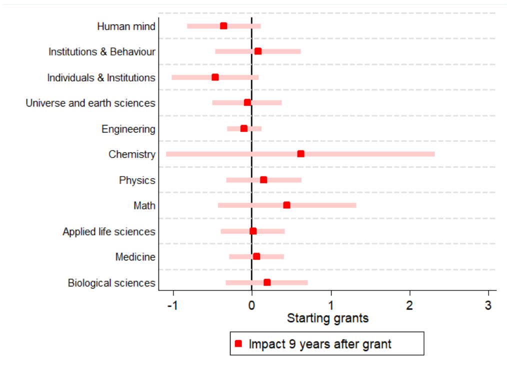
(a) AdG: h-index



(b) SG: h-index



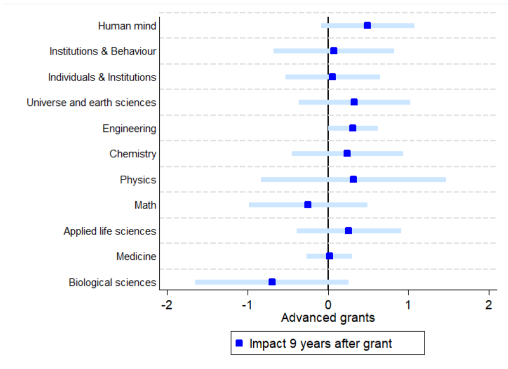
(c) AdG: FWCI



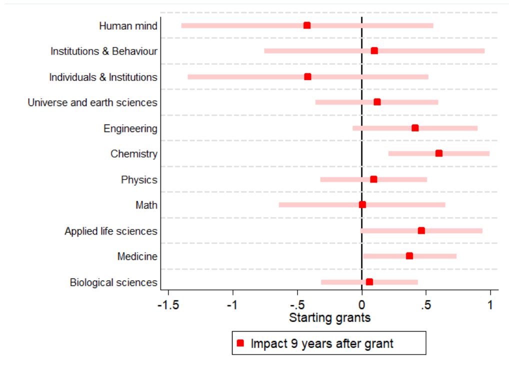
(d) SG: FWCI

Note: Estimated DID coefficients for h-index and FWCI. Grey coefficients refer to estimations for which the trends between treated and controls before treatment are not parallel, despite controlling for pre-treatment covariates in the estimation. For comparison and illustration purposes, the outcome variables are standardized with respect to mean and standard deviation in each micro-field, so that they have all mean 0 and standard deviation equal to one.

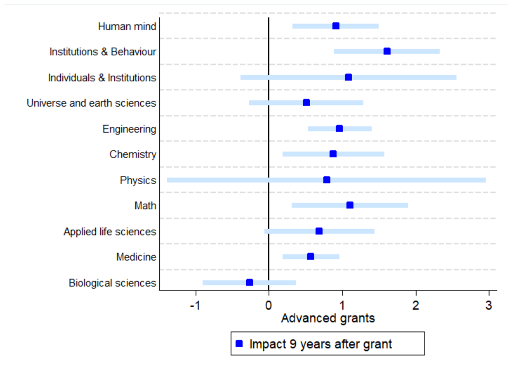
Figure 6: DID estimated coefficients by grant type and micro-field. 9-year outcomes for obtaining EU funds. Top losers versus All winners.



(a) AdG: cum. Total funds



(b) SG: cum. Total funds



(c) AdG: cum. EU funds

(d) SG: cum. EU funds

Note: Estimated DID coefficients cumulative total funds and cumulative EU funds. Grey coefficients refer to estimations for which the trends between treated and controls before treatment are not parallel, despite controlling for pre-treatment covariates in the estimation. For comparison and illustration purposes, the outcome variables are standardized with respect to mean and standard deviation in each micro-field, so that they have all mean 0 and standard deviation equal to one.

Table 5: Map of ERC effects by micro-fields on outcome sets. Top losers versus All winners.

	Scientific Productivity						Scientific Impact				Research Funding			
	# Pub.		# Top 1%		# Top 10%		H-Index		FWCI		Eu funds		Tot. Funds	
Micro-field	AdG	StG	AdG	StG	AdG	StG	AdG	StG	AdG	StG	AdG	StG	AdG	StG
LS - Biological Sciences	**−**		**−**	+	−	+		+			−	**+**	−	
LS - Medicine	+	+		**+**	+	+		+			**+**	**+**		**+**
LS - Applied Life Sciences	+		+	+	+	+		−			+	**+**	+	**+**
PE - Math						−					**+**	**+**		
PE - Physics								+			+	**+**	+	+
PE - Chemistry	+	**+**	+	**+**	+	**+**	+	**+**			**+**	**+**	+	**+**
PE - Engineering	+	+	+	+	+		+	+			**+**	**+**	**+**	+
PE - Universe and Earth Science	**+**	+	+	+	**+**			+			+	**+**	+	+
SH - Individuals and Institutions	**−**		−	+	−	+								
SH - Institutions & Behaviours		**+**	−	**+**		**+**		+			**+**	**+**		
SH - Human Mind Studies	**+**	−	+								**+**		+	−

Note: A **+** means that in the event study, the coefficients before the grant assignment suggest that the parallel trend is valid, and the coefficients after the grant assignment show a significant and positive effect of the ERC grant on the considered outcome. A − means that in the event study, the coefficients before the grant assignment suggest that the parallel trend is valid, and the coefficients after the grant assignment suggest a positive, although insignificant, effect of the ERC grant on the considered outcome. A **−** means that the coefficients after the grant assignment show a negative and significant effect of the ERC grant on the considered outcome, and the coefficients before the grant assignment suggest that the parallel trend is valid. A − means that in the event study, the coefficients before the grant assignment suggest that the parallel trend is valid, and the coefficients after the grant assignment suggest a negative, although insignificant, effect of the ERC grant on the considered outcome. The absence of symbols means that the parallel trend is either not valid or the effect is zero.

6.2.3 DID: using different treatment groups

The previous results by type of grant and field are based on the analysis comparing all winners and 'top-rank' non-winners. We repeat the DID analysis by distinguishing also between top winners (those highly placed in the ranking) and bottom-rank winners (winners who are, instead, close to the threshold). In both cases, we use as a control group the subsample of 'top-rank' non-winning applicants. The first exercise, in which we compare 'top-rank' losers with 'bottom-rank' winners, is close in spirit to the RDD setting, which focuses locally on researchers scoring around the selection threshold. The second exercise instead allows us to investigate heterogeneous effects and assess whether ERC grants are (at all) beneficial to top ranked scholars.

We carry out this analysis at the aggregated level. As expected, results based on the subsample of bottom-ranked winners are in line with our RDD findings and show no significant effects. Conversely, when using top-ranked winners we obtain positive and significant effects, which lead us to conclude that the results are likely to be driven by the top ranked. To save space, all figures are relegated in Sections B.1 and B.2 of the Online Appendix. In particular, ERC grants have a positive and significant effect for bottom-ranked winners only on EU funding (both Starting and Advanced Grants), whereas there is no effect on outcomes measuring scientific productivity and scientific impact (see Section B.1 of the Online Appendix). By contrast, when focusing on top-ranked winners, both ERC grants (StG and AdG) increase scientific production (number of publications, publications in top 1% and top 10% ranked journals) and scientific impact (H-index) (see Section B.2 of the Online Appendix).

7 Discussion and policy implications

To sum up, our analysis yields the following results. First, if anything, the grant has positive effects on researcher productivity only in the long-term, i.e. 9 years after applying for the grant (i.e. 4 years after the end of the 5 year ERC grant). This is understandable since research takes time and the outcome variables used to measure productivity evolve slowly (and with a well-known publication lag), so any effect on productivity requires observing bibliometric outcomes for a long time span.

Second, the positive effects of ERC grants on bibliometric outcomes are only suggestive (i.e. positive but insignificant) when we focus on winners who, according to the ranking variable, are close to the threshold and to the control group. This emerges both when we apply the RDD approach and when we arbitrarily split the sub-sample of winners in two and consider only bottom-rank winners in a DID framework.

Third, in contrast, the positive effect on researcher productivity is largely significant for top-rank winners. This suggests that the grant improves productivity for top-rank winners scholars. Note that since the estimated trend before the treatment is flat at zero, this effect is causal and not driven by the fact that, by definition, top-ranked scholars have higher productivity than all other researchers.

Fourth, we find strong evidence in favour of the Matthew effect, i.e. being awarded an EU grant increases the chances of obtaining other EU grants in the future. This holds for the entire distribution of winners both in StG and AdG. Moreover, receiving an ERC grant increases the probability of receiving another European grant in the future but does not have any impact on the total number of grants received in the nine years after. This means that non-beneficiaries are able to obtain more non-EU funds (national, regional or university grants) to counterbalance the higher probability of getting additional EU grants for the beneficiaries. Unfortunately, we have no credible data on the amount of money received from non-EU grants which prevent us from going deeper into the funding analysis. This result has also implications for our findings regarding productivity. That is, given that obtaining ERC grants increases the probability of obtaining other EU grants, we cannot rule out the possibility that our evidence in favour of long-term positive effects on researcher productivity is due to all grants received and not exclusively to ERC grants. More generally, this caveat should be kept in mind because bibliometric measures are in fact related to the productivity of the network of co-authors rather than referring exclusively to individual researchers (that is, a researcher benefits from grants obtained by his/her co-authors and not only from his/her grants). All in all, our evidence suggests that being awarded an ERC grant increases the probability of receiving other EU grants in the long run probably because they either gain reputation as well as experience in managing resource funds. Productivity (as measured by publications in top-ranked journals) improves significantly only for top-rank winners scholars. Our findings are not incompatible with the hypothesis that the lower part of the distribution of winners may also benefit from the grant in terms of productivity in the longer term. However, with the data at hand, we cannot confirm this.

Our results confirm that ERC funds improve significantly standard bibliometric outcomes of scientific productivity, impact, and research funding of the top-ranked winners. However, we find only suggestive evidence of such an effect (positive but not statistically significant coefficients, if any), for winners who fall near the funding threshold.

These results could have practical implications for improving the management of the ERC funds with the aim to increase the effectiveness of these policy instruments. One way could be through the current selection process of the ERC project, which can be costly. While this mechanism can be justified for top-ranked winners (based on our results), this may not hold for winners close to the threshold score, since we find no evidence that obtaining ERC funds yield any positive and significant effect.

The standard selection mechanism based on peer review may not be optimal for applicants with scores slightly above and below the funding threshold. Results of recently launched and ongoing projects which focus on partial-randomization of research funding[32] may shed light on potential benefits vis-a-vis disadvantages of this new selection practices to better understand if this could be a way forward at least for those applicants which ranked close to the assignment threshold.

8 Conclusions

This paper investigates the causal effect of European Research Council (ERC) grants on the scientific productivity, scientific impact and research funding of researchers. Despite the large amount of funding offered, most available evidence on the impact of these grants is anecdotal or descriptive, and not causal. This analysis aims to fill this gap, exploiting information on the selection and assignment mechanism for ERC grants.

Every year, there is an open call for ERC grants and applicants are evaluated and ranked by panels of experts. Each application is assigned a score, and the highest-ranked are awarded the grant until all funds are allocated. This setting is ideal for the use of a sharp regression discontinuity design (RDD) to estimate the impact of an ERC grant by comparing the publication outcomes of winning and non-winning applicants. Moreover, we also employ a difference-in-differences (DID) approach, exploiting the availability of a long time series of bibliometric indicators. The parameters retrieved using the two methods are very different in nature: while RDD helps estimate the effect of the grants only for scholars who are locally close to the assignment threshold, DID allows estimating an average effect, including top ranked scholars who are away from the selection threshold.

Estimating the RDD, we find that ERC grants do not significantly improve researcher

[32] This is the case of RoRI's RANDOMISATION project pursued by several funders, including the Volkswagen Foundation, the Swiss National Science Foundation (SNSF), the Austrian Science Fund (FWF) and the Health Research Council of New Zealand, which adopted the partial-randomization concept to bring about improved funding outcomes for their research funding schemes. See here for more details.

productivity—although some positive effects are found in certain fields i.e. in Physics for StG)—but that ERC Grants significantly increase the probability of receiving other EU grants. This is the well-known Matthew effect. Using DID, we confirm that both Advanced and Starting Grants increase research productivity and help applicants receive other EU grants (the Matthew effect) in the 9 years after grant assignment.

When we split the treated group into bottom-rank and top-rank winners, we see that the results are not significant for the first but positive and significant for the second, which leads us to conclude that top-rank winners are those driving the positive results. Exploring heterogeneous effects by micro-field, we find that the positive long-term effect on productivity and excellence shows up in the fields of Chemistry, Universe and Earth Sciences, Institutions and Behaviours, Human Mind Studies and Medicine.

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Appendix

A ERC grants micro-fields

Table A.1: Correspondence between panel and derived fields

Panel description	Panel	Derived field
Cellular and Developmental Biology	LS3	Biological Sciences
Molecular and Structural Biology and Biochemistry	LS1	
Physiology, Pathophysiology and Endocrinology	LS4	
Genetics, Genomics, Bioinformatics and Systems Biology	LS2	
Immunity and infection	LS6	Medicine
Neurosciences and neural disorders	LS5	
Diagnostic tools, therapies and public health	LS7	
Evolutionary, population and environmental biology	LS8	Applied life sciences
Applied life sciences and biotechnology	LS9	
Mathematical foundations	PE1	Math
Fundamental constituents of matter	PE2	Physics
Condensed matter physics	PE3	
Physical and Analytical Chemical sciences	PE4	Chemistry
Materials and Synthesis	PE5	
Products and process engineering	PE8	Engineering
Systems and communication engineering	PE7	
Computer science and informatics	PE6	
Universe sciences	PE9	Universe and earth sciences
Earth system science	PE10	
Individuals, institutions and markets	SH1	Individuals and Institutions
Environment and society	SH3	Institutions and behaviour
Institutions, values, beliefs and behaviour	SH2	
The Human Mind and its complexity	SH4	Human mind
The study of the human past	SH6	Not assigned
Cultures and cultural production	SH5	

B Research Funding data

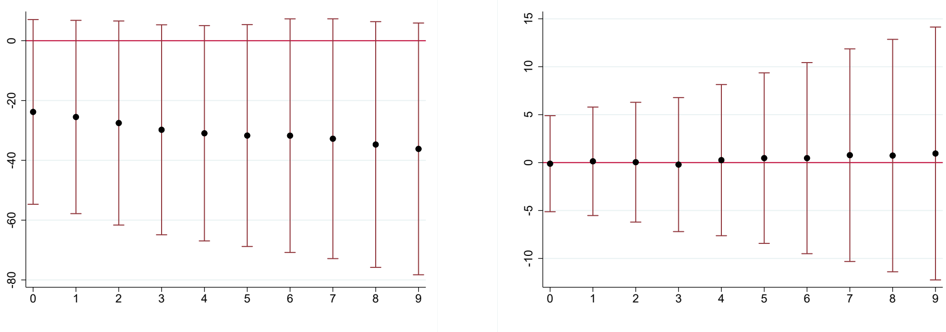
To build the variables related to the research fundings acknowledged in each paper, we downloaded the funding information as reported in Scopus, and we retained only the fundings that show a valid funding id number (named $FUNDING\_ID$ in Scopus). To identify the *EU funds* among all existing funding bodies, we isolated all fundings having a funding name, a funding id, or a funding acronym which contains one or several of the following words: "ERC", "H2020", "FP7", "MSCA" or "Marie-Curie". Other EU funds were classified as *EU other* if they contain "EC; EU" in their funding acronym or name and were not already classified as *EU funds* in the previous step. All the remaining funds having a valid funding identifier and not being classified as *EU funds* or *EU other* funds were then classified as *Other funds*. Finally, the total number of funds received by a PI network (*Total funds*) was constructed as the simple sum of *EU funds*, *EU other* and *Other funds*. Despite the huge effort exerted by Scopus Elsevier in recent years in order to retrieve and classify the information regarding research funding bodies from the acknowledgements of the papers, it is still far from being perfect.

Extracting this info is not an easy task given the different funding recognition practices in different disciplines and in different countries, given also the possibly different editorial instructions for acknowledging funders adopted by different scientific journals, even due to the different languages in which the name of the funder may be reported. Finally, Scopus also acknowledges the existing difficulties in the disambiguation between funding organizations given the lack of any standardization in how authors report funders' information in their papers. All these difficulties may hinder the correct extraction of the funder's information and make the accuracy of this variable limited (Liu, 2020). However, this is the best available information on funding and we should be aware of the fact that it may be not accurate and reliable enough in some disciplines (in particular for SSH if compared to PE and LS) and especially for analyses of research funded by national bodies (Pranckutė, 2021). This is the reason why we distinguished only among EU and other sources of funding.

C Additional figures

C.1 Regression Discontinuity results

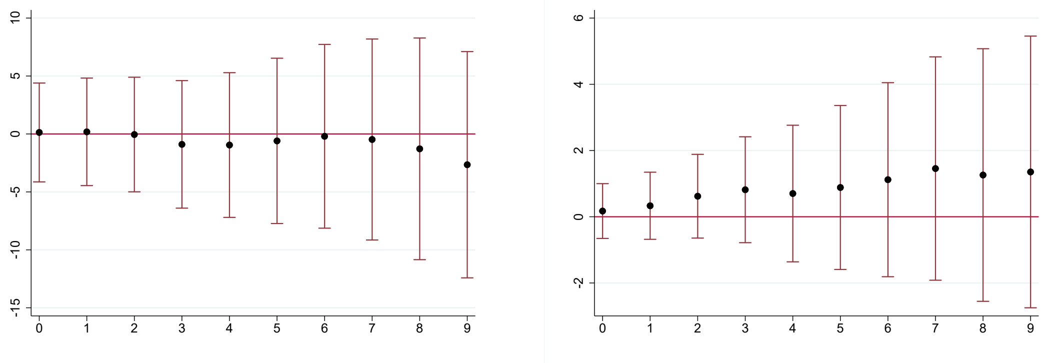
Figure C.1: Number of published articles (cumulative)



(a) Advanced Grants (b) Starting Grants

Note: The figures report RDD estimates of Eq. 1 by different type of grant. Eq. 1 is estimated with the optimal bandwidth, triangular kernel, and local linear polynomial. The RDD coefficients are bias-corrected with robust standard errors. Each point in the graphs represents the RDD coefficient of distinct regressions (along with its confidence interval), in which the outcome is measured each year from the application year (0 on the horizontal axis) until 9 years after the grant. The outcome is the cumulative number of distinct published articles, measured year by year.

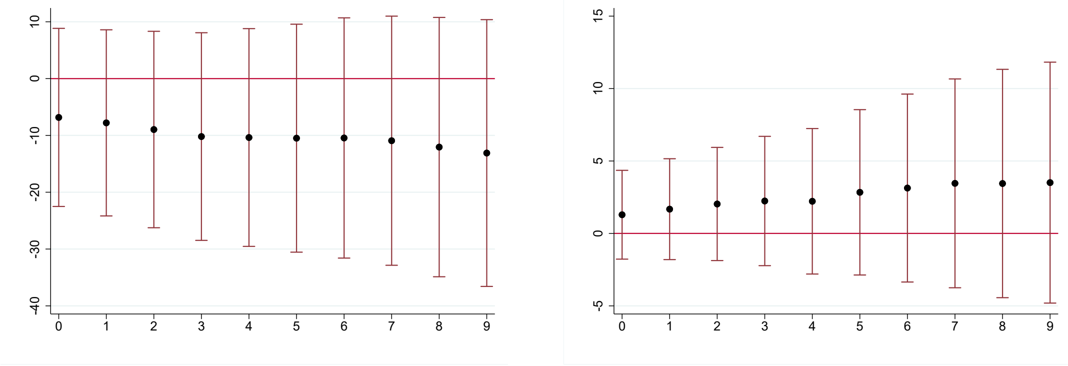
Figure C.2: Number of articles published in the 1% top-ranked journals (cumulative)



(a) Advanced Grants (b) Starting Grants

Note: The figures report RDD estimates of Eq. 1 by different type of grant. Eq. 1 is estimated with the optimal bandwidth, triangular kernel, and local linear polynomial. The RDD coefficients are bias-corrected with robust standard errors. Each point in the graphs represents the RDD coefficient of distinct regressions (along with its confidence interval), in which the outcome is measured each year from the application year (0 on the horizontal axis) until 9 years after the grant. The outcome is the cumulative number of distinct articled published in the 1% top-ranked journals, measured year by year.

Figure C.3: Number of articles published in the 10% top-ranked journals (cumulative)

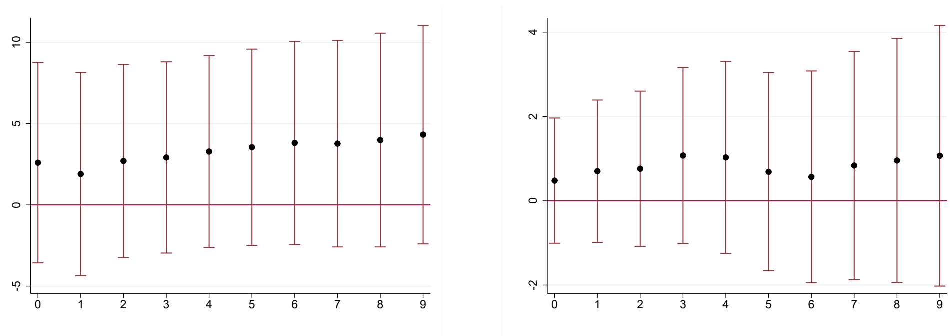


(a) Advanced Grants

(b) Starting Grants

Note: The figures report RDD estimates of Eq. 1 by different type of grant. Eq. 1 is estimated with the optimal bandwidth, triangular kernel, and local linear polynomial. The RDD coefficients are bias-corrected with robust standard errors. Each point in the graphs represents the RDD coefficient of distinct regressions (along with its confidence interval), in which the outcome is measured each year from the application year (0 on the horizontal axis) until 9 years after the grant. The outcome is the cumulative number of distinct articled published in the 10% top ranked journals, measured year by year.

Figure C.4: H index

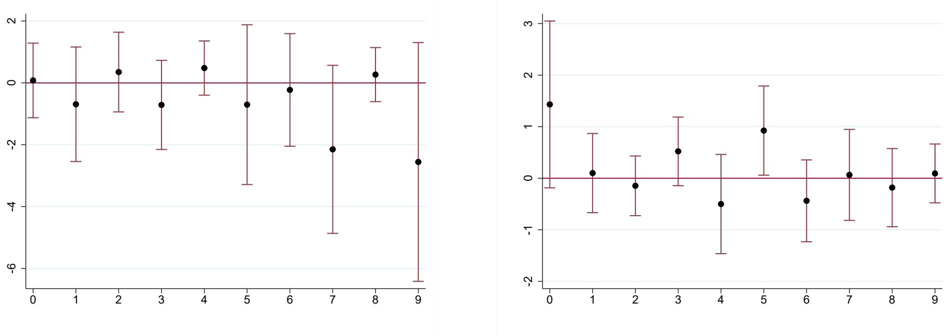


(a) Advanced Grants

(b) Starting Grants

Note: The figures report RDD estimates of Eq. 1 by different fields and type of grant. Eq. 1 is estimated with the optimal bandwidth, triangular kernel, and local linear polynomial. The RDD coefficients are bias-corrected with robust standard errors. Each point in the graphs represents the RDD coefficient of distinct regressions (along with its 95% confidence interval), in which the outcome is measured each year from the application year (0 on the horizontal axis) until 9 years after the grant.

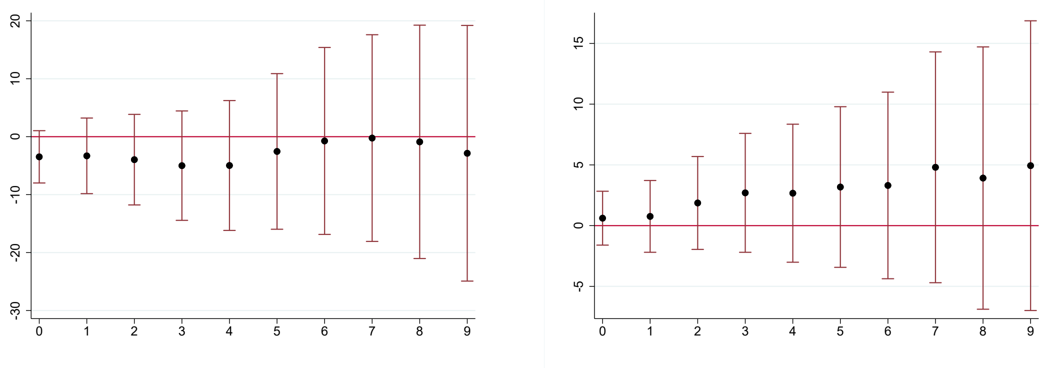
Figure C.5: Field weighted citation impact



(a) Advanced Grants (b) Starting Grants

Note: The figures report RDD estimates of Eq. 1 by different fields and type of grant. Eq. 1 is estimated with the optimal bandwidth, triangular kernel, and local linear polynomial. The RDD coefficients are bias-corrected with robust standard errors. Each point in the graphs represents the RDD coefficient of distinct regressions (along with its 95% confidence interval), in which the outcome is measured each year from the application year (0 on the horizontal axis) until 9 years after the grant.

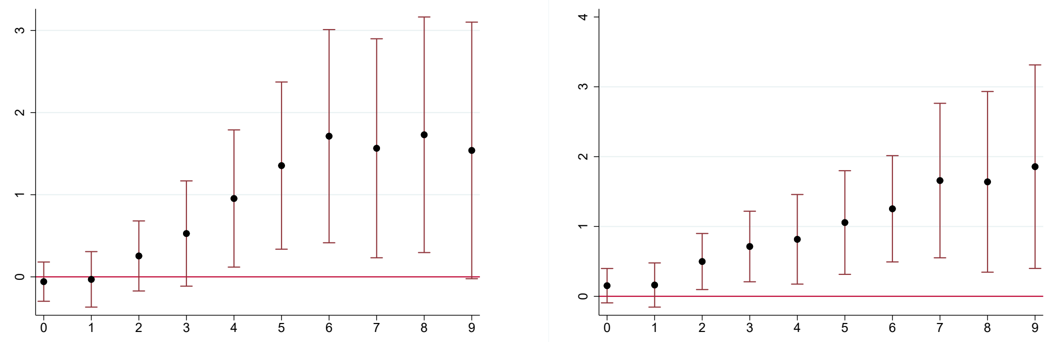
Figure C.6: Number of distinct funds (cumulative)



(a) Advanced Grants (b) Starting Grants

Note: The figures report RDD estimates of Eq. 1 by different fields and type of grant. Eq. 1 is estimated with the optimal bandwidth, triangular kernel, and local linear polynomial. The RDD coefficients are bias-corrected with robust standard errors. Each point in the graphs represents the RDD coefficient of distinct regressions (along with its 95% confidence interval), in which the outcome is measured each year from the application year (0 on the horizontal axis) until 9 years after the grant.

Figure C.7: Number of distinct European funds (cumulative)



(a) Advanced Grants (b) Starting Grants

Note: The figures report RDD estimates of Eq. 1 by different fields and type of grant. Eq. 1 is estimated with the optimal bandwidth, triangular kernel, and local linear polynomial. The RDD coefficients are bias-corrected with robust standard errors. Each point in the graphs represents the RDD coefficient of distinct regressions (along with its 95% confidence interval), in which the outcome is measured each year from the application year (0 on the horizontal axis) until 9 years after the grant.

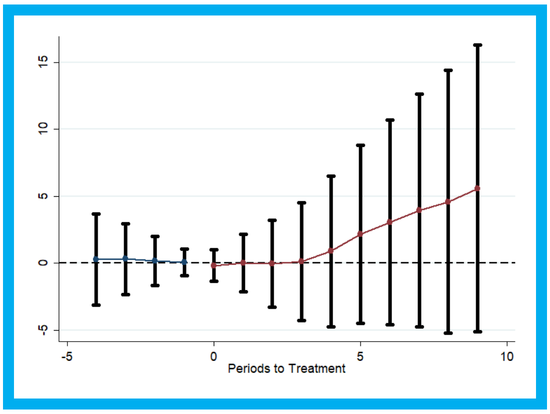
D Difference-in-Differences: Aggregated Results

Note, to ease the reading of the results we organized the graphs of this section as follows: (i) the rows of each panel refer to a type of grant (Advanced grant in the top row, Starting grant in the bottom one); (ii) the columns of each panel refer to whether the specification includes pre-treatment covariates to adjust for the parallel trend, or not (on the left-hand side, no covariates are included; on the right-hand side pre-treatment covariates are included).

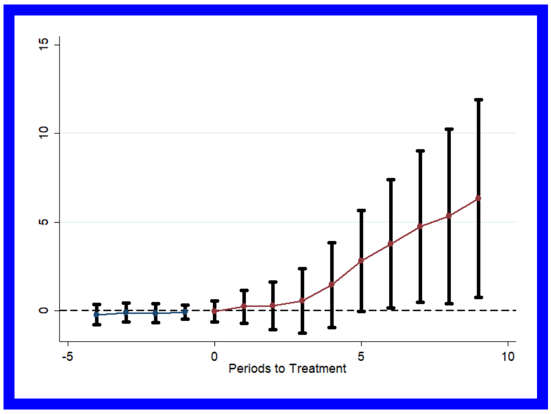
In addition, to help the reader we highlight the significant and interesting results according to the following criteria:

- we frame into a blue square the graphs showing significant positive effect of the grant (after treatment) and valid parallel trend (before the treatment);
- we frame into a light-blue square the graphs showing positive at the 5% level - although not significant - effect of the grant (after treatment) and valid parallel trend (before the treatment). We consider this as suggestive evidence in favour of the hypothesis that the ERC grants have positive effect on the considered outcome (at least in the FP7 sample at our disposal);
- we frame into a red square the graphs showing significant negative effect of the grant (after treatment) and valid parallel trend (before the treatment);
- we frame into a pink square the graphs showing negative at the 5% level - although not significant - effect of the grant (after treatment) and valid parallel trend (before the treatment). We consider this as suggestive evidence in favour of the hypothesis that the ERC grants have negative effect on the considered outcome (at least in the FP7 sample at our disposal);
- all remaining (not highlighted) graphs are such that either the parallel trend does not hold or the parallel trend holds but the effect of the grant is close to zero.

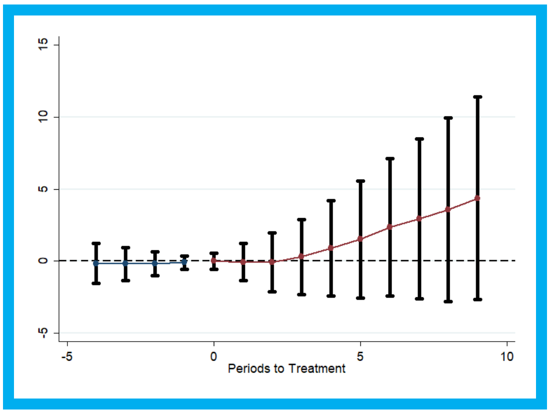
Figure D.1: Number of publications



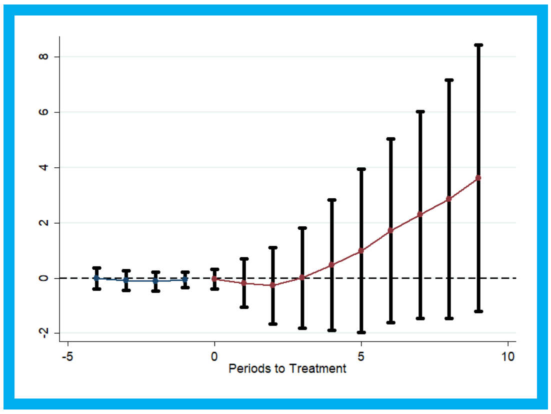
(a) AdG



(b) AdG PP



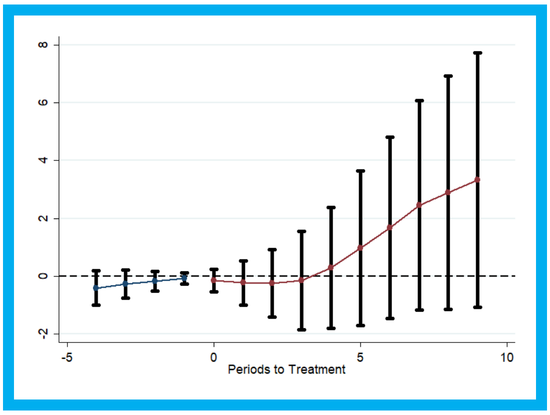
(c) StG



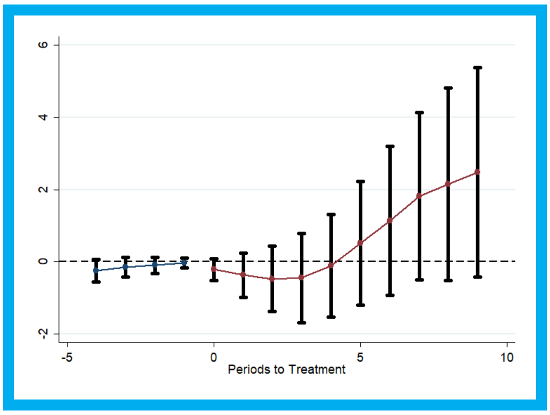
(d) StG PP

Note: The figures report DiD estimates by different fields and type of grant. Each point in the graphs represents estimates and confidence intervals for each time period before and after treatment. The outcome is measured each year from 5 years before the application year until 9 years after the grant.

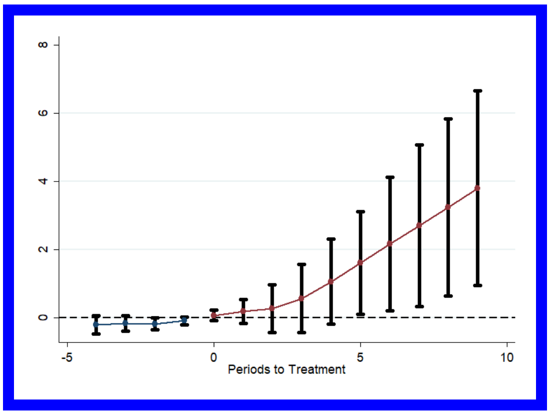
Figure D.2: Number of articles published in the 1% top-ranked journals (cumulative)



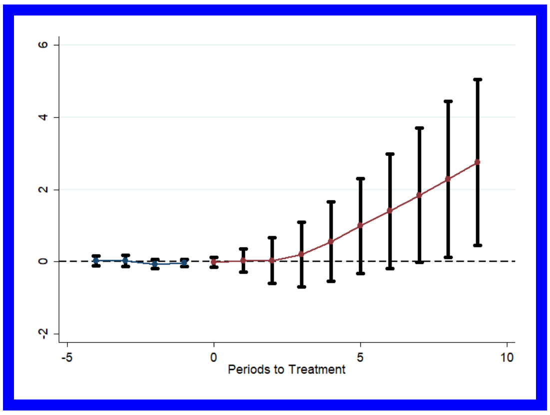
(a) AdG



(b) AdG PP



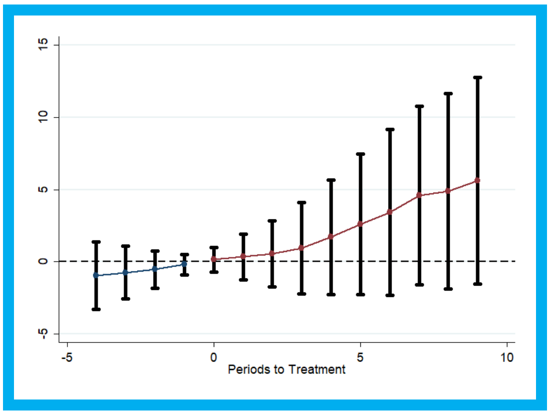
(c) StG



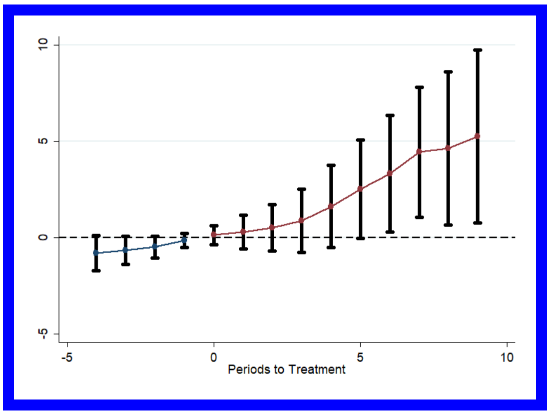
(d) StG PP

Note: The figures report DiD estimates by different fields and type of grant. Each point in the graphs represents estimates and confidence intervals for each time period before and after treatment. The outcome is measured each year from 5 years before the application year until 9 years after the grant.

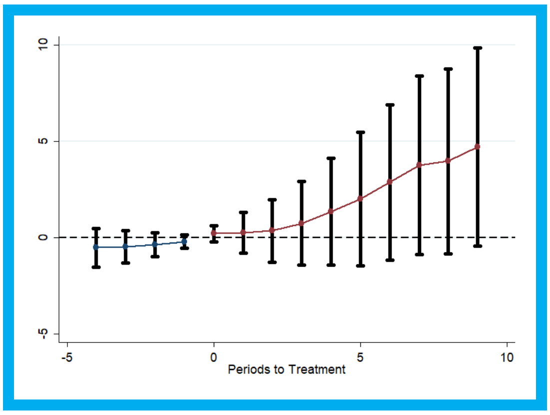
Figure D.3: Number of articles published in the 10% top-ranked journals (cumulative)



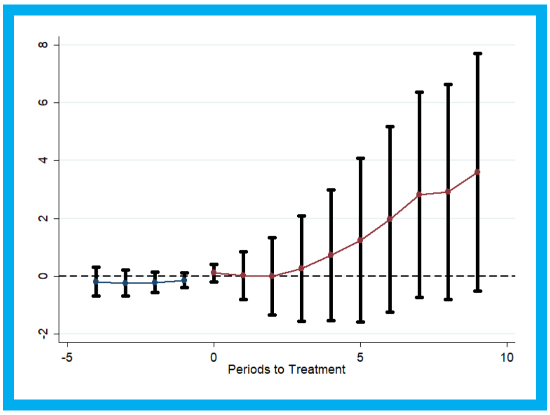
(a) AdG



(b) AdG PP



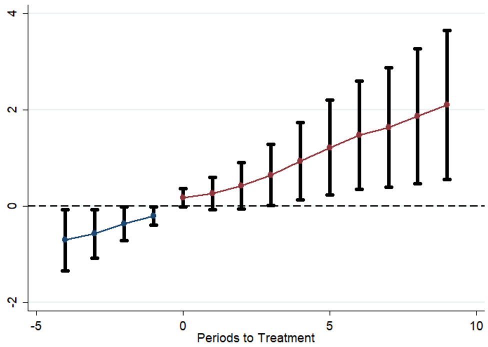
(c) StG



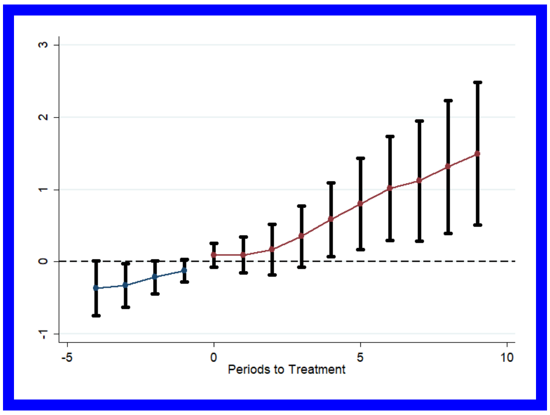
(d) StG PP

Note: The figures report DiD estimates by different fields and type of grant. Each point in the graphs represents estimates and confidence intervals for each time period before and after treatment. The outcome is measured each year from 5 years before the application year until 9 years after the grant.

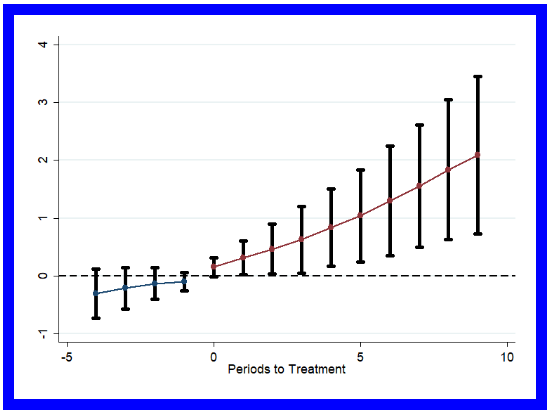
Figure D.4: H-index



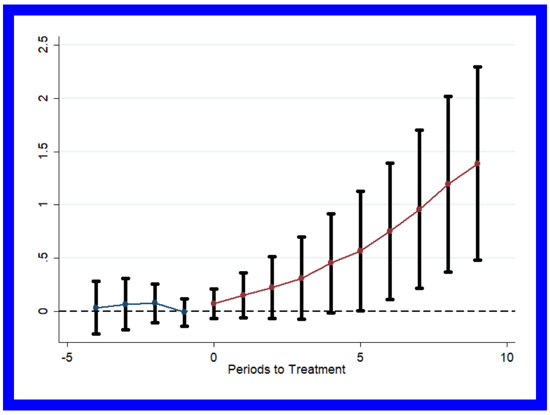
(a) AdG



(b) AdG PP



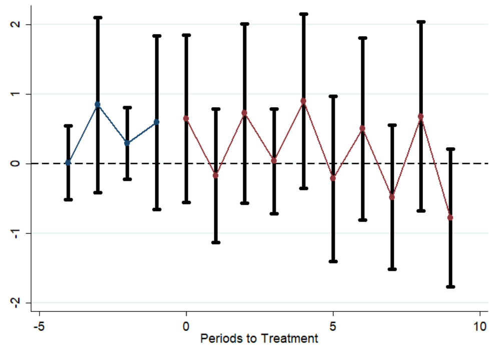
(c) StG



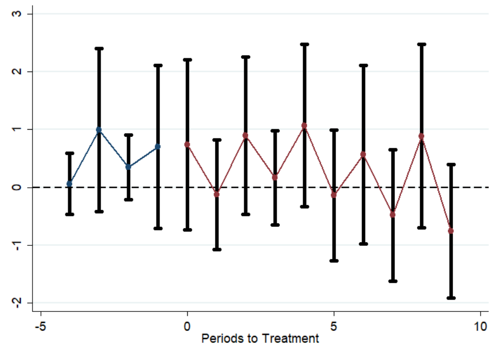
(d) StG PP

Note: The figures report DiD estimates by different fields and type of grant. Each point in the graphs represents estimates and confidence intervals for each time period before and after treatment. The outcome is measured each year from 5 years before the application year until 9 years after the grant.

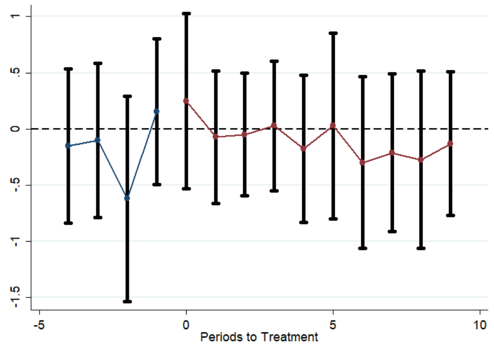
Figure D.5: Field Weighted Citation Impact (FWCI)



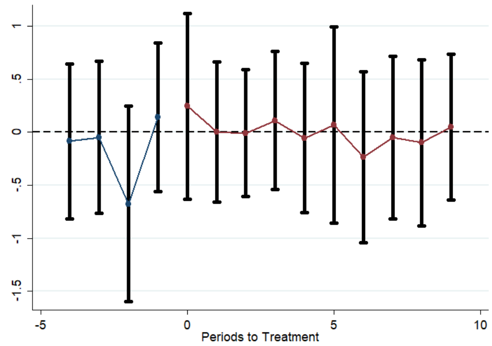
(a) AdG



(b) AdG PP



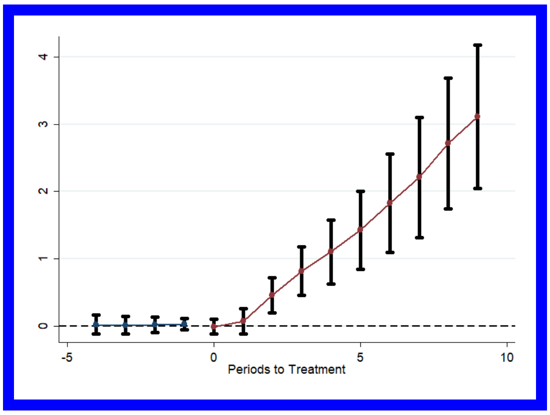
(c) StG



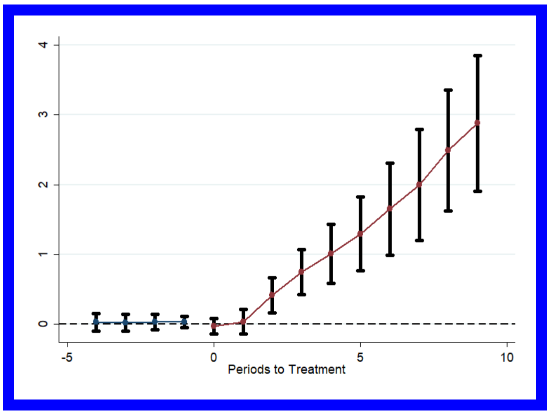
(d) StG PP

Note: The figures report DiD estimates by different fields and type of grant. Each point in the graphs represents estimates and confidence intervals for each time period before and after treatment. The outcome is measured each year from 5 years before the application year until 9 years after the grant.

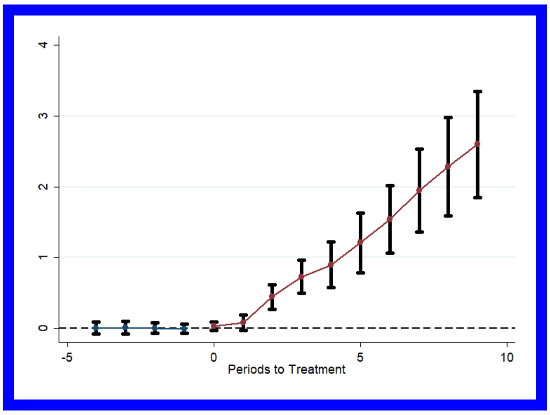
Figure D.6: Number of distinct European funds (cumulative)



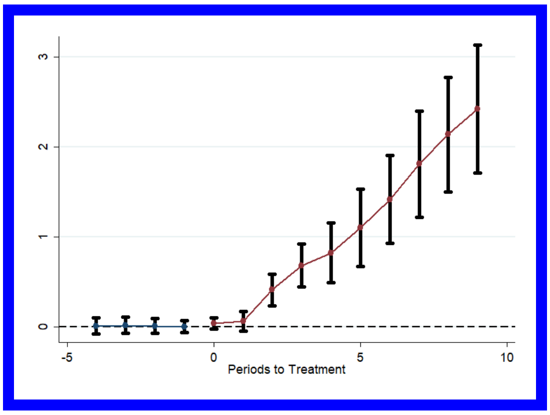
(a) AdG



(b) AdG PP



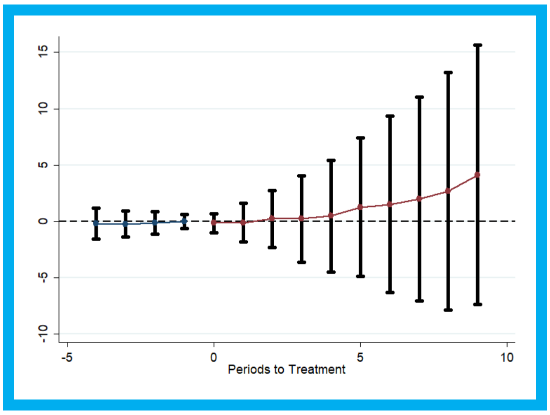
(c) StG



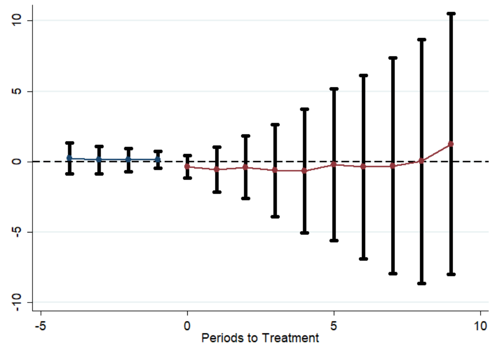
(d) StG PP

Note: The figures report DiD estimates by different fields and type of grant. Each point in the graphs represents estimates and confidence intervals for each time period before and after treatment. The outcome is measured each year from 5 years before the application year until 9 years after the grant.

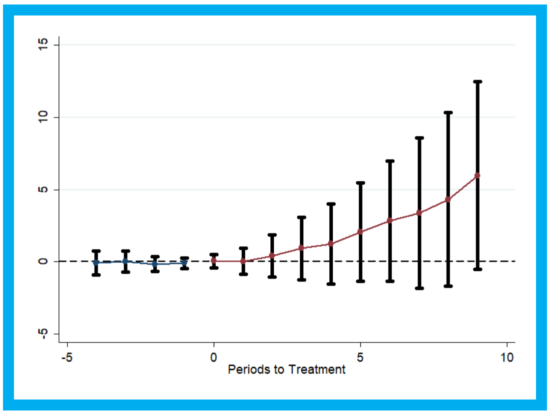
Figure D.7: Number of total funds (cumulative)



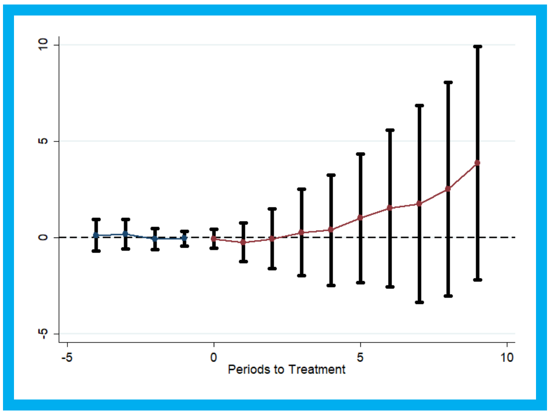
(a) AdG



(b) AdG PP



(c) StG



(d) StG PP

Note: The figures report DiD estimates by different fields and type of grant. Each point in the graphs represents estimates and confidence intervals for each time period before and after treatment. The outcome is measured each year from 5 years before the application year until 9 years after the grant.

Online Appendix

Please see here the Online Appendix.