# The impact of mobility grants on researchers*

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**Abstract**

The international mobility of researchers has been central to the policy-makers' agendas for several decades. Despite the growing presence of mobility grants within public funding agencies' portfolios, empirical evidence on their effects remains scant. In this paper, we contribute to the literature by studying the Marie Skłodowska-Curie Individual Fellowships, the flagship program of the EU, providing competitive grants to researchers to spend a research period abroad. Based on data for the universe of applicants to the Seventh Framework Programme (2007-2013), we exploit the discontinuity in grant assignment to uncover causal effects on individual researchers. Results show that Individual Fellowships are indeed conducive to higher chances of experiencing mobility to the scientists' country of choice. Additionally, we show that grants supporting extra-European mobility, as opposed to those supporting mobility within Europe, lead to an increase in terms of publication quantity and quality, and help researchers expand their collaboration networks. This suggests that grants are most effective when targeting mobility flows subject to larger frictions.

**Keywords**: Research grants, Mobility, Marie Skłodowska-Curie, Regression discontinuity
**JEL**: H0, H51, I28, O3, O38

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# 1 Introduction

International mobility represents a widespread phenomenon within the academic community. Survey evidence suggests that most PhD researchers have experienced some form of international mobility in their career (Guthrie et al., 2017).[1] Mobility has been increasingly associated with scientific quality and excellence (Ackers, 2008; Hunter et al., 2009), and most empirical evidence indicates that mobile researchers enjoy a premium in terms of scientific productivity (Netz et al., 2020), quality (Franzoni et al., 2014; Sugimoto et al., 2017), feature larger research networks (Scellato et al., 2015), and more favorable career progression (Lawson and Shibayama, 2015).

However, significant barriers impede access to cross-border experiences, particularly for researchers at their initial phase of their career. Among these challenges, the difficulty in securing funding stands out as a primary obstacle (see e.g. IDEA Consult et al., 2013; European Commission, 2021).[2] Lack of funding opportunities at early career stages is particularly troublesome if considering the current paucity of postdoctoral researchers in the US and EU (Woolston, 2022; Langin, 2024). Reduced opportunities for mobility not only affect individual researchers, but have broader implications for the production and transfer of knowledge and the competitiveness of national research systems. As a result, governments have been implementing a variety of schemes aimed at facilitating these exchanges. These initiatives seek to lower the barriers to international mobility, enabling researchers to pursue academic and professional development opportunities abroad. However, robust empirical evidence on the effects of these policy initiatives on individual researchers remains remarkably scant (Baruffaldi et al., 2020; Non et al., 2022a).

This paper provides causal evidence on one of the most renowned mobility-based schemes in the world, the Marie Skłodowska-Curie Actions (MSCA). Active since the early 90s, the program has financed more than 145,000 researchers, with a budget of approximately €14 billion during the period 1990-2020. In our work we focus on MSCA Individual Fellowships which provide funding for research stays abroad to individual scientists after their PhD. We leverage data on all applica-

[1] For instance, IDEA Consult et al. (2013) find that 48% EU university researchers with PhDs had mobility experiences of at least three months; Børing et al. (2015) report that 57% of EU university researchers have experienced international mobility at least once in their research careers. Franzoni et al. (2015) find that around 40% of scientists in 16 countries are immigrants.

[2] According to IDEA Consult et al. (2013), securing funding remains the primary challenge faced by European academics regarding doctoral and postdoctoral mobility. This issue is cited by 64% of doctoral researchers and 43% of postdoctoral researchers. Non-EU mobile researchers consider funding as the second most significant hurdle to mobility, with finding a job for their spouse being the primary concern.

tions submitted during the Seventh Framework Programme (2007-2013). We link these data with Scopus to retrieve information on applicants' affiliations and publications. To gauge causal effects, we exploit the presence of discontinuities in grant assignment and adopt a Fuzzy Regression Discontinuity Design (RDD).

We start by investigating whether grants affect mobility. In other words, we are interested in understanding whether public support is instrumental to mobility, or if researchers end up moving to their country of choice irrespective of the grant. Exploiting affiliation data, we show that Individual Fellowships have positive effects on researchers' mobility. In more detail, we find that within 5 years from a given competition, grantees experience a 31-34 percentage points increase in the likelihood of being affiliated with an institution of the destination country indicated in their application. This suggests that grants are indeed decisive in reducing the frictions affecting the cross-country circulation of researchers.

We also examine potential effects concerning researchers' productivity, measured by the number of publications and their average impact factor, and their collaboration networks. On average, we do not find evidence suggesting that grants boost productivity or increase the number new collaboration. However, the broad scope of the program puts us in the unique position of investigating heterogeneous effects across a set of dimensions. Notably, we test whether effects vary depending on the type of mobility supported by Individual Fellowships. We show that grants supporting extra-European mobility (i.e. from or to Third Countries) as opposed to those supporting mobility within Europe, generally yield more positive effects across most outcomes. Likewise, we also report evidence suggesting that longer grants may have more beneficial effects in terms of publication output and quality with respect to shorter grants. These findings are consistent with the idea that mobility is not necessarily inherently beneficial for researchers' performance, and that mobility grants are more effective when they support moves that are more challenging—whether due to distance, diverse country contexts, or access to prestigious institutions—while also offering longer project durations.

The paper contributes to a number of strands in the literature. First, we build on existing studies on international mobility and its consequences for individual researchers (see Guthrie et al. 2017 and Netz et al. 2020 for reviews of recent evidence).[3] Most literature demonstrates a posi-

[3] In Online Appendix Section 2, we provide a more comprehensive review of the main strands of literature our paper

tive association between international mobility and various metrics of research performance, including publication rates, citation impact, and the establishment of international collaborations (Dubois et al., 2014; Franzoni et al., 2014; Lawson and Shibayama, 2015; Robinson-Garcia et al., 2019; Zabetta and Geuna, 2019).[4] Mobility is frequently posited as a mechanism for knowledge exchange, skill acquisition, and network expansion, which in turn can catalyze innovation and enhance the visibility and influence of researchers' work. However, interpreting these associations as causal effects presents significant challenges (Fernandez-Zubieta et al., 2015). A fundamental obstacle is the presence of unobservable factors that may influence both a researcher's decision to pursue mobility opportunities and their subsequent academic success. Attributes, such as personal willingness to relocate, the availability of financial and institutional resources to facilitate such moves, and career aspirations, are difficult to measure and account for in empirical studies. This complexity introduces ambiguity into the assessment of the direct impact of mobility on academic outcomes. Differently from most literature in this field, our research design allows for a causal interpretation of the results and can inform on the effects of international mobility on researchers' performance, and on the heterogeneous effects of different types of mobility.

Second, the paper adds to the literature addressing the effects of grants to individual researchers (see, e.g., Jacob and Lefgren, 2011; Wang et al., 2019; Ghirelli et al., 2023; Barnett et al., 2024). Most importantly, it contributes to the small ensemble of studies that examine the effects of mobility grants. Acknowledging the potential benefits of researchers' mobility, a variety of programs aimed at supporting cross-country circulation of scientists have been implemented around the world.[5] These initiatives are designed to mitigate the financial and logistical barriers to international collaboration and research exchanges. Yet, the available evidence on the effectiveness of such policies remains very sparse and features mixed findings, which limits our understanding of whether and how these policies work. Among the few studies addressing the causal effects stem-

build on. These include, i) extant evidence on mobility and researchers' performance, ii) the effects of research grants on individual academics, and iii) the impact of mobility grants on scientists outcomes.

[4]As reported by Netz et al. (2020), while most studies report positive effects, extant empirical evidence also finds no effect or negative effects of mobility on scientific quantity (e.g. Antonio-García et al., 2014), quality (e.g. Payumo et al., 2018) and occupational situation (e.g. Cruz-Castro and Sanz-Menéndez, 2010).

[5]Examples include: Fulbright Postdoctoral Awards (US); UKRI International Fellowships (UK); PAGES African Mobility Fellowship (African countries); Swedish Research Council mobility grants (Sweden); Danish Council for Independent Research International postdoctoral grants (Denmark); Hermès program and Hubert Curien partnerships (France); Rubicon mobility grant (The Netherlands); The Research Council of Norway mobility grants; Co-Funded Brain Circulation Scheme (Turkey); Swiss National Science Foundation postdoc mobility scholarship (Switzerland).

ming from mobility grants, Baruffaldi et al. (2020) adopts a RDD framework to examine a Swiss National Science Foundation (SNSF) postdoc mobility scholarship. Results document that SNSF fellowships significantly increase the mobility of researchers in the short and medium term. Receiving a grant has a positive effect on the quality of a researcher's scientific output (measured by the average impact factor). However, there is no significant effect on the quantity of output (measured by the number of publications) or on career progression (the probability of being promoted to a professorship). The study also shows that receiving the grant gives researchers access to broader and higher quality co-authorship networks and leads them to broaden their research fields. Non et al. (2022a) study the impact of the Rubicon program, a Dutch competitive mobility grant, on the quantity and quality of a researcher's publications, the number of co-authors, and the probability of leaving academia. Using a RDD framework, the authors document the absence of statistically significant effect of the grant on all these outcomes. Shi et al. (2023) provide evidence on reintegration grants, namely, the China's Young Thousand Talents (YTT). The YTT supports early-career Chinese scientists working in STEM to return home from abroad. The paper finds that the beneficiaries outperform their overseas peers in post-return publication, largely due to their access to greater funding and larger research teams. Finally, closely related to our work is the recent study by Yildiz et al. (2024). Using a RDD, they use data from MSCA Individual Fellowships during Horizon 2020 and focus on whether these help scientists diversifying into new topics. Results document that grantees indeed increase the share of publications with new topics, though only in the aftermath of receiving the grant.

In sum, the variance in findings across studies highlights a crucial gap in the literature, that is, a systematic understanding of whether these grants influence mobility and how different types of mobility grants influence academic outcomes and under what conditions their benefits are most pronounced. Moreover, the literature's current focus on a few national-level grant programs limits our understanding of the broader implications of mobility for researchers' careers and the scientific community. We contribute to the field by providing the first systematic causal evidence on MSCA Individual Fellowships, one of the largest and most prestigious mobility programs worldwide. Our findings underscore the imporant role of grants in facilitating mobility and help clarify the contradicting evidence concerning researchers' performance reported in the few existing studies by isolating the distinct effects of different types of mobility grants, showing that the impact varies by the kind of mobility undertaken and the nature of support provided.

The remainder of the paper proceeds as follows. Section 2 describes the institutional framework and presents the data used in the analysis. Section 3 offers on overview of the estimation strategy, whereas Section 4 contains the main results, including a number of additional tests aimed at testing the sensitivity of our findings. Section 5 concludes the paper.

# 2 Empirical setting

## 2.1 Institutional framework

Since the mid-1980s, the promotion of scientific mobility has occupied a central position in the European Union's strategy for research and innovation.[6] This derived from the recognition that the free circulation of researchers leads to a better allocation of resources across Member States, and hence better research quality and higher international competitiveness. This commitment was reflected through the integration of targeted initiatives aimed at enhancing the cross-border movement of researchers within the European Framework Programmes (FPs) for Research and Technological Development.[7] In particular, the launch of the Third Framework Programme (FP3) in 1990 represented a significant milestone setting the 'increased mobility of research staff' as a key objective and introducing the EU fellowship program for transnational mobility of researchers. The program was officially named Marie Curie Actions in 1996 during FP4, in honor of the double Nobel Prize laureate Marie Skłodowska-Curie. Over the years, the scheme has evolved into a flagship initiative of the European Union, symbolizing its commitment to advancing scientific excellence and collaboration across borders. Today, officially known as Marie Skłodowska-Curie Actions, it stands alongside the US Fulbright scheme as one of the world's most renowned and sought-after mobility programs.

[6] The initial Treaty establishing the European Economic Community (EEC) of 1958, did not explicitly mention research and innovation policy. The Single European Act (SEA) in 1986 provided the legal foundations for the European Community's research policies. With the explicit goal of enhancing "the scientific and technological basis of European industry and encouraging it to become more competitive at the international level," the Act underscored the importance of stimulating the training and mobility of researchers, among other aspects. The importance of researchers' mobility was later reiterated and identified as a central objective in the development of the European Research Area (ERA) which entered into force in 2009 and aimed at fostering freedom of movement for researchers and the free exchange of scientific knowledge and technology.

[7] Early examples were the SCIENCE program (1988-1992), the SPES program (1989-1992) and the large-scale facilities program (1989-1992).

The primary goals of MSCA encompass facilitating researcher mobility across Europe, improving researchers' career development and making Europe a more attractive place to carry out research and encouraging top researchers to stay in Europe. As a result, with a budget of approximately €14 billion during the period 1990-2020[8], Marie Curie Actions have been providing grants to more than 145,000 researchers, of which 18 are Nobel Laureates[9].

MSCA offer different types of Individual Fellowships. Under FP7, which run from 2007 to 2013, individual researchers could apply to a number of mobility grants supporting different types of mobility. These can be grouped into grants supporting either intra-European or extra-European mobility. The former encompass the Intra-European Fellowships (IEF) and the European Reintegration Grants (ERG), which provide support for researchers moving within Europe; the latter include the International Incoming Fellowships (IIF), the International Outgoing Fellowships (IOF), and the International Reintegration Grants (IRG), which provide support for researchers moving from or to Third Countries.[10]

In order to participate in these actions during FP7, individuals had to be "experienced researchers". These are defined as researchers who, at the time of the application deadline either hold a PhD or have 4 years of full-time research experience following the award of their degree (excluding career breaks). Each Action invites applicants to respond to a particular "Call for Proposals". These are launched at different times of the year and therefore the deadlines vary.

MSCA have a bottom-up approach, that is, research fields are chosen freely by the applicants and all domains are eligible for funding. At time of proposal submission, individual researchers choose the scientific domain (i.e. panel) to which their proposals will be associated to. In other words, researchers responding to a given call, end up competing with other researchers working or submitting proposals in the same scientific area. The panels comprise the following eight ma-

[8] MSCA's budget has been steadily increasing over time. During FP3 (1990-1994), the budget for precursor to MSCA fellowships was €562 million. Throughout FP4 and FP6 (1994-2006) the budget was €3.2 billion; FP7 (2007-2013) saw a remarkable increase with a budget of €4,7 billion, which was then followed by Horizon 2020 (2014-2020) with €6.2 billion. The current FP (i.e. Horizon Europe), which runs for the period 2021-2027, has a similar budget with €6.6 billion.

[9] https://rea.ec.europa.eu/news/celebrating-156th-anniversary-marie-sklodowska-curies-birth-legacy-nobel-laureate-brilliance-2023-11-07_en.

[10] In 2011, the ERG and IRG were consolidated into one scheme called CIG (Career Integration Grant) allowing applications from researchers that wanted to reintegrate either from outside or within the EU. See Appendix for a more detailed description of each of these fellowships. MSCA also encompass other initiatives, labeled "host actions", which require the institution to apply for funding. These are Initial Training Networks (ITN), including European Industrial Doctorate (EID) and Innovative Doctoral Programme (IDP); Industry-Academia Partnerships and Pathways (IAPP), International Research Staff Exchange Scheme (IRSES); Co-funding of regional, national, international programmes (COFUND).

jor areas: Chemistry, Social and Human Sciences, Economic Sciences, Information science and Engineering, Environmental and Geo-Sciences, Life Sciences, Mathematics, and Physics.[11]

During FP7, proposals were first screened against basic eligibility checks (e.g. deadline respected, completeness of submission, status of experienced researcher). After that, the evaluation proceeded according to two steps. In the first step, each proposal was assigned to at least three independent experts.[12] They carried out their evaluation remotely and individually according to five criteria: science and technological quality, transfer of knowledge, researcher, implementation, and impact.[13] Each criterion was scored on a scale from 0 to 5, with 5 being the maximum. Scores were assigned with a resolution of one decimal place and each of the five criteria had weightings that could vary across the different MSCA. Once all the experts had completed their individual assessment, the second step entailed a consensus meeting among the experts involved in the evaluation of a given proposal. The outcome of this meeting produced the final score assigned to a proposal, which could range from 0 to 100. In order to be considered for funding a proposal had to reach an overall score of at least 70 out of 100. The consensus scores assigned to all proposals within a given panel determined the final rankings within each of the eight panels. Based on these rankings, grants were offered starting from top ranked proposals until funds were exhausted (i.e. "main list"). Proposals that were ranked immediately after, but were not initially offered a grant due to budgetary constraints, may have been later selected for funding. This scenario could happen, for instance, when researchers that were initially included in the "main list" in a given competition ended up refusing the grants or being rejected due to additional eligibility

[11]There is no predefined budget allocation among the panels in the call for proposals. As a general rule the budget will be distributed over the panels based on the proportion of eligible proposals received in each panel. See Appendix Section 1 for further details concerning the panels.

[12]Independent evaluators were selected from a database of interested experts who have registered through the European Commission's Participant Portal or Funding & Tender Opportunities Portal. Experts must profile their expertise, experience, and qualifications for selection. A minimum of three experts, chosen by the European Research Executive Agency (REA) to cover the necessary scientific expertise and maintain balance in geography and gender without conflicts of interest, evaluate each proposal. Initial matches between proposals and experts are based on keywords, with subsequent refinement to ensure optimal expert-proposal alignment.

[13]Examples of specific aspects experts were asked to consider for each criteria are the following: i) Science and Technological Quality: scientific excellence and originality of the project, connection of the project with the hosting institution's expertise, and the quality of the team leading the research; ii) Transfer of Knowledge: project's ability to facilitate knowledge exchange in Europe, and researcher's experience, past research outputs, and capacity for independent thought, leadership, and knowledge dissemination; iii) Researcher: assessment of researcher's personal qualifications, achievements and their alignment with the project; iv) Implementation: feasibility of the project, including the quality of the host institution's infrastructure and international collaborations; v) Impact: project's potential to forge long-term, mutually beneficial collaborations between Europe and third countries, including its contribution to enhancing European scientific excellence and competitiveness, as well as the broader benefits of the researcher's mobility to the European Research Area.

checks. These grants were then reallocated and offered to researchers with lower rankings.

The financial support granted by Individual Fellowships took the form of a grant covering up to 100% of the budget for the entire research stay, according to a system of flat rates for eligible cost categories. These included, for instance, a monthly living allowance, a monthly mobility allowance, monthly training expenses and a monthly contribution to overheads. The grant amount, which on average was around €140,000 annually, was subject to corrections depending, e.g., on the family status of the researcher and the cost of living in the host country[14].

## 2.2 Data

Our analysis is based on data for all applicants to the MSCA Individual Fellowships. Data are sourced from the COmmon Research DAta Warehouse (CORDA), the database curated by the European Commission's Directorate-General for Research and Innovation (DG-RTD), which contains confidential information on all applicants seeking financial support from European FPs. Specifically, our focus is on applications submitted to Individual Fellowships under the Seventh Framework Programme (FP7), spanning the years 2007 to 2013. This decision gives us the advantage to ensure a sufficient observation window post-grant period , allowing for a comprehensive assessment of the fellowship's long-term impact on researchers' outcomes and avoid issues stemming e.g. from publication lag inherent in scientific research. This represents an ideal setting, whereas data from more recent FPs such as Horizon 2020 or Horizon Europe would allow only a very limited post-treatment period to effectively gauge the effects of the program.[15]

Our initial dataset contains a total of 41,766 unique applications to Individual Fellowships, encompassing both grantees and non-grantees. We exclude a small number of proposals that were considered ineligible, or that were withdrawn. This brings our final dataset to 41,269 unique proposals, of which 8,899 were awarded funding. We further discard some applications due to difficulties in finding accurate matches in Scopus (see details in Appendix Section 5), which further re-

[14]For instance, under FP7, an experienced researcher with family obligations, coming from Bucharest to Paris for 2 years with an IEF in 2013 would receive annually a living allowance of €58,500, a mobility allowance of €12,000, training expenses of €9,600, and overheads contribution of €8,400. With a correction coefficient of 116.1%, the grant would amount to around €101,000 euros yearly.

[15]The time-span used in our study allows us to evaluate effects over a ten year period. This is generally longer than what found in existing studies on mobility schemes (see, e.g. Baruffaldi et al., 2020; Non et al., 2022b) and those focusing on MSCA (see, e.g. Fraunhofer et al., 2014; European Commission and Directorate-General for Research and Innovation, 2023; Yildiz et al., 2024) which typically limit their analysis to around 5 years.

duces our sample to 41,024 applicants and 8,837 beneficiaries. These applications spanned across 236 distinct Individual Fellowships competitions held throughout the duration of FP7. Competitions are defined as the unique combination between a given Action (e.g. IEF), the call for proposals, and the scientific panel (e.g. ECO). They identify the specific group of researchers who compete against each other for the same grant they are applying for.

Descriptive statistics on MSCA competitions are reported in Table 1. The average competition receives proposals from 190 researchers, with an average evaluation score of 80 out of 100. Around 21% of these applicants are eventually offered a grant (i.e. "main list"). Eventually, approximately 22% applicants receive a mobility grant from MSCA.

Table 2 reports summary statistics at the applicant-level. On average, applications submitted to the program come more often from male researchers (62% of applicants), with an age of around 34 years old at proposal submission, and who declare to be in possession of a PhD degree (84%). The duration of the average research stay is around 28 months[16]. In a given competition, 20% of all applications come from researchers that have already submitted an application to at least one MSCA Individual Fellowship during FP7. Table 2 also reports mean differences between treated and control researchers, indicating substantial disparity across the two groups.

We enriched applicant data with researchers' affiliations and publication outcomes derived from Elsevier's Scopus (Rose and Kitchin, 2019). Retrieving this information allows us to study the effects of Individual Fellowships on two sets of outcomes, which reflect the expected researcher-level impact of the program (see Figure A1). The first is mobility based on affiliations declared by researchers on their published work. The use of bibliometric data to track mobility flows of researchers is widely adopted in empirical research (see, e.g., Moed et al., 2013; Moed and Halevi, 2014; Robinson-Garcia et al., 2019; Zabetta and Geuna, 2019 ; De Fraja, 2023).[17] The second is connected to the effects of mobility grants on scientific productivity and impact, as well as on collaborations.

We precisely match applicant researchers with author profiles in the Scopus database. Scopus

[16]The duration of research stays vary across MSCA: up to 2 years for IEF and IIF; up to 3 years for IOF and up to 4 years for CIG.

[17]While bibliometric data are an admittedly imperfect source to capture mobility, several studies have documented the accuracy of publication data to track scientists' migration relative to alternative sources such as CVs, ORCID, or survey data (see, e.g. Moed and Halevi, 2014; Kawashima and Tomizawa, 2015; Aman, 2018). In our setting, collecting data on applicants' job positions from their CVs, LinkedIn, or personal webpages (Baruffaldi et al., 2020) would be particularly arduous given the large number of observations in our sample.

provides curated author identifiers, but author disambiguation remains conservative (Baas et al., 2020).[18] To ensure accuracy, we employ a detailed approach that combines highly informative features, based on name similarity, email usage, field match, implied age at first and last publication, text similarity between proposals and publications, search URLs similarity from online web searches (Autor et al., 2020), and location information. We manually processed and matched 8,810 applicants near the acceptance threshold, ensuring the highest precision for this critical subset. We then adopt a machine learning classification approach, using a random forest model (Donner, 2022; Heinisch et al., 2020), trained on the manually labeled data, to extend accurate matching predictions to the full sample. This combination of manual efforts and automated classification results in high precision and recall.[19] Appendix 5 provides a detailed account of the matching procedure and performance.

The average applicant has 11 publications by the time of application submission, with an average journal impact factor (JIF) of around 20. These figures are slightly higher when publications include not only scientific papers and conference proceedings but also other output such as book chapters and reviews (respectively, 12 and 22). The average number of unique co-authors is around 26. As for other variables, bibliometric data confirm that control and treated researchers differ, with the latter featuring higher scientific productivity, quality, a larger number of first-authored works and co-authors network during the pre-competition period (see Table 2).

## 3 Estimation strategy

The primary concern when estimating the effects of MSCA Individual Fellowships is that mobility grants are not randomly assigned. As a result, discerning the causal impact is challenging as both observable and unobservable characteristics of applicants influence not only their ability to secure the fellowship, but also their subsequent academic outcomes. To address this issue, we leverage the grant allocation mechanism described in Section 2.1 and adopt a Fuzzy RDD.

Our data allows us to observe the score and related ranking assigned to all applications submit-

[18] The most common error is that multiple author identifiers are associated with a single scientist, while it is rare that one identifier is linked to more than one scientist. Accordingly, Baas et al. (2020) find, at publication level, 98.1% in precision and recall equal to 94.4%.

[19] The model achieves approximately 99% precision and 95% recall, likely even higher due to additional manual checks.

ted to any given competition, and whether an application is initially offered a grant ("main list") or not. We also observe whether proposals are eventually awarded funding or not. Within a given competition, we identify the threshold score as the one assigned to the last applicant who is offered a grant (i.e. the last ranked applicant in the "main list"), regardless of whether she/he ends up receiving funding. The score of all applicants is normalized relative to this threshold score and represents the so-called running variable in our Fuzzy RDD. Consequently, the running variable of the last applicant offered a grant is set to zero. Applicants with centered scores above this threshold are assigned positive values, while those with scores below receive negative values.

As showed in Figure 1, which plots a set randomly picked competitions, some researchers who are initially offered a grant do not receive it, whereas some researchers who are not initially offered funding end up receiving it. This prefigures a Fuzzy RDD setting with two-sided non-compliance. As a result, the treatment status (i.e., receiving funding) is not strictly determined by being above or below the competition-specific threshold. Hence, there exists a nonlinear relationship between the centered evaluation score and receiving a grant (see Figure 2).

Against this backdrop, we estimate the following set of local polynomial regressions:

$$D_{ic} = \beta_1 Z_{ic} + f(x_{ic}) + X_{ic} + \gamma_c + u_{ic} \tag{1}$$

$$Y_{ic} = \tau \hat{D_{ic}} + f(x_{ic}) + X_{ic} + \gamma_c + \epsilon_{ic} \tag{2}$$

where $D_{ic}$ is a binary treatment indicator that equals 1 if researcher $i$ receives the MSCA grant in competition $c$, and 0 otherwise. $Y_{ic}$ denotes post-competition outcomes, such as mobility or scientific productivity generally measured over 5 or 10 years since the competition takes place. $Z_{ic}$ is a dummy variable indicating whether the application is ranked within the "main list". $x_{ic}$ represents the centered evaluation score, serving as the running variable. $f(x_{ic})$ is a linear polynomial of the running variable on both sides of the threshold, while $X_{ic}$ includes a set of covariates, such as the pre-competition dependent variable to increase precision (Lee and Lemieux, 2010). $\gamma_c$ represents competition fixed effects, which effectively restrict comparison among researchers applying to the same grants[20].

[20]Given that each competition has its distinct threshold score, centering the running variable based on the score of the last researcher offered a grant results in a significant concentration of observations where the running variable's value equals zero. Fort et al. (2022) show that potential bias associated with the estimated RDD coefficient can be

Equations (1) and (2) respectively represent the first-stage and second-stage regressions which are estimated in a two-staged least squares model, where the instrument for treatment $D_{ic}$ is the indicator variable $Z_{ic}$. $\hat{D_{ic}}$ is the predicted value of the treatment $D_{ic}$ from the first stage. $\tau$ is the parameter of interest that recovers the average treatment effect for compliers and, as such, it is not immediately generalizable to the entire population of applicants. All regressions are estimated following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel, and clustering standard errors at the competition-level.

### 3.1 Validity of the research design

In our setting, it is essential to ensure that there are no discontinuities in the density of the running variable around the cutoff, which could indicate manipulation of the assignment variable. This is tested using graphical analysis and the formal statistical density test developed by McCrary (2008). Manipulation density plots and tests are reported in Online Appendix Section 3.1 and reassure on the absence of any discontinuity in the running variable around the threshold.

Another critical assumption in designs like ours is the continuity of pre-determined covariates and potential outcomes at the cutoff. To that end, we report both graphical and statistical analyses to test for potential imbalancing across competition-specific thresholds. Figure 3 reports results for selected variables using MSE-optimal bandwidths which restrict the sample to observations around the threshold. No apparent graphical discontinuity emerges, indicating that researchers on either side of the cut-off show similar features at the time of application. Table 3 takes this further and presents the results of a sharp RDD testing whether applicants on either side of the competition-specific threshold differ across a wide set of observable characteristics. In this case too, we can confirm the absence of any statistically significant discontinuity, thus reassuring on the validity of the design. Additional graphical and statistical evidence on this is reported in Online Appendix Section 3.1.

effectively eliminated through the inclusion of competition fixed effects.

# 4 Results

This section reports our main results. In Section 4.1 we first focus on the impact of grants on researchers' mobility, while Section 4.2 provides evidence concerning publication outcomes in terms of both quantity and quality. Section 4.4 estimates heterogeneous treatment effects and Section 4.5 contains a number of robustness checks.

## 4.1 Mobility

We start by focusing on the effects of grants on researchers' mobility. Evidence on whether mobility grants effectively influence researchers' decisions to relocate abroad is very limited (Baruffaldi et al., 2020), though this represents the primary expected outcome of such programs. Hence, we ask whether grants allow researchers to move to their desired destination countries. In other words, is the grant instrumental in the realization of the mobility or researchers move to their country of choice independently of such financial support?

To empirically assess this, we employ bibliometric data as a basis for constructing a proxy for mobility, based on the affiliations reported in their publications.[21] Specifically, we define a dummy variable which is assigned a value of 1 if a researcher is observed to have published with an affiliation in their intended destination country within 5 years since the competition. Conversely, the variable is assigned a value of 0. This binary variable, thus, serves as an indicator of whether or not the grant has a differential effect on the ability of researchers to perform research activity in their intended destination country.[22]

Before presenting the estimation results, Figure 4 reports RDD plots for post-competition outcomes. Given our setting with two-sided non-compliance, RDD plots serve to potentially visualize *intention-to-treat* (ITT) effects, which may be different from treatment effects. Plots show a jump in the probability of being affiliated to an institution in the host country during the five years after the

[21] Our results are robust to the inclusion of CV-based mobility data drawn from LinkedIn, ORCID, and manually collected curricula. Measuring mobility solely through changes in affiliations reported in scientific publications entails several caveats. First, because mobility is only observable conditional on publishing, it may be captured with a delay or missed entirely, generally resulting in a downward bias. At the same time, CV information can be incomplete or often impossible to find. The fact that our estimates remain consistent when both sources of information are used jointly suggests that they are only marginally affected by the respective limitations. See Appendix Table A8 for details.

[22] Note that this variable is agnostic to whether the scientist was already affiliated with an institution in the intended destination country at the moment of application. Thus, it captures variation that may derive both from changes in affiliations and prolonged permanence in the intended destination country.

competition, suggesting a positive ITT on mobility. To effectively infer treatment effects in terms of mobility, we estimate our baseline Fuzzy RDD. Figure 4 reports our results across a variety of specifications which include different sets of control variables. Point estimates tend to be positive and statistically significant throughout. In more detail, securing a grant increases the likelihood of being affiliated to an institution of the intended destination country by 31-34 percentage points.[23] This is a substantial effect size, given that the mean of the dependent variable for controls around the threshold is 63%.[24] This finding is not trivial as researchers around the threshold tend to be high-quality scientists with arguably good options to access to alternative resources, e.g. national schemes, to realize their desired mobility.[25] It is also possible that applying to a mobility grant enables applicants to establish contacts that facilitate mobility, whether or not they receive the grant (Ayoubi et al., 2019). Above and beyond this, the reported evidence is instrumental to the identification of additional treatment effects. If grants do not exert a differential effect on the realization of the desired mobility across treated and control groups, it could suggest that observing an effect on other outcomes is also less plausible. In sum, these results indicate that grants appear to be decisive in fostering cross-country mobility.

### 4.2 Scientific productivity

Increase in research productivity is often reported in survey-based evidence as being one of the main benefits accrued from MSCA Individual Fellowships.[26]

To study the effects of mobility grants on publication output, we consider the number of scientific articles and conference proceedings. We use the publication count winsorized at 99% to reduce the influence of extreme outliers, whereas in other specifications, we also use the log of publications plus one. Additionally, we employ different time-spans since the year of competition

[23] Using shorter or longer time-span yields very similar results (see A5 and A6).

[24] Note that Table 3 reports the balancing test for pre-competition mobility variable indicating no statistically significant differences across the threshold.

[25] Notably, in more recent years, some European universities provide Marie Curie applicants, who passed the first quality threshold but did not receive the grant, with local funding.

[26] According to Fraunhofer et al. (2014), surveyed recipients of MSCA grants claim that the program increases their research productivity if compared with what declared by a control group of similar researchers based on matching on observables. In particular, researchers that benefited from Individual Fellowships have on average five more publications. These results are in line with most quantitative and qualitative literature studying the effects of mobility on scientists' productivity (Guthrie et al., 2017; European Commission, 2021). Yet, more recent evidence using H2020 data for MSCA and more robust econometric techniques does not confirm these findings (see e.g. p. 1033 in European Commission and Directorate-General for Research and Innovation, 2023) in line with our evidence.

(i.e. 5 and 10 years) to account for potential long-run effects of mobility grants on researchers performance. Before moving to estimation results, Figure 5 presents RDD plots for post-competition outcomes, which again allow to potentially visualize *intention-to-treat* effects. These do not present visible discontinuities, suggesting the absence of ITT effects of mobility grants on productivity. Next, we estimate the Fuzzy RDD and report results in Table 5 for publications outcomes during the 5 years following a competition. The first three columns on the left employ the count of publications as dependent variables, whereas columns 4-6 uses the log of publications plus 1. Point estimates are generally indistinguishable from zero, thus confirming the absence of any statistically significant effects on scientific output. The only exception is column (3) where the coefficient is only marginally statistically significant (p-value = 0.096). Table 6 presents the same estimations but considering a time-span of 10 years after the competition. Results do not show any sensible change.

In sum, we do not detect any clear positive impact of MSCA Individual Fellowships in terms of the amount of publications, irrespective of the time-span examined. Similar results are obtained when considering the total amount of publications (see Online Appendix Section 4.4). Overall, our findings align with the ones obtained by studies focusing on national-level mobility grants such as Baruffaldi et al. (2020) and Non et al. (2022a).

We next examine whether grants induce an increase in scientific quality. Studies such as Jonkers and Cruz-Castro (2013), Franzoni et al. (2014) find that experiencing international mobility is associated with publishing more in higher impact journals. Baruffaldi et al. (2020) show that grants for mobility induce similar outcomes, in line with qualitative evidence on Marie Curie grants (Fraunhofer et al., 2014). To that end, we employ the average Journal Impact Factor (JIF) as dependent variable. This is a widely used measure for scientific quality as it indicates to which extent researchers publish in prominent journals and proxy for the influence an author's work has on the advancement and shaping of research.[27] Results concerning scientific impact are reported in Tables 7 and 8. Contrary to the studies cited above, we do not find any effects in terms of grants facilitating the production of high-impact scientific work, as coefficient are consistently indistinguishable from zero.

[27]One of the advantages of using JIF as proxy for research impact is that other metrics such as citations are not ideal for recent publications, as time elapsed from publication is short and the number of citations can be a noisy indicator of quality. In the Appendix, we also report results using citations and field-weighted citations and obtain similar findings.

### 4.3 Researchers' collaborations

Experiencing a research stay abroad is often considered as an effective strategy in creating and maintaining ties with scientists working in other countries (Netz et al., 2020). This can facilitates direct interactions with distinguished and high-impact researchers. Furthermore, it can broaden researchers' professional networks and provides secondary network connections through the new international contacts (Jonkers and Cruz-Castro, 2013), which in turn could potentially enhance a scientist's innovation and output (Granovetter, 1973; Ito et al., 2024). To test whether grants have such effects, we examine whether researchers increase the number of new co-authors after the competition. Table 9 and 10 report our Fuzzy RDD estimates for 5 and 10 years after the competition, respectively. We do not find any indication that grants help increase the number of new co-authors.

### 4.4 Heterogeneous effects

In this section we explore potential heterogeneous effects of the program. This is relevant for a number of reasons, notably the presence of differential effects across different types of mobility documented by prior studies. There exists evidence suggesting that the type of mobility researchers undertake is conducive to differential treatment effects (Veugelers and Van Bouwel, 2015; Netz et al., 2020). To this end, we leverage the fact that MSCA Individual Fellowships support different types of mobility. As described in Section 2.1, grants essentially support two types of mobility: i) intra-European mobility (i.e. mobility across European countries), or ii) extra-European mobility (i.e. mobility to Europe from Third Countries or vice-versa). In more detail, IEF support intra-European mobility, whereas IOF and IIF support extra-European mobility. To this end, we run a split-sample analysis across IEF vs IOF-IIF and report results in Figure 6. We find that grants supporting mobility within European countries generally do not yield statistically significant estimates. However, estimates for programs supporting extra-European mobility seem to accrue positive results across the various outcomes. Additionally, we also run a split-sample analysis classifying each application into either intra-European or extra-European based on the origin and host countries reported in each individual application. Results reported in Appendix Figure A17 corroborate our findings.[28] In sum, these suggest that grants have larger effects when it comes to promoting extra-European circulation, which is arguably more difficult and suffers from bigger frictions if compared with mobility across European countries.

Furthermore, we investigate whether the quality of the host institution is a source of heterogeneous effects. Prior research suggests that the caliber of the host institution could significantly influence the outcomes of mobility experiences (Shen et al., 2017; Granato et al., 2024), boosting productivity and career progression. By using the 2013 Scimago Institutions Rankings, we perform a split-sample analysis and compare applicants to top 50 research institutions versus the rest. Our analysis, presented in Figure 7, reveals that fellows at higher-ranked institutions tend to exhibit greater gains in research output and collaborative networks compared to those at lower-ranked institutions. This suggests that the resources, mentorship, and collaborative opportunities available at prestigious institutions may amplify the benefits of the fellowship. However, the increased demands and expectations at these institutions could also present challenges, potentially affecting the performance of some researchers.

We also explore whether longer research stays affect outcomes in a differential fashion. The idea is that a longer research stay may allow scientists to reap more benefits (e.g. establish stronger network ties) from their international mobility experience, consistent with what found in Watson et al. (2010). Results reported in Figure 8 provide some support for the conjecture that a more prolonged period abroad leads to larger positive effects for researchers. Indeed, longer periods abroad seem to have slightly more beneficial impacts on both quantity and quality of publications and the number of co-authors.

Additionally, mobility grants may have differential effects depending on other observable characteristics (e.g. researchers' age, gender). We report detailed results in the Appendix, though none of them gives clear indications of heterogeneous treatment effects.

### 4.5 Robustness

In this section we list additional results and robustness checks, though we leave a more detailed discussion of these aspects to the Online Appendix. Appendix Section 3 provides further graph-

[28] In additional analyses, we also investigated to which extent these results are driven by researchers moving either to or from the US. We do not find strong evidence of this, as our results hold when excluding all applications that list US as either origin or destination country (see Figure A18 and A19).

ical and statistical evidence showing no discontinuity in pre-competition covariates and in the density of the running variable thus supporting the validity of the research design. Appendix Section 4.1 explores whether results are sensitive to alternative bandwidth choices around the threshold. Appendix Section 4.2 presents results from specifications using a quadratic adjustment of the running variable. In Appendix Section 4.3 we report robustness tests concerning our results on mobility, whereas in Appendix Section 4.4 we employ alternative publication outcomes and find no substantial changes concerning the impact of grants on scientists' productivity. Appendix Section 4.5 reassures on the absence of bias due to the presence of repeated applicants. Appendix Section 4.6 contains additional results on heterogeneous treatment effects.

## 5 Conclusions

Supporting researchers' mobility is a common policy goal of governments and science funding agencies around the world. Despite the long-standing prominence of such programs in policy-makers agendas, there is a very limited evidence on the effectiveness of these initiatives. This constitutes a serious impediment to our understanding of such programs, and severely limits the efforts aimed at improving them. Against this backdrop, the paper provides causal evidence on the impact of MSCA Individual Fellowships on single researchers. This program, implemented since the early 90s, is arguably among the most prestigious mobility schemes worldwide. Exploiting discontinuities in grant assignment, we employ a Fuzzy RDD approach to infer causal effects. Our results document that grants have indeed a decisive role in promoting mobility. In other words, researchers would not have moved to their intended destination had they not received the grant. This is not trivial as researchers around the threshold tend to be high-quality scientists with arguably good options to access to alternative funding sources, e.g. national schemes, other mobility grants, or local funding, to realize their desired mobility.

Our analysis does not find a positive impact of mobility grants on scientific productivity and collaborations on average. Nonetheless, we leverage the broad nature of MSCA and examine heterogeneous effects across the different types of mobility supported by the program. In particular, we report the presence of heterogeneous effects across grants supporting extra-European vs intra-European mobility. Indeed, grants facilitating the circulation of researchers from Europe to Third

Countries (or vice-versa) tend to produce more beneficial effects over several outcomes, e.g., on publication output. This suggests that grants may be particularly effective when it comes to reducing the higher barriers characterizing intercontinental exchanges, compared to the relatively smoother mobility within Europe. It also indicates that mobility may not be inherently positive for researchers, but that it proves to be particularly beneficial under certain conditions.

These results come with a series of caveats. On average, the results of MSCA Individual Fellowships did not show a clear average positive impact of these grants on outcomes such as publications or collaborations. This evidence, however, should not be taken as evidence against the program. Instead, these findings offer valuable insights into the wider debate on the consequences of mobility for researchers. Although most academic studies tend to support the notion that mobility can enhance researchers' outcomes, establishing causal effects has been traditionally hampered by factors that are difficult to account in empirical settings. Our study, which allows for causal interpretation, suggests that mobility may not necessarily translate into improved academic outcomes for researchers. However, the evidence presented here suggests that mobility can lead to more favorable outcomes under certain conditions. Among other aspects, when interpreting these findings it is important to keep in mind that we only evaluate the direct effects of the policy on individual researchers. While informative, this does not take into account potential spillover effects that may accrue to other researchers (non-participants) or at the level of both host and origin institutions. Indeed, while targeting individual scientists, the program aims at enriching the scientific ecosystem and the cross-fertilization of ideas across disciplines and geographies which can go beyond the individual-level and are hard to account for in our setting. Likewise, our analysis focuses on Individual Fellowships and results are not directly generalizable to other components of MSCA which are not examined in this study.

Our findings must be interpreted with caution regarding their external validity. While our identification approach is able to uncover causal effects, due to treatment being approximately random at the threshold, it does not necessarily apply to the entire pool of applicants. Furthermore, the external validity of our results may be limited by the unique characteristics of MSCA Individual Fellowship, which is known for its competitiveness and prestige. The researchers applying for such grants may not be representative of the wider research community, and the effects observed may not hold for other programs with different selection processes or for less competitive funding environments.

## References


Ackers, L. (2008). Internationalisation, mobility and metrics: A new form of indirect discrimination? *Minerva*, 46(4):411–435.

Aman, V. (2018). Does the scopus author id suffice to track scientific international mobility? a case study based on leibniz laureates. *Scientometrics*, 117(2):705–720.

Antonio-García, M. T., López-Navarro, I., and Rey-Rocha, J. (2014). Determinants of success for biomedical researchers: a perception-based study in a health science research environment. *Scientometrics*, 101:1747–1779.

Autor, D., Dorn, D., Hanson, G. H., Pisano, G., and Shu, P. (2020). Foreign competition and domestic innovation: Evidence from us patents. *American Economic Review: Insights*, 2(3):357–374.

Ayoubi, C., Pezzoni, M., and Visentin, F. (2019). The important thing is not to win, it is to take part: What if scientists benefit from participating in research grant competitions? *Research Policy*, 48(1):84–97.

Baas, J., Schotten, M., Plume, A., Côté, G., and Karimi, R. (2020). Scopus as a curated, high-quality bibliometric data source for academic research in quantitative science studies. *Quantitative Science Studies*, 1(1):377–386.

Barnett, A., Blakely, T., Liu, M., Garland, L., and Clarke, P. (2024). The impact of winning funding on researcher productivity, results from a randomized trial. *Science and Public Policy*, page scae045.

Baruffaldi, S. H., Marino, M., and Visentin, F. (2020). Money to move: The effect on researchers of an international mobility grant. *Research Policy*, 49(8):104077.

Børing, P., Flanagan, K., Gagliardi, D., Kaloudis, A., and Karakasidou, A. (2015). International mobility: Findings from a survey of researchers in the eu. *Science and Public Policy*, 42(6):811–826.

Calonico, S., Cattaneo, M. D., Farrell, M. H., and Titiunik, R. (2017). rdrobust: Software for regression-discontinuity designs. *The Stata Journal*, 17(2):372–404.

Cruz-Castro, L. and Sanz-Menéndez, L. (2010). Mobility versus job stability: Assessing tenure and productivity outcomes. *Research policy*, 39(1):27–38.

De Fraja, G. (2023). *International Mobility of Academics: Theory and Evidence*. Centre for Economic Policy Research.

Donner, P. (2022). Algorithmic identification of ph. d. thesis-related publications: a proof-of-concept study. *Scientometrics*, 127(10):5863–5877.

Dubois, P., Rochet, J.-C., and Schlenker, J.-M. (2014). Productivity and mobility in academic research: Evidence from mathematicians. *Scientometrics*, 98:1669–1701.

European Commission (2021). *MORE4–Support data collection and analysis concerning mobility patterns and career paths of researchers. Survey on researchers outside Europe*. Publications Office.

European Commission and Directorate-General for Research and Innovation (2023). *Evaluation study of the European framework programmes for research and innovation for excellent science – Horizon 2020 – Annexes*. Publications Office of the European Union.

Fernandez-Zubieta, A., Geuna, A., and Lawson, C. (2015). What do we know of the mobility of research scientists and impact on scientific production. In *Global mobility of research scientists*, pages 1–33. Elsevier.

Fort, M., Ichino, A., Rettore, E., and Zanella, G. (2022). Multi-cutoff rd designs with observations located at each cutoff: problems and solutions.

Franzoni, C., Scellato, G., and Stephan, P. (2014). The mover's advantage: The superior performance of migrant scientists. *Economics Letters*, 122(1):89–93.

Franzoni, C., Scellato, G., and Stephan, P. (2015). International mobility of research scientists: Lessons from globsci. In *Global mobility of research scientists*, pages 35–65. Elsevier.

Fraunhofer, I., Associati, E., GfK, E., et al. (2014). Marie curie researchers and their long-term career development: a comparative study.

Ghirelli, C., Havari, E., Meroni, E. C., and Verzillo, S. (2023). The long-term causal effects of winning an erc grant. *Banco de Espana Working Paper No. 2213*.

Granato, S., Havari, E., Mazzarella, G., and Schnepf, S. V. (2024). Study abroad programmes and student outcomes: Evidence from erasmus. *Economics of Education Review*, 99:102510.

Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology*, 78(6):1360–1380.

Guthrie, S., Lichten, C., Harte, E., Parks, S., and Wooding, S. (2017). International mobility of researchers. *RAND EUROPE*.

Heinisch, D. P., Koenig, J., and Otto, A. (2020). A supervised machine learning approach to trace doctorate recipients' employment trajectories. *Quantitative Science Studies*, 1(1):94–116.

Hunter, R. S., Oswald, A. J., and Charlton, B. G. (2009). The elite brain drain. *The Economic Journal*, 119(538):F231–F251.

IDEA Consult et al. (2013). Support for continued data collection and analysis concerning mobility patterns and career paths of researchers. *Final report MORE 2, Prepared for: European Commission Research Directorate-General Directorate B – European Research Area.*

Ito, R., Chavarro, D., Ciarli, T., Cowan, R., and Visentin, F. (2024). Connecting the dots: The role of internationally mobile scientists in linking nonmobile with foreign scientists.

Jacob, B. A. and Lefgren, L. (2011). The impact of research grant funding on scientific productivity. *Journal of public economics*, 95(9-10):1168–1177.

Jonkers, K. and Cruz-Castro, L. (2013). Research upon return: The effect of international mobility on scientific ties, production and impact. *Research Policy*, 42(8):1366–1377.

Kawashima, H. and Tomizawa, H. (2015). Accuracy evaluation of scopus author id based on the largest funding database in japan. *Scientometrics*, 103(3):1061–1071.

Langin, K. (2024). Fewer u.s. scientists are pursuing postdoc positions, new data show. *Science*.

Lawson, C. and Shibayama, S. (2015). International research visits and careers: An analysis of bioscience academics in japan. *Science and Public Policy*, 42(5):690–710.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, 48(2):281–355.

Mayer, T. and Zignago, S. (2011). Notes on cepii's distances measures: The geodist database.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of econometrics*, 142(2):698–714.

Moed, H. F., Aisati, M., and Plume, A. (2013). Studying scientific migration in scopus. *Scientometrics*, 94:929–942.

Moed, H. F. and Halevi, G. (2014). A bibliometric approach to tracking international scientific migration. *Scientometrics*, 101:1987–2001.

Netz, N., Hampel, S., and Aman, V. (2020). What effects does international mobility have on scientists' careers? a systematic review. *Research evaluation*, 29(3):327–351.

Non, M., van Honk, J., van Houten, V., van der Weijden, I., and van Leeuwen, T. (2022a). Getting off to a flying start? the effects of an early-career international mobility grant on scientific performance. Technical report, CPB Netherlands Bureau for Economic Policy Analysis.

Non, M., van Honk, J., van Houten, V., van der Weijden, I., and van Leeuwen, T. (2022b). Getting off to a flying start? the effects of an early-career international mobility grant on scientific performance. Technical report, CPB Netherlands Bureau for Economic Policy Analysis.

Payumo, J. G., Lan, G., and Arasu, P. (2018). Researcher mobility at a us research-intensive university: Implications for research and internationalization strategies. *Research Evaluation*, 27(1):28–35.

Robinson-Garcia, N., Sugimoto, C. R., Murray, D., Yegros-Yegros, A., Larivière, V., and Costas, R. (2019). The many faces of mobility: Using bibliometric data to measure the movement of scientists. *Journal of informetrics*, 13(1):50–63.

Rose, M. E. and Kitchin, J. R. (2019). pybliometrics: Scriptable bibliometrics using a python interface to scopus. *SoftwareX*, 10:100263.

Scellato, G., Franzoni, C., and Stephan, P. (2015). Migrant scientists and international networks. *Research Policy*, 44(1):108–120.

Shen, W.-Q., Liu, D., and Chen, H. (2017). Chinese ph. d. students on exchange in european union countries: Experiences and benefits. *European Journal of Higher Education*, 7(3):322–335.

Shi, D., Liu, W., and Wang, Y. (2023). Has china's young thousand talents program been successful in recruiting and nurturing top-caliber scientists? *Science*, 379(6627):62–65.

Sugimoto, C. R., Robinson-García, N., Murray, D. S., Yegros-Yegros, A., Costas, R., and Larivière, V. (2017). Scientists have most impact when they're free to move. *Nature*, 550(7674):29–31.

Veugelers, R. and Van Bouwel, L. (2015). The effects of international mobility on european researchers: Comparing intra-eu and us mobility. *Research in Higher Education*, 56:360–377.

Wang, Y., Jones, B. F., and Wang, D. (2019). Early-career setback and future career impact. *Nature communications*, 10(1):4331.

Watson, J., Ludden, V., Gutheil, M., Harrap, K., Ackers, L., and Van de Sande, D. (2010). Ex-post impact assessment study concerning the 'marie curie actions' under the sixth framework programme. *FRAMEWORK CONTRACT ON EVALUATION AND EVALUATION-RELATED SERVICES (Contract Notice 2006/S/64-066221)*.

Woolston, C. (2022). Lab leaders wrestle with paucity of postdocs. *Nature*.

Yildiz, Y., Bohorquez, D. C., Visentin, F., and Ciarli, T. (2024). Expanding horizons: The impact of postdoctoral mobility grants on research diversification.

Zabetta, M. C. and Geuna, A. (2019). International postdoctoral mobility and career effect in italian academia–1986-2015. In *17th International Conference on Scientometrics and Informetrics, ISSI 2019-Proceedings*, volume 2, pages 2448–2459. International Society for Scientometrics and Informetrics.

# Figures and Tables

Table 1: Descriptive statistics on Marie Curie competitions

| | Mean | SD | Min | Median | Max | N |
|---|---|---|---|---|---|---|
| Nr. applicants | 192.11 | 218.87 | 1 | 116 | 1411 | 41024 |
| Evaluation score | 79.90 | 11.17 | 0 | 82 | 100 | 41024 |
| Main list (d) | 0.21 | 0.41 | 0 | 0 | 1 | 41024 |
| Treated (d) | 0.22 | 0.41 | 0 | 0 | 1 | 41024 |

Notes: summary statistics computed for applicants to MSCA Individual Fellowships during FP7 (2007-2013).

Table 2: Descriptive statistics on applicants to MSCA

| | (1) All | (2) *U* | (3) *T* | (4) Diff | (5) *p-value* | (6) N *U* | (7) N *T* |
|---|---|---|---|---|---|---|---|
| Female | 0.38 | 0.39 | 0.36 | 0.03 | 0.00 | 32187 | 8837 |
| Age | 34.35 | 34.43 | 34.04 | 0.39 | 0.00 | 32187 | 8837 |
| Professor | 0.05 | 0.05 | 0.05 | -0.01 | 0.01 | 32165 | 8837 |
| Doctor | 0.84 | 0.83 | 0.87 | -0.04 | 0.00 | 32165 | 8837 |
| Applied before | 0.20 | 0.19 | 0.21 | -0.01 | 0.01 | 32187 | 8837 |
| European national | 0.66 | 0.66 | 0.68 | -0.02 | 0.00 | 32187 | 8837 |
| EU27 national | 0.61 | 0.60 | 0.64 | -0.04 | 0.00 | 32187 | 8837 |
| European resident | 0.65 | 0.66 | 0.61 | 0.05 | 0.00 | 32187 | 8837 |
| EU27 resident | 0.57 | 0.58 | 0.54 | 0.04 | 0.00 | 32187 | 8837 |
| Same nationality as host inst. | 0.18 | 0.16 | 0.26 | -0.10 | 0.00 | 32042 | 8811 |
| Host is Higher ed. institution | 0.74 | 0.74 | 0.74 | 0.00 | 0.69 | 32187 | 8837 |
| Host is Research organization | 0.22 | 0.22 | 0.23 | -0.01 | 0.04 | 32187 | 8837 |
| Host is Other organization | 0.04 | 0.04 | 0.03 | 0.01 | 0.00 | 32187 | 8837 |
| Proposal duration | 28.42 | 27.67 | 31.17 | -3.49 | 0.00 | 32187 | 8837 |
| Host Scimago Ranking | 632.10 | 652.75 | 559.96 | 92.79 | 0.00 | 23329 | 6680 |
| Host country GDP per capita | 37516.80 | 37517.46 | 37514.39 | 3.07 | 0.98 | 32026 | 8810 |
| Distance | 3287.47 | 3334.49 | 3116.51 | 217.99 | 0.00 | 32026 | 8810 |
| Aff. in host country (pre) | 0.26 | 0.23 | 0.37 | -0.14 | 0.00 | 32152 | 8833 |
| Pubs all (pre) | 12.04 | 11.16 | 15.22 | -4.06 | 0.00 | 32152 | 8833 |
| Average JIF all (pre) | 21.89 | 18.64 | 33.72 | -15.08 | 0.00 | 32152 | 8833 |
| Pubs 1st author all (pre) | 5.32 | 4.92 | 6.77 | -1.85 | 0.00 | 32152 | 8833 |
| Pubs last author all (pre) | 2.36 | 2.18 | 3.00 | -0.82 | 0.00 | 32152 | 8833 |
| Pubs (pre) | 11.06 | 10.29 | 13.88 | -3.59 | 0.00 | 32152 | 8833 |
| Average JIF (pre) | 20.04 | 17.19 | 30.44 | -13.26 | 0.00 | 32152 | 8833 |
| Pubs 1st author (pre) | 4.82 | 4.48 | 6.06 | -1.58 | 0.00 | 32152 | 8833 |
| Pubs last author (pre) | 2.06 | 1.92 | 2.60 | -0.68 | 0.00 | 32152 | 8833 |
| Co-authors (pre) | 26.38 | 24.53 | 33.13 | -8.60 | 0.00 | 32152 | 8833 |

Notes: summary statistics computed for applicants to MSCA Individual Fellowships during FP7 (2007-2013). Columns *T* and *U* refer to treated and untreated researchers, respectively. All variables are measured at the time (year) of application submission. Publications variables refer to the period preceding a given competition. Scimago Institution Rankings refer to 2013, GDP per capita (USD PPP) figures are sourced from the World Bank and refer to 2010. Distance in km from host and origin countries is sourced from GeoDist (Mayer and Zignago, 2011)

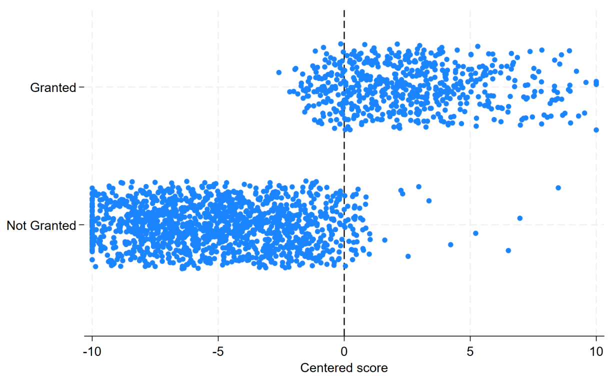



Figure 1: Treatment compliance

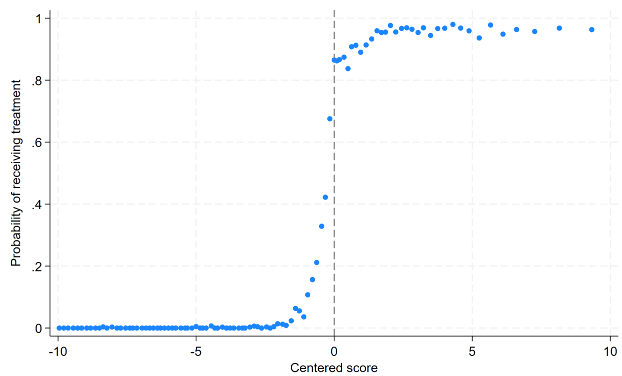
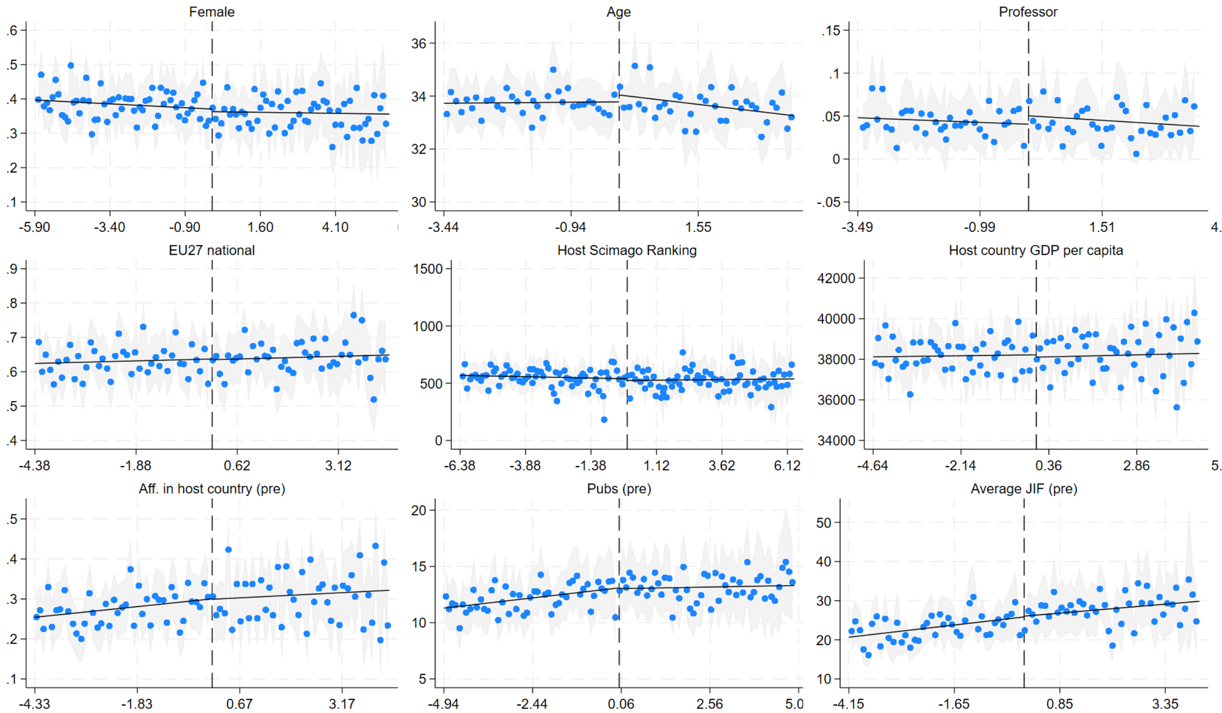



Figure 2: Probability of grant assignment

Notes: Figure 1 plots 15 randomly selected competitions in our sample showing two-sided non-compliance around the threshold. Applicants on the right side of the threshold are mainlisted though not all of them end up receiving the grant. Applicants on the left side are not mainlisted but some of them end up receiving the treatment. Figure 2 reports a binscatter plot with the probability of receiving a grant around the threshold for our entire sample of applicants. In both figures the x-axis reports competition-specific evaluation scores centered in zero.

Figure 3: Smoothness of pre-determined covariates close to the threshold



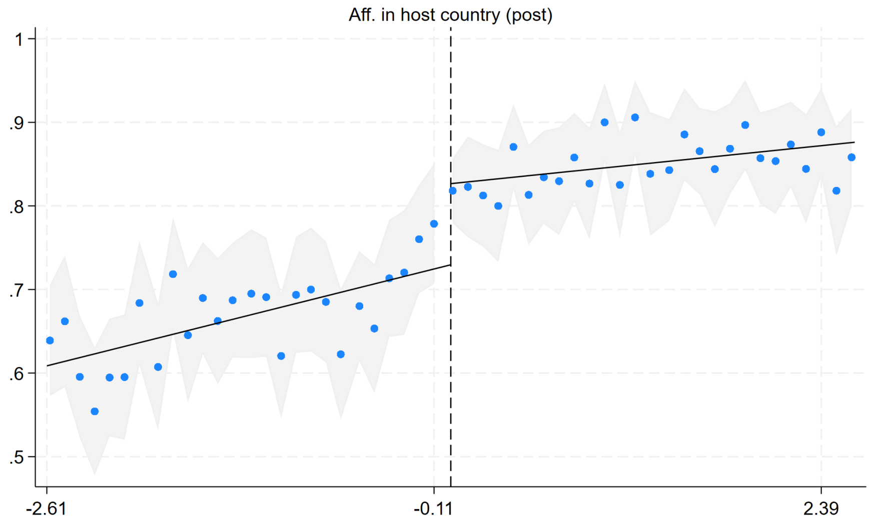

Notes: plots show smoothness around the threshold for a number of pre-determined variables. MSE-optimal bandwidths computed following Calonico et al. (2017). Fitted lines are polynomials of order one. Shaded area represents 95% confidence intervals.

Table 3: Balancing tests for pre-determined covariates

| | Diff. | P-value | N left | N right | N |
|---|---|---|---|---|---|
| Female | -0.011 | 0.580 | 7228 | 5885 | 41024 |
| Age | 0.296 | 0.135 | 4918 | 4641 | 41024 |
| Professor | 0.004 | 0.430 | 7226 | 5884 | 41002 |
| Doctor | 0.001 | 0.910 | 7939 | 6235 | 41002 |
| Applied before | -0.003 | 0.918 | 8318 | 6374 | 41024 |
| European National | 0.006 | 0.782 | 7556 | 6070 | 41024 |
| EU27 National | 0.009 | 0.525 | 8522 | 6460 | 41024 |
| European resident | 0.009 | 0.483 | 7756 | 6179 | 41024 |
| EU27 resident | 0.017 | 0.179 | 7941 | 6236 | 41024 |
| Same nationality as host inst. | 0.018 | 0.132 | 4741 | 4489 | 40853 |
| Host is Higher ed institution | 0.015 | 0.381 | 7228 | 5885 | 41024 |
| Host is Research organization | -0.021 | 0.142 | 9032 | 6654 | 41024 |
| Host is other organization | 0.006 | 0.212 | 5800 | 5147 | 41024 |
| Proposal duration | 0.059 | 0.513 | 5800 | 5147 | 41024 |
| Host Scimago Institution Ranking | -37.076 | 0.119 | 4589 | 3987 | 30009 |
| Host country GDP per capita | -249.273 | 0.322 | 5610 | 5045 | 40836 |
| Distance | 52.338 | 0.478 | 8286 | 6354 | 40836 |
| Aff. in host country (pre) | -0.013 | 0.249 | 6342 | 5430 | 40985 |
| Pubs all (pre) | -0.300 | 0.592 | 8680 | 6514 | 40985 |
| Average JIF all (pre) | -0.247 | 0.798 | 7401 | 5990 | 40985 |
| Pubs 1st author all (pre) | -0.164 | 0.500 | 7937 | 6232 | 40985 |
| Pubs last author all (pre) | -0.260 | 0.414 | 6861 | 5689 | 40985 |
| Pubs(pre) | -0.263 | 0.610 | 8680 | 6514 | 40985 |
| Average JIF (pre) | -0.318 | 0.736 | 7553 | 6066 | 40985 |
| Pubs 1st author (pre) | -0.113 | 0.586 | 7752 | 6175 | 40985 |
| Pubs last author (pre) | -0.209 | 0.454 | 6861 | 5689 | 40985 |
| Co-authors (pre) | 0.054 | 0.911 | 8314 | 6370 | 40985 |

Notes: the table reports balancing tests for pre-determined covariates around the threshold. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level.

Figure 4: ITT plot for mobility



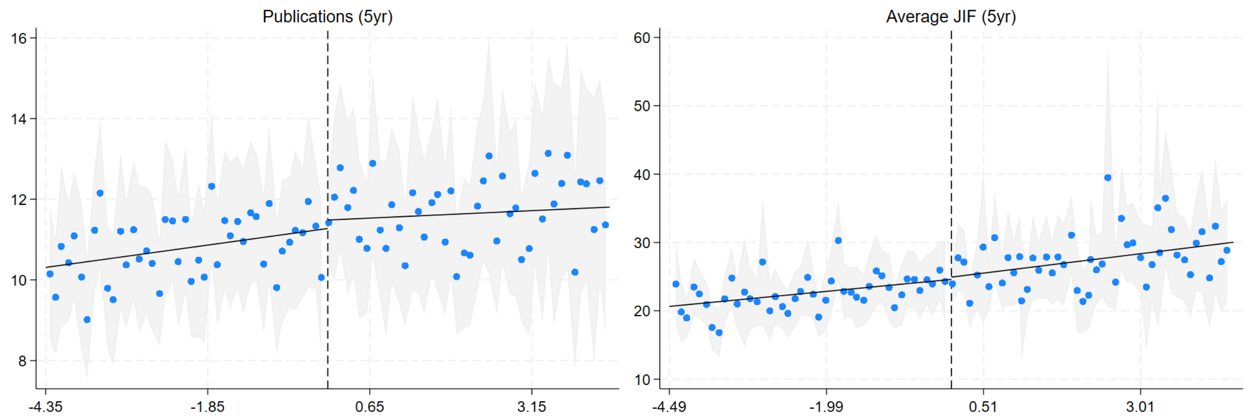

Notes: plot reports *intention-to-treat* (ITT) plots for the probability of being affiliated with an institution in the country of choice within five years since the competition. MSE-optimal bandwidths computed following Calonico et al. (2017). Fitted lines are polynomials of order one. Shaded area represents 95% confidence intervals.

Table 4: Fuzzy RDD estimates on mobility (5 years)

| | Mobility | Mobility | Mobility |
|---|---|---|---|
| RD Estimate | 0.312*** | 0.327*** | 0.340*** |
| | [0.066] | [0.065] | [0.064] |
| Mean dep var | 0.63 | 0.63 | 0.63 |
| Pol. order | 1 | 1 | 1 |
| BW | 2.1 | 2.2 | 2.2 |
| N (left) | 3385 | 3385 | 3385 |
| N (right) | 3470 | 3470 | 3470 |
| N | 40985 | 40985 | 40985 |
| p-value | 0.000 | 0.000 | 0.000 |
| Robust p-value | 0.000 | 0.000 | 0.000 |
| F-stat 1st stage | 47.575 | 48.011 | 50.364 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Figure 5: ITT plots for scientific productivity and impact




Notes: plots reports *intention-to-treat* (ITT) plots for publication quantity and quality within five years since the competition. MSE-optimal bandwidths computed following Calonico et al. (2017). Fitted lines are polynomials of order one. Shaded area represents 95% confidence intervals.

Table 5: Fuzzy RDD estimates on scientific productivity (5 years)

| | Pubs | Pubs | Pubs | Pubs (log) | Pubs (log) | Pubs (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 2.123 | 2.509 | 3.606* | 0.240 | 0.095 | 0.196 |
| | [1.590] | [2.072] | [2.342] | [0.318] | [0.229] | [0.232] |
| Mean dep var | 10.78 | 10.87 | 10.76 | 2.07 | 2.07 | 2.07 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 2.3 | 1.8 | 1.7 | 1.5 | 1.5 | 1.5 |
| N (left) | 3741 | 2899 | 2725 | 2243 | 2397 | 2397 |
| N (right) | 3758 | 3060 | 2908 | 2497 | 2628 | 2628 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.182 | 0.226 | 0.124 | 0.451 | 0.680 | 0.399 |
| Robust p-value | 0.159 | 0.188 | 0.096 | 0.395 | 0.652 | 0.349 |
| F-stat 1st stage | 59.410 | 28.407 | 22.358 | 10.962 | 13.338 | 12.993 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table 6: Fuzzy RDD estimates on scientific productivity (10 years)

| | Pubs | Pubs | Pubs | Pubs (log) | Pubs (log) | Pubs (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 5.979 | 4.194 | 6.830 | 0.397 | 0.235 | 0.370 |
| | [5.947] | [4.506] | [6.048] | [0.418] | [0.301] | [0.294] |
| Mean dep var | 21.86 | 22.03 | 21.73 | 2.64 | 2.64 | 2.64 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.7 | 1.8 | 1.6 | 1.4 | 1.5 | 1.5 |
| N (left) | 2725 | 2899 | 2397 | 2243 | 2243 | 2243 |
| N (right) | 2908 | 3060 | 2628 | 2497 | 2497 | 2497 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.315 | 0.352 | 0.259 | 0.341 | 0.435 | 0.208 |
| Robust p-value | 0.275 | 0.313 | 0.216 | 0.275 | 0.379 | 0.160 |
| F-stat 1st stage | 21.148 | 27.161 | 15.048 | 8.788 | 11.010 | 11.304 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table 7: Fuzzy RDD estimates on scientific impact (5 years)

| | Avg JIF | Avg JIF | Avg JIF | Avg JIF (log) | Avg JIF (log) | Avg JIF (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 3.145 | 4.637 | 10.503 | 0.130 | -0.061 | 0.097 |
| | [7.758] | [6.458] | [9.482] | [0.493] | [0.308] | [0.327] |
| Mean dep var | 22.84 | 22.84 | 22.82 | 2.58 | 2.56 | 2.56 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.6 | 1.7 | 1.5 | 1.4 | 1.5 | 1.4 |
| N (left) | 2584 | 2725 | 2397 | 2064 | 2243 | 2243 |
| N (right) | 2799 | 2908 | 2628 | 2357 | 2497 | 2497 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.685 | 0.473 | 0.268 | 0.792 | 0.843 | 0.767 |
| Robust p-value | 0.648 | 0.421 | 0.213 | 0.753 | 0.812 | 0.748 |
| F-stat 1st stage | 17.732 | 21.564 | 11.792 | 7.336 | 11.086 | 9.598 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table 8: Fuzzy RDD estimates on scientific impact (10 years)

| | Avg JIF | Avg JIF | Avg JIF | Avg JIF (log) | Avg JIF (log) | Avg JIF (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 5.919 | 8.604 | 16.367 | 0.415 | 0.184 | 0.384 |
| | [14.170] | [11.824] | [17.413] | [0.558] | [0.358] | [0.365] |
| Mean dep var | 44.35 | 45.26 | 44.30 | 3.16 | 3.15 | 3.15 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.7 | 1.8 | 1.6 | 1.4 | 1.5 | 1.4 |
| N (left) | 2725 | 2899 | 2397 | 2064 | 2243 | 2243 |
| N (right) | 2908 | 3060 | 2628 | 2357 | 2497 | 2497 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.676 | 0.467 | 0.347 | 0.457 | 0.607 | 0.293 |
| Robust p-value | 0.654 | 0.433 | 0.301 | 0.391 | 0.564 | 0.239 |
| F-stat 1st stage | 22.090 | 27.366 | 13.992 | 7.257 | 10.258 | 9.722 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table 9: Fuzzy RDD estimates on co-authors (5 years)

| | Co-authors | Co-authors | Co-authors | Co-authors (log) | Co-authors (log) | Co-authors (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 0.985 | -1.021 | -1.482 | 0.250 | -0.124 | 0.000 |
| | [11.141] | [7.923] | [14.200] | [0.524] | [0.361] | [0.359] |
| Mean dep var | 33.43 | 34.35 | 33.55 | 2.83 | 2.83 | 2.83 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.8 | 1.9 | 1.5 | 1.4 | 1.5 | 1.5 |
| N (left) | 2725 | 3062 | 2397 | 2243 | 2243 | 2243 |
| N (right) | 2908 | 3186 | 2628 | 2497 | 2497 | 2497 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.930 | 0.897 | 0.917 | 0.632 | 0.730 | 0.999 |
| Robust p-value | 0.912 | 0.888 | 0.914 | 0.564 | 0.709 | 0.993 |
| F-stat 1st stage | 24.916 | 33.285 | 12.027 | 8.198 | 11.236 | 10.989 |

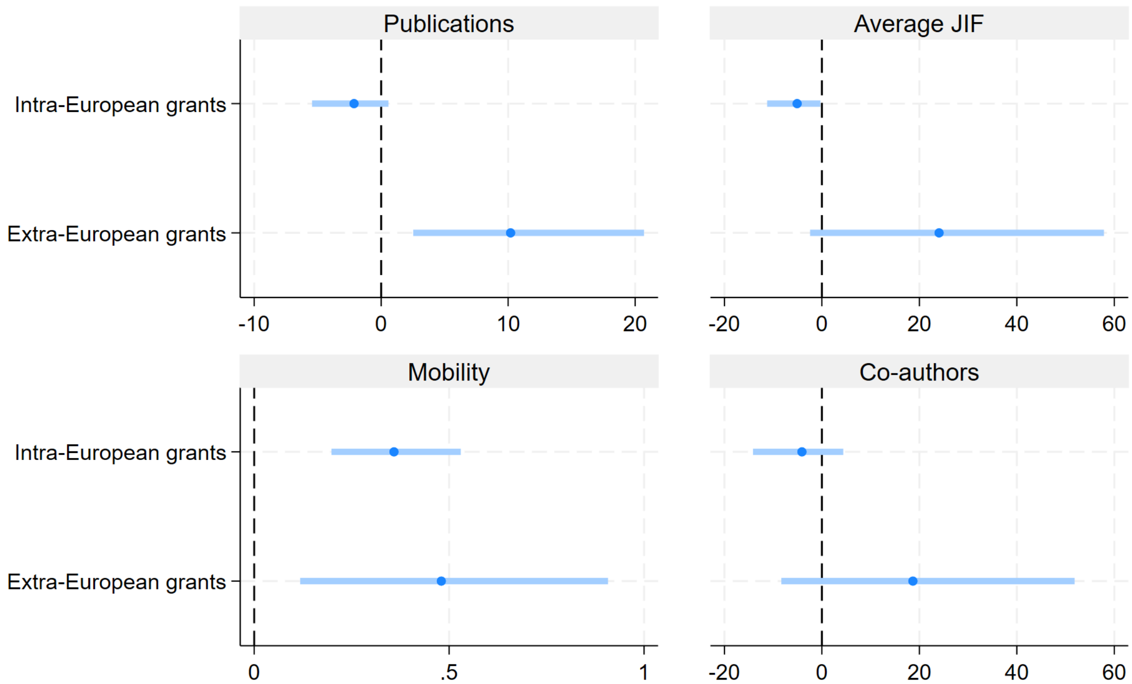
Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table 10: Fuzzy RDD estimates on co-authors (10 years)

| | Co-authors | Co-authors | Co-authors | Co-authors (log) | Co-authors (log) | Co-authors (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 13.102 | 10.199 | 8.003 | 0.432 | 0.051 | 0.214 |
| | [21.199] | [13.549] | [26.294] | [0.551] | [0.400] | [0.381] |
| Mean dep var | 82.08 | 82.11 | 80.05 | 3.61 | 3.61 | 3.61 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.9 | 2.2 | 1.6 | 1.4 | 1.5 | 1.5 |
| N (left) | 2899 | 3575 | 2584 | 2243 | 2243 | 2243 |
| N (right) | 3060 | 3636 | 2799 | 2497 | 2497 | 2497 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.537 | 0.452 | 0.761 | 0.433 | 0.899 | 0.575 |
| Robust p-value | 0.489 | 0.401 | 0.723 | 0.352 | 0.866 | 0.512 |
| F-stat 1st stage | 31.355 | 53.373 | 15.811 | 8.785 | 10.845 | 11.017 |

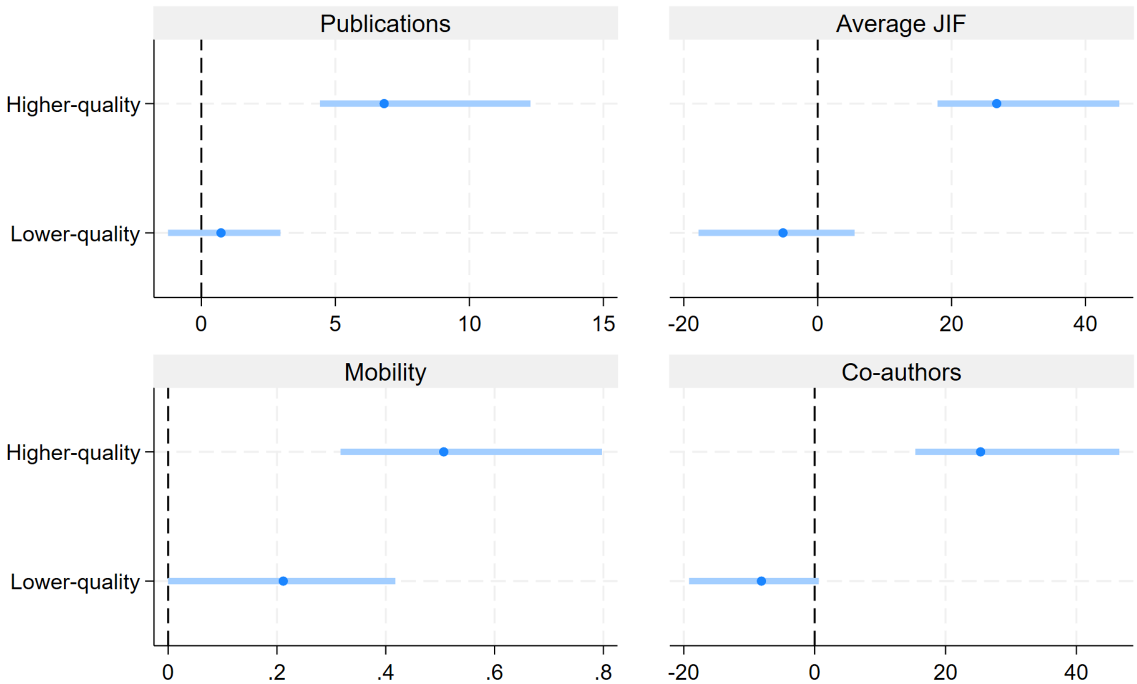
Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Figure 6: Heterogeneous effects across type of mobility grants



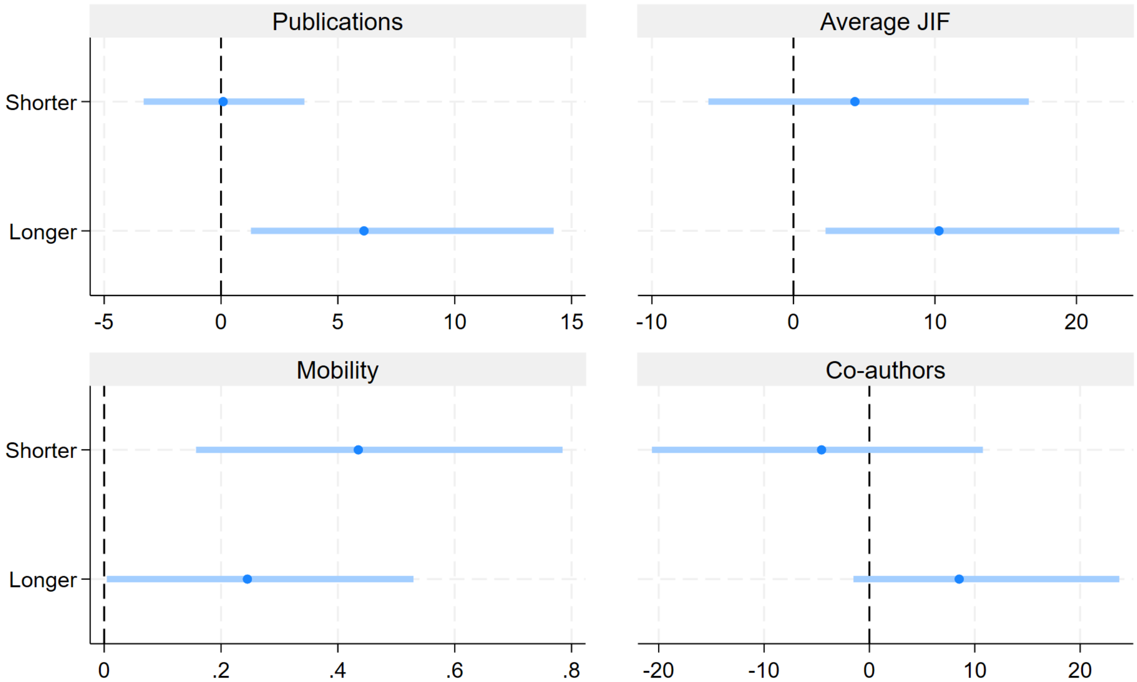

Notes: plots reports Fuzzy RDD estimates by splitting sample across types of mobility grants: intra-European (i.e. IEF) and extra-European mobility grants (i.e. IIF, IOF). Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure 7: Heterogeneous effects across quality of host institutions




Notes: plots reports Fuzzy RDD estimates by splitting sample across research institutions ranked within the first 50 positions of the 2013 Scimago Institutions Rankings (higher-quality) versus the rest (lower quality). Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure 8: Heterogeneous effects across duration of research stay




Notes: plots reports Fuzzy RDD estimates by splitting sample across above and below median duration of research stay abroad. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

# The impact of mobility grants on researchers: Online Appendices

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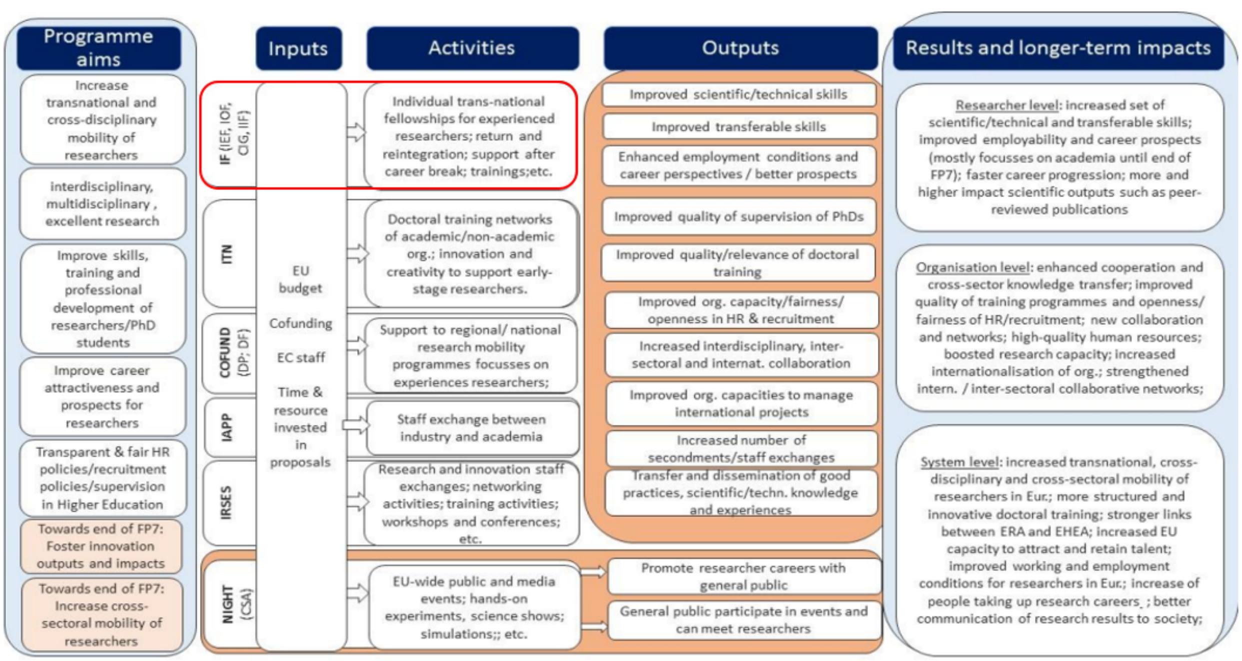
July 9, 2025

## Contents

# 1 MSCA Individual Fellowships

This section provides an overview of the MSCA Individual Fellowships which are object of our analysis. Over the last two decades, the MSCA program has provided approximately 145,000 researchers with the resources necessary to advance their research pursuits and career trajectories both within Europe and globally. The facilitation of researcher mobility stands as a central tenet of the European Research Area (ERA) and is a critical component not only of the EU's research policy framework but also of its broader strategy to stimulate growth and enhance competitiveness. Financial support for mobility initiatives has been a feature of the Framework Programme (FP) since its early iterations in the 1990s. Commencing with the Third Framework Programme (FP3), these initiatives have been consolidated under the aegis of the Marie Curie Actions (MCA) during FP4. Later re-branded as Marie Skłodowska-Curie Actions within the Horizon 2020 framework, its funding trajectory has observed a marked escalation, with budgetary provisions expanding from 260 million ECU during FP4 to 4.75 billion EUR throughout FP7.

Figure A1: Intervention logic of Marie Curie Actions during FP7




Notes: The red part concerns the part of the program we examine, namely, the MSCA Individual Fellowships. Source: Franke et al. (2017).

Concurrently, the array of fellowships on offer has broadened substantially, evolving to encompass a variety of targets (such as those aimed at early-stage researchers), delivery mechanisms (including those driven by host institutions), and specific objectives (such as fellowships focusing on reintegration or industry exchanges). Figure A1 elucidates the intervention logic of Marie Curie Actions within the context of FP7, with a particular emphasis on Individual Fellowships, which are highlighted in red within the figure. In terms of the expected impact at the researcher-level, grants are supposed to improve scientific skills, career prospects, collaboration networks, and both the quantity and quality of scientific outputs.

**Research areas.** Marie Curie Actions are characterized by their bottom-up approach, allowing applicants to select their research topics without restriction. Unlike challenge or topic-specific calls, researchers have the flexibility to propose projects in any area of scientific inquiry. The allocation of funds across various research disciplines is commensurate with the volume of proposals received in each scientific domain, ensuring a proportional distribution of the budget. There are eight panels to which applicants can submit their proposal. These are:

1. **Chemistry (CHE)**: This panel covers research in all areas of chemistry, including chemical biology, nuclear chemistry, materials chemistry, and theoretical and computational chemistry.

2. **Economic Sciences (ECO)**: For research focused on economics, econometrics, finance, and other related disciplines.

3. **Information Science and Engineering (ENG)**: This panel encompasses research in computer science and informatics, systems and communication engineering, electrical engineering, electronic engineering, and information systems.

4. **Environmental and Geosciences (ENV)**: This panel includes research related to environmental science, earth system science, environmental biology, and agricultural, animal and food science.

5. **Life Sciences (LIF)**: Covering all areas of the biological sciences, including molecular biology, biochemistry, biotechnology, genetics, health sciences, and ecology.

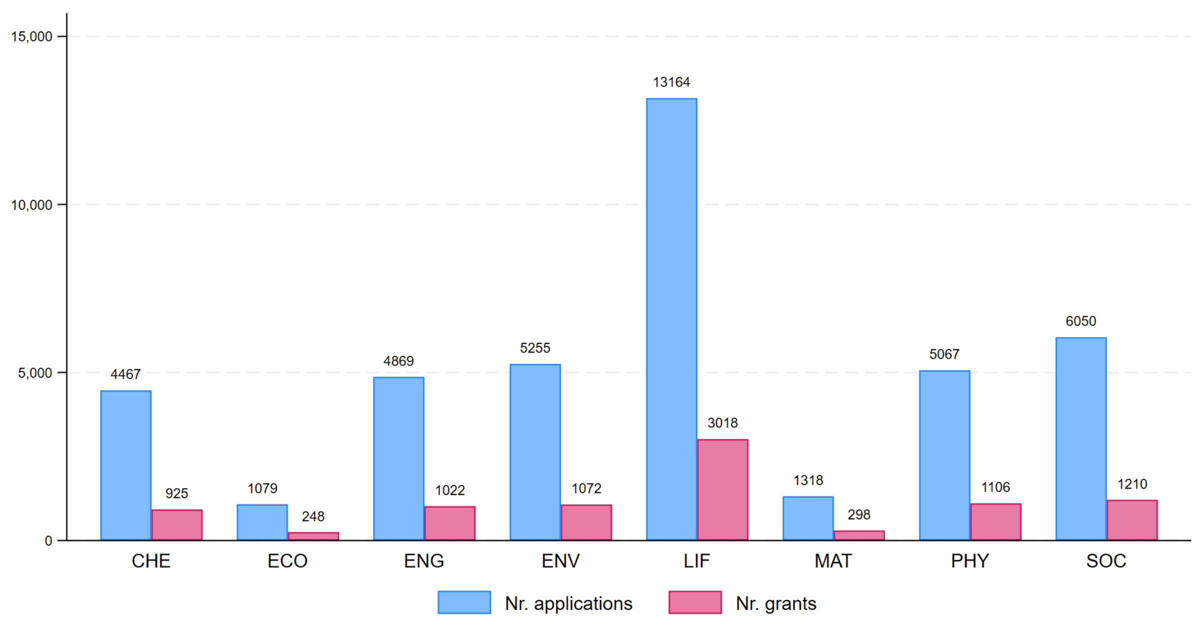
6. **Mathematics (MAT)**: For research in pure and applied mathematics, statistics, and mathematical foundations of scientific computing.

7. **Physics (PHY)**: This panel covers research in the field of physics, including condensed matter physics, particle physics, astrophysics, plasma physics, and optics.

8. **Social Sciences and Humanities (SOC)**: This panel is dedicated to research in the social sciences and humanities, including sociology, psychology, political science, law, cultural studies, and history.

Figure A2 reports the number of submitted applications and awarded grants across all eight panels. The bulk of applications to Individual Fellowships belong to life sciences (LIF), which account for around 32% of all submitted proposals. This is followed by social sciences and humanities (SOC), physics (PHY), environmental sciences (ENV), engineering (ENG), chemistry (CHE), mathematics (MAT) and economics (ECO).

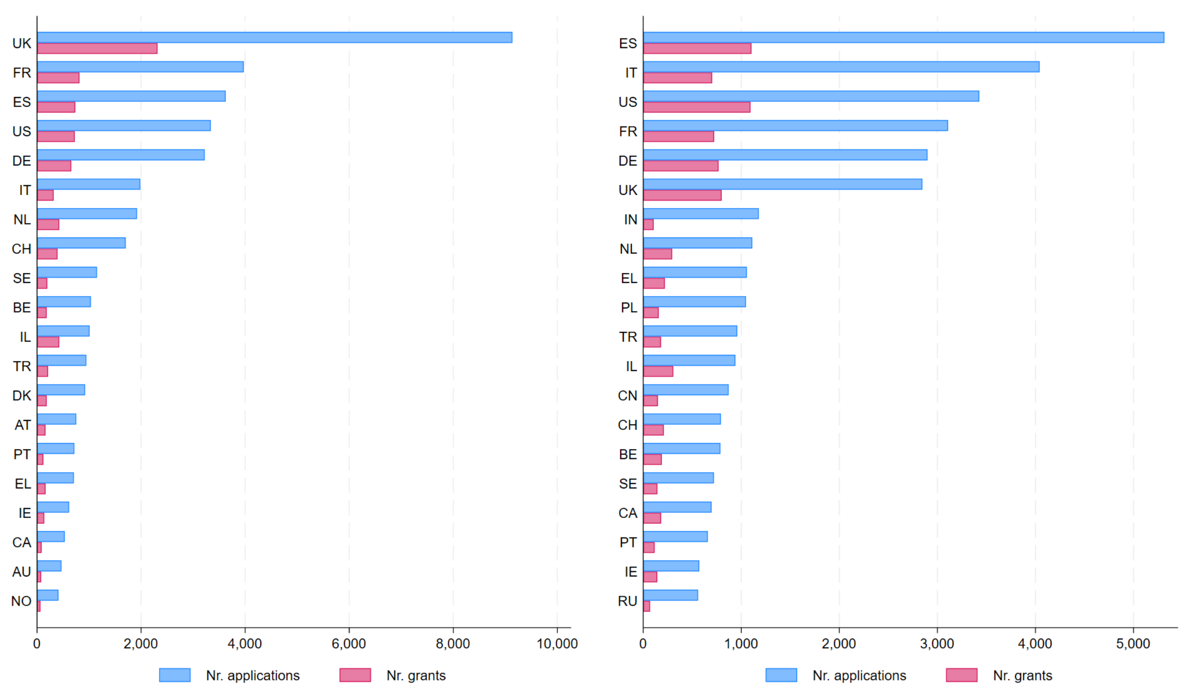
Figure A2: Applications and grants awarded by panel




Notes: bar chart reporting the number of applications and grants across all eight panels during FP7.

**Origin and host countries.** Throughout FP7, MSCA Individual Fellowships received around 41,269 applications. Each application represents a potential mobility event, from the researcher's origin country (i.e. the country where the researcher is at the time of application), to a host country (i.e. the country where the researcher intends to move for the fellowship). Owing to its prestigious status, Individual Fellowships see a broad array of origin and host countries represented in its applications. In total, there are 125 unique origin countries and 156 unique host countries accounted for across all applications. Nevertheless, the majority of applications—and consequently the awarded grants—pertain to EU Member States and a select number of other countries (see Figure A3). Spain emerges as the origin country with the highest number of applications, followed by Italy and the United States. In terms of target destinations, the United Kingdom ranks as the most popular host country for Individual Fellowships applications. France comes in as the second most favored host country, though the number of applications it attracts is less than half of those received by the UK. The distribution of applications, grants, and success rates by country does not necessarily correlate with the size of the country. Instead, these trends are likely influenced by a constellation of factors, such as disparities in job opportunities and variations in national research funding systems (Fraunhofer et al., 2014).

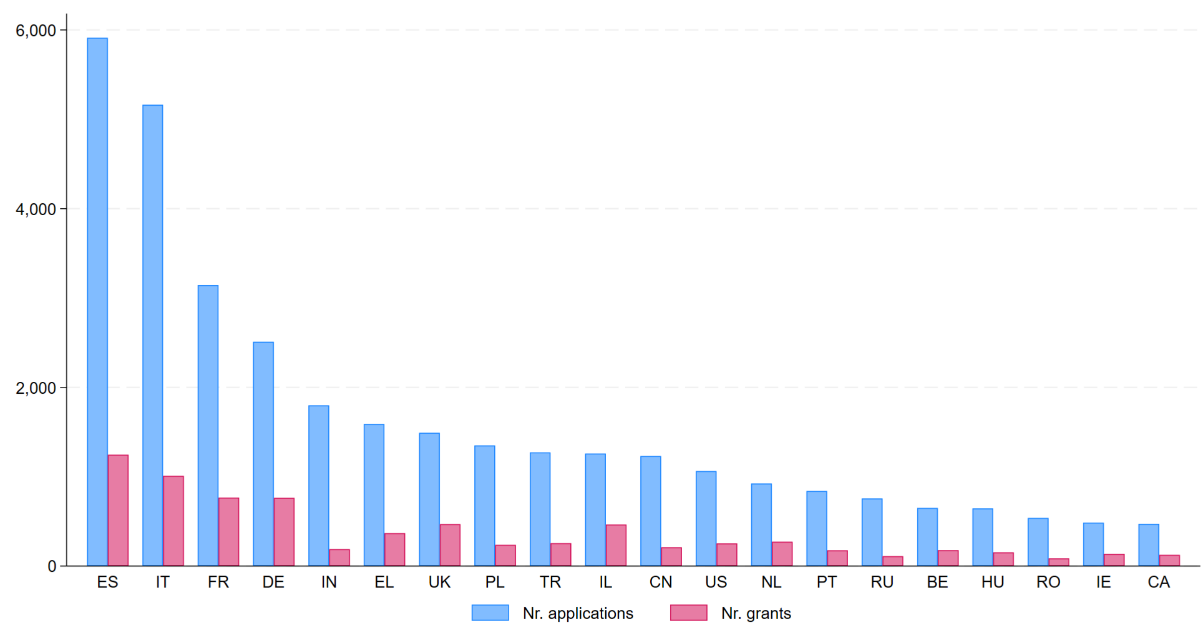
Figure A3: Top destination (left) and origin (right) countries




Notes: the bar chart shows the number of applications and awarded grants based on researchers' nationality. Only the top 20 countries in terms of applications are displayed. Countries are ordered based on the number of applications.

**Nationalities.** FP7 introduced the possibility for third country nationals to compete for MSCA grants. As a result, across all applications submitted during this period, the number of unique nationalities reaches 141. Figure A4 zooms into the top 20 countries based on researchers' nationalities. Spanish nationals are those with the highest number of both applications and grants, followed by researchers with Italian nationality. Applications from these two nationalities represent around one fourth of all submitted proposals. French and German nationals follow suit, with a relatively high number of grants, thus indicating high success rates, which could be indicative of a higher quality of applications. Spaniard, Italian, French and German researchers account for around one half of all Individual Fellowships grantees. Among non-EU nationals, a high number of applications was received from Indian, Turkish, China and US nationals. There are countries that are not featured among the top origin or destination countries, which have a relatively high number of applications, such as Greece and Poland. On the contrary, there are countries with top rankings in either origin or host countries but in lower positions according to nationality such as the US. This is expected as most applications of researchers moving to or from the US is actually submitted by European nationals.

Figure A4: Top nationalities




Notes: the bar chart shows the number of applications and awarded grants based on the country of destination (left panel), and the country of origin of the researcher (right panel). Only the top 20 countries in terms of applications are displayed. Countries are ordered based on the number of applications.

**Actions.** MSCA Individual Fellowships comprise a set of grants supporting different types of mobility for individual researchers.[1] They can be categorized among those that have a European or an international dimension. The Actions promoting mobility within Europe are the following ones:

- **Intra-European Fellowships (IEF)**: This action aims at supporting experienced researchers at various stages of their career, helping them in acquiring new research skills or to undertake inter-sectoral experiences. Eligible researchers are those from Member States or Associated Countries in possession of a doctoral degree, or having at least 4 years of full-time equivalent research experience after obtaining the degree allowing them to embark on a doctorate. Financial support will be provided to the best proposals for a period of 12 to 24 months (full-time equivalent). Funding is provided for advanced training (including complementary skills) and transnational mobility, on the basis of a "personal career development plan" established by the researcher with her/his personal supervisor in the host organisation. It includes in particular a salary for the researcher and a contribution towards research-related costs.

- **European Reintegration Grants (ERG)**: This action is intended help researchers reintegrate into a European research career after a period of mobility abroad. ERG provide financial assistance to researchers who are looking for a long-term employment in research after they have concluded their training within a Marie Curie Action under the 6th or the 7th Framework programme. The grant amounts to €15,000 per year during the period of reintegration which can last from 2 to 3 years.

On the contrary, the Actions with an international dimension are the following ones:

- **International Outgoing Fellowships (IOF)**: This action offers European researchers the opportunity to be trained and to acquire new knowledge in a third country high-level research organization, and subsequently return to an organization in a Member State or Associated Country. Eligible researchers are those from a Member State or Associated Country in possession of a doctoral degree or with at least 4 years full-time equivalent research experience

[1] Marie Curie Actions also encompass other initiatives, labeled "host-driven actions" (as opposed to "research-driven actions"), which require the institution to apply for funding and as such are not part of our analysis. These are Initial Training Networks (ITN), including European Industrial Doctorate (EID) and Innovative Doctoral Programme (IDP); Industry-Academia Partnerships and Pathways (IAPP), International Research Staff Exchange Scheme (IRSES); Co-funding of regional, national, international programmes (COFUND).

after obtaining the degree which allows them to embark on a doctorate. Financial support will be provided to the best proposals for a period of up to 3 years, including an initial outgoing phase (1-2 years) in a third country and a mandatory reintegration phase.

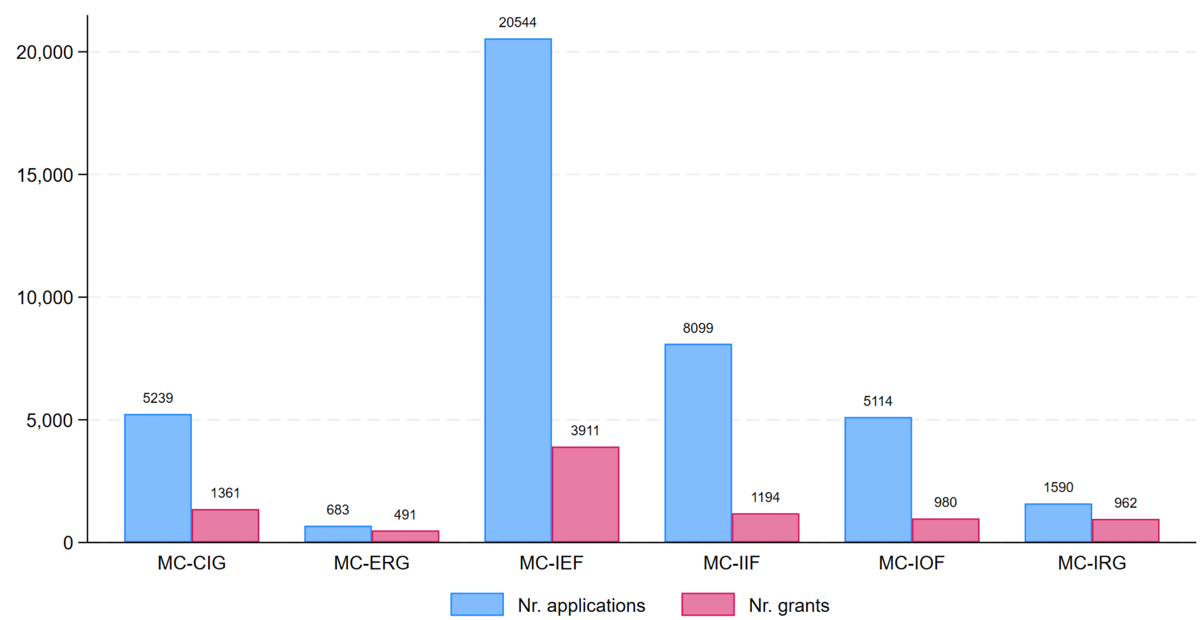
- **International Incoming Fellowships (IIF)**: This action encourages top class researchers from third countries to work on research projects in EU Member State or Associated Country, with a view to developing mutually beneficial research co-operations between Europe and third countries. Eligible researchers are those from third countries in possession of a doctoral degree and with at least 4 years full-time equivalent research experience after obtaining the degree which allows them to embark on a doctorate. Financial support will be provided to the best proposals for a period of 1 to 2 years.
- **International Reintegration Grants (IRG)**: This action encourages researchers to reintegrate in a European MS or Associated Country. This is designed to offer researchers opportunities to capitalize in Europe on their international experience and, ultimately, to counter European 'brain drain' to third countries. Re-integration includes mobility to the country of nationality of the applicant. Eligible researchers must have carried out research outside Europe for at least 3 years at the relevant submission date. The grant amounts to €25,000 per year during the period of reintegration which can last from 2 to 4 years.

In 2011, the Reintegration Grants (ERG and IRG) have been refocused into a single action called Career Integration Grants (CIG), with the objective of reinforcing the attractiveness of the European Research Area as a destination for establishing a stable research career.

- **Career Integration Grants (CIG)**: this action is intended to improve considerably the prospects for the permanent integration of researchers who are offered a stable research post in Europe after a mobility period in a country different from the country where the researcher has been active during the past years (i.e. the researcher has to be mobile but can come from anywhere in the world – moving within Europe or coming from outside Europe). Eligible researchers are those with at least 4 years full-time postgraduate research experience or a doctoral degree of any nationality who, at the time of the relevant deadline for submission of proposals, have not resided or carried out their main activity (work, studies, etc) in the country of their host organization for more than 12 months in the 3 years immediately prior to the reference deadline (short stays, as holidays, are not taken into account). A researcher who has benefited or is benefiting from a FP6 or FP7 Reintegration Grant is ineligible for funding under this call. Financial support is a fixed amount of €25.000 per researcher per year during the period of integration for 2 up to 4 years

As can be seen in Figure A5, most applications (approx. 50%) and grants (approx. 45%) belong to the IEF scheme providing mobility grants for researchers moving within Europe. This is followed by mobility grants from third countries (IIF), the reintegration grants (CIG, ERG, and IRG), and finally those fellowship supporting mobility outside Europe (IOF).

Figure A5: Applications and grants awarded by sub-program

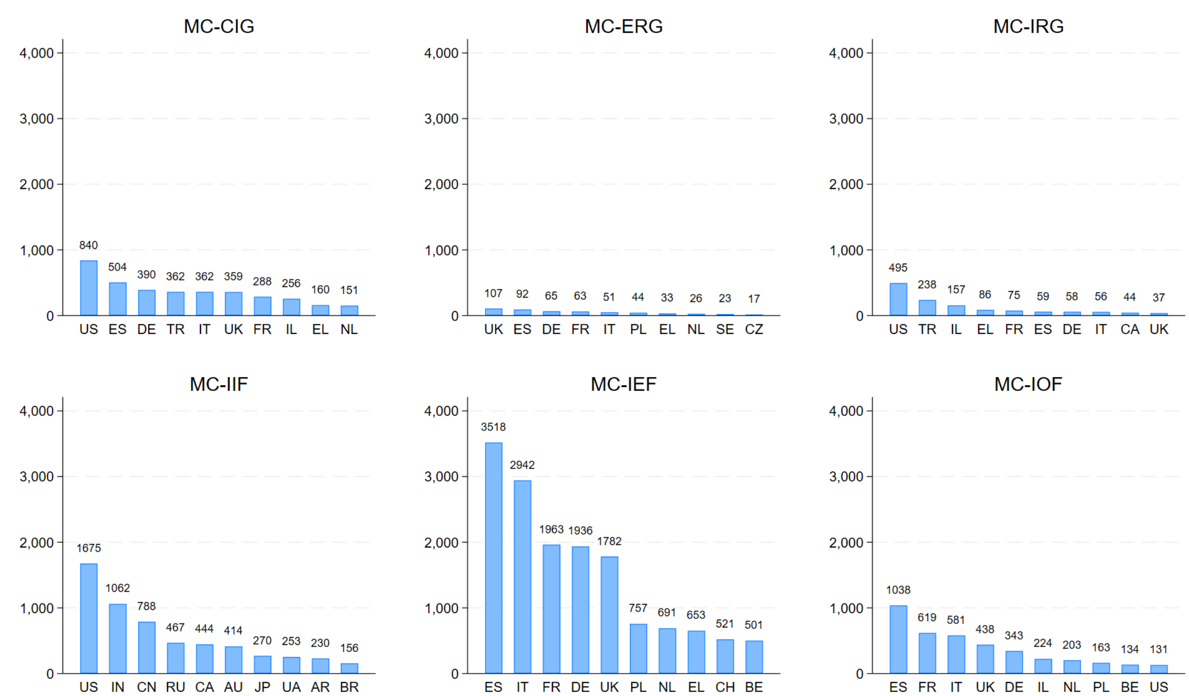



Notes: plots the number of applications and grants by action during FP7.

Figure A6 report aggregate descriptives concerning mobility from origin and host countries. This masks substantial heterogeneity across the single actions as they promote different types of mobility. We delve deeper into this heterogeneity by plotting applications according origin and destination countries across the different actions. In particular, for each action, we report the applications considering the top countries (see Figure A6 and Figure A7). Descriptives regarding IEF, which constitutes a big share of the total number of applications as seen in Figure A5, are closely in line with those reported for the overall program. Most differences emerge when looking at the other actions. For instance, grants promoting mobility from Third Countries to Europe (IIF), see a large share of proposals submitted by researchers whose country of origin at the time of application is the US. This is followed by India, China, Russia, Canada and Australia. Other interesting patterns emerge when looking at the top destinations for IOF grants, namely, those promoting mobility from Europe to Third Countries.

Figure A8 reports the top nationalities of applicants across the different sub-programs. For both intra-european grants (e.g. IIF) and grants towards Third countries (i.e. IOF), most applicants are from the largest EU countries such as Spain, Italy, France and Germany. Applications from Third Country nationals to move to EU countries are mostly coming from India, China, US, and Russia.

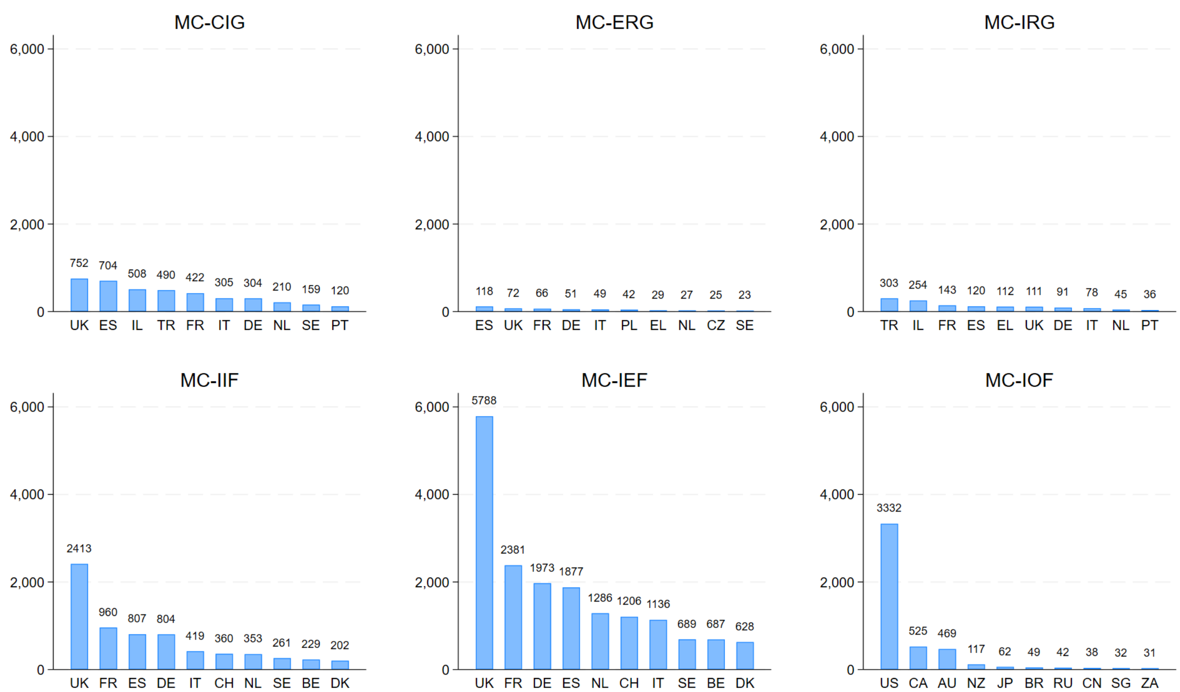
Figure A6: Top origin countries by sub-program




Notes: the bar charts show the number of applications by country of origin across the different sub-programs. Only the top 10 countries for each sub-program are displayed.

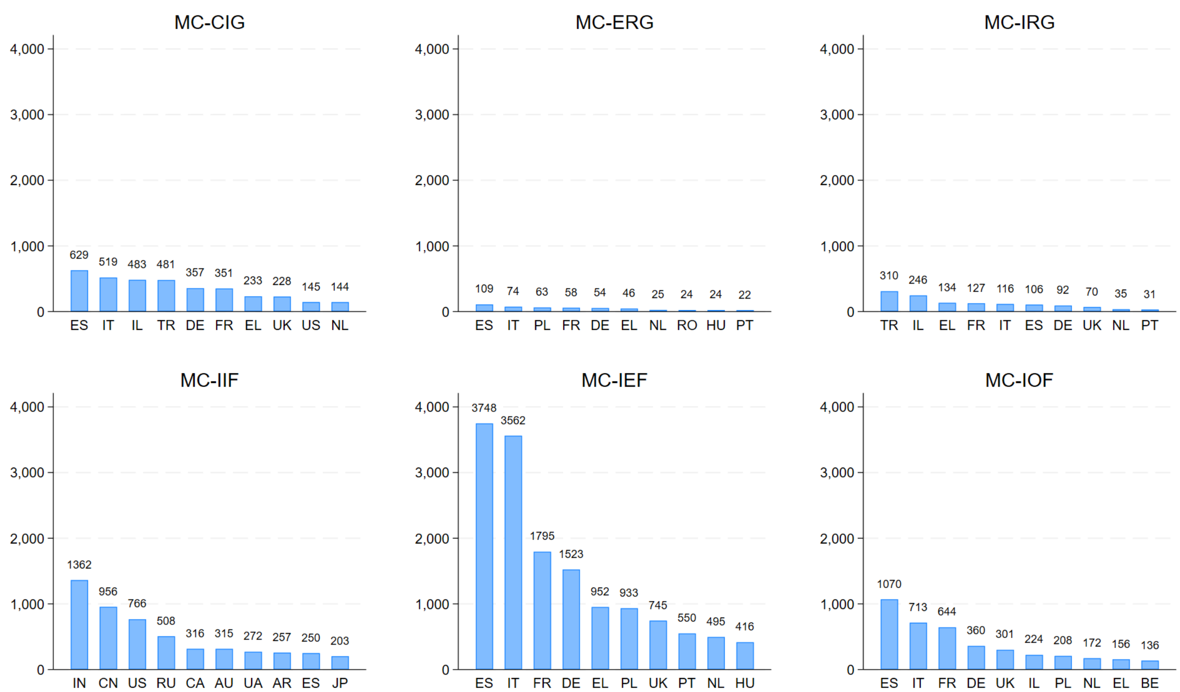
An additional dimension worth describing concerns the direction of the flows proposed in applications and ultimately supported by the program. For instance, researchers may apply to move

Figure A7: Top destination countries by sub-program




Notes: the bar charts show the number of applications by country of destination across the different sub-programs. Only the top 10 countries for each sub-program are displayed.

Figure A8: Top nationalities by sub-program




Notes: the bar charts show the number of applications by nationality across the different sub-programs. Only the top 10 countries for each sub-program are displayed.

to relatively similar institutions/countries or, on the contrary, to spend their mobility in richer institutions/countries. To provide evidence on this, we report the constant from a linear regression with dependent variable the difference in GDP per capita (USD) between the destination country and the host country in 2013, controlling for competition fixed effects. As reported in Table A1, researchers tend to propose moves to countries with higher GDP per capita. Similar patterns emerge when restricting the sample to beneficiaries (Table A2). This hold for the entire sample and for the various sub-program, with the exception of CIG. This is expected, as CIG supports reintegration of researchers into their home countries, thus involving return mobility to their home countries rather than upward economic moves.

Table A1: GDP per capita difference between destination and origin countries

| | All schemes | MC-IIF | MC-IOF | MC-IEF | MC-CIG |
|---|---|---|---|---|---|
| Constant | 4651.9*** | 10720.6*** | 8965.1*** | 3771.5*** | -1678.0*** |
| | [62.8] | [202.3] | [176.8] | [73.2] | [166.1] |
| N | 40721 | 7916 | 4913 | 20389 | 5214 |
| R-squared | 0.14 | 0.07 | 0.04 | 0.01 | 0.02 |

**Notes:** The dependent variable is the difference in GDP per capita (in constant PPP terms) between the destination and origin countries. All regression include competition fixed effects. Standard errors are robust. * 0.10 ** 0.05 *** 0.01

Table A2: GDP per capita difference between destination and origin countries (only beneficiaries)

| | All schemes | MC-IIF | MC-IOF | MC-IEF | MC-CIG |
|---|---|---|---|---|---|
| Constant | 2013.9*** | 6131.8*** | 9048.8*** | 2918.2*** | -2999.1*** |
| | [121.5] | [499.1] | [342.0] | [163.7] | [304.0] |
| N | 8796 | 1164 | 952 | 3871 | 1356 |
| R-squared | 0.17 | 0.11 | 0.11 | 0.03 | 0.04 |

**Notes:** The dependent variable is the difference in GDP per capita (in constant PPP terms) between the destination and origin countries. All regression include competition fixed effects. Standard errors are robust. * 0.10 ** 0.05 *** 0.01

## 2 Related literature

A growing body of literature examines the impact of research funding on various aspects of researchers' careers, including productivity, long-term mobility, the impact on researchers' scientific output, collaborations and the likelihood of obtaining follow-up funding. Here we aim to provide a more comprehensive overview of the existing evidence with respect to the one already presented in the introductory section of the paper.

There are two main strands of literature which examine the impact of research funding on universities and individual researchers. While the former confirms a positive relationship between research funding and publication outcomes, the latter tends to produce mixed results depending on the country, the position of the researcher and the outcomes studied (Ghirelli et al., 2023).

Most studies on the impact of research funding on individual researcher outcomes are limited to one country or one type of research funding program. In particular, the first studies comparing successful and unsuccessful applicants examine US data on National Institute of Health (NIH) and National Science Foundation (NSF) grants (Arora and Gambardella, 2005; Jacob and Lefgren, 2011; Wang et al., 2019). Arora and Gambardella (2005) study the effect of NSF grants on US economists. The authors find no effect of these grants on researchers' publications, except for a small positive effect limited to younger researchers. Similarly, Jacob and Lefgren (2011) examine the effect of receiving an NIH grant on researchers' publications, citations, and likelihood of future research funding. Again, the authors find no significant effect of the grant on publications or citations in the five years following the application. However, they do document a positive effect on the likelihood of receiving research funding in future. Both studies conclude that the lack of effect on researchers' productivity is due to the fact that most unsuccessful applicants manage to find alternative sources of funding to carry out their research. Wang et al. (2019) focus on the sub-sample of early-career researchers who applied for NIH grants between 1990 and 2005. Using a fuzzy RDD design, the authors find no effect on the quantity of publications and a negative effect on the quality of publications in the nine years following the application. They explain their findings by the fact that, despite a higher attrition rate among unsuccessful applicants, those who actually manage to continue their academic careers tend to perform better than winners in terms of publication quality.

Ghirelli et al. (2023) provide the first causal assessment of grants assigned to individual scientists by the prestigious European Research Council (ERC). Using a RDD approach, they report null effects of ERC grants on researchers' productivity and impact. When using the full sample and adopting a DID approach, they show positive results in terms of scientific productivity, impact and the likelihood of obtaining further EU funds. Evidence indicates that these findings are driven by top-ranked applicants. Similar findings are reported by Barnett et al. (2024). The authors employ a randomized experimental study design leveraging a modified lottery to assign funding by the Health Research Council of New Zealand. Their results document no clear impact of funding on research outputs or employment outcomes.

Another set of studies focuses on the national research funding schemes of individual European countries, including the Swiss National Science Foundation (SNSF) (Heyard and Hottenrott, 2021; Baruffaldi et al., 2020; Ayoubi et al., 2021), the French Agence Nationale de la Recherche (ANR) (Carayol and Lanoë, 2017), the Danish and Norwegian Open Mode grant schemes (Langfeldt et al., 2015) and the Luxembourg National Research Fund (FNR) (Hussinger and Carvalho, 2022), among others.

Using data on successful and unsuccessful applicants to the Swiss National Science Foundation (SNSF), Heyard and Hottenrott (2021) investigate the effect of receiving an SNSF grant on researchers' future publications and their dissemination. The authors find that the receipt of such a grant leads to one additional peer-reviewed publication in the three years following funding, compared to comparable unsuccessful applicants. In addition, these publications become more prominent in terms of the number of citations they subsequently receive. A recent study by Ayoubi et al. (2021) examines one of the flagship programs of the SNSF funding portfolio - SINERGIA - a collaborative research funding program aimed at promoting scientific breakthroughs by interdisciplinary research teams. Using the difference-in-differences (DID) methodology, the authors report a significant increase in the number of publications (43%) and the average impact factor (7%) of the researchers who applied for the grant, but no additional effect on the scientific productivity of the researchers who actually won the grant. Carayol and Lanoë (2017) use data on research project-based funding by the ANR in France during 2005-2009. The study concludes that a grant increases the number of citation-weighted publications by 15%. The study also finds a positive effect on the size of the collaborators' network and on the turnover of collaborators, including international collaborations.

Similarly, Langfeldt et al. (2015) examines the extent to which Danish and Norwegian open-mode grant schemes affect publication and citation rates. The general result of the study is a higher increase in productivity (measured as number of publications per year) for grant recipients, while no significant effect on the number of citations is observed. Furthermore, the authors find a positive effect on the number of highly cited articles for Norwegian grantees, while no such effect is documented for Denmark. Finally, Hussinger and Carvalho (2022) examine the impact of individual grants from the Luxembourg National Research Fund (FNR) on the scientific output of funded university professors. Using DID analysis, the authors find that receiving a grant increases the scientific publication output of a funded university professor by 31%, which corresponds to almost one additional publication. Furthermore, the authors find that the academic output premium of grantees disappears within five years of receiving the grant. Finally, some studies focus instead on countries characterized by limited alternative sources of funding, such as countries in the former Soviet Union (Ganguli, 2017) or South America (Benavente et al., 2012; Chudnovsky et al., 2008). All these studies document a significant positive impact of research funding on scientific productivity (measured by the number of publications), leading on average to 1-2 additional peer-reviewed articles.

Most relevant to our study is the literature on the role of international mobility, and in particular mobility grants, on researchers' career outcomes.[2] Indeed, internationally mobile researchers could have access to broader research networks and acquire new knowledge not available in their home countries (Aman, 2018; Baruffaldi et al., 2020). From this perspective, international mobility should be beneficial for their publication record, impact, research network and career growth (Gu et al., 2024; Liu and Hu, 2022). However, the existing literature provides mixed results (**?**). Some studies document positive effects of international mobility on researcher productivity (Dubois et al., 2014; Momeni et al., 2022; Franzoni et al., 2014; Robinson-Garcia et al., 2019), while others report no significant or even negative effects (Baruffaldi et al., 2020; Shin et al., 2014). Similarly, inconsistent results are documented on the impact of international mobility on researchers' collaborative networks (Netz et al., 2020). Such inconsistent results may be due to a number of factors,

[2] A less related strand of recent studies focus on the effects of mobility for students in the case of the Erasmus program (De Benedetto et al., 2023; Granato et al., 2024). These report positive outcomes in terms of final graduation marks and labor market outcomes.

including the type and timing of the mobility, and discipline (Horta et al., 2018, 2020; Shen et al., 2022). Moreover, early studies on the role of international mobility mostly focused on researchers from developed countries (Lawson and Shibayama, 2015). However, an increasing number oft studies examines the impact of international mobility on researchers from developing countries (Aykac, 2021; Fangmeng, 2016; Shen et al., 2017; Gu et al., 2024).

Despite mixed evidence, research managers and science funding agencies see international mobility as an essential factor for the formation of researchers and for knowledge transfer between countries (Non et al., 2022; Robinson-Garcia et al., 2019; Shen et al., 2022). Moreover, a number of national and supranational bodies, including the European Commission, continue to place policies supporting international mobility of researchers at the centre of their research and innovation policy mix (Ghirelli et al., 2023). In most cases, mobility grants are offered on a competitive basis to young researchers in the early and most important stages of their careers (Baruffaldi et al., 2020; Oyer, 2006; Stephan, 2012). It is worth noting that while there is a wealth of evidence on the superior performance of migrant scientists in general, there is relatively little evidence on the role of mobility grants (Non et al., 2022; Baruffaldi et al., 2020; Gu et al., 2024; Shi et al., 2023).

One of the few studies on this topic, Baruffaldi et al. (2020), examines the impact on researchers of an international mobility grant program sponsored by the Swiss National Science Foundation (SNSF). The authors assess the impact of SNSF grants on researchers' mobility and productivity in the short and medium term, and examine changes in their research networks and career trajectories. The results of the study confirm that SNSF fellowships significantly increase the mobility of researchers in the short and medium term. Receiving a grant has a positive effect on the quality of a researcher's scientific output (measured by the average impact factor). However, there is no significant effect on the quantity of output (measured by the number of publications) or on career progression (the probability of being promoted to a professorship). The study also shows that receiving the grant gives researchers access to broader and higher quality co-authorship networks and leads them to broaden their research field without changing their specialisation. Interestingly, the grants seem to benefit first-time winners in particular.

Similarly, Gu et al. (2024) study the impact of international mobility on doctoral students funded by the China Scholarships Council (CSC) program during 2007-2017. Using a combination of propensity score matching and DID approaches, the authors find that government-sponsored international mobility has a significant positive effect on researchers' collaborative network and scientific output. The effect on research output is mainly attributed to an increase in the size of collaborative teams. Furthermore, the authors find significant heterogeneity in the effects: the effects vary by gender, the prestige of the doctoral institution, the destination and the timing of the mobility.

Shi et al. (2023) provides evidence on reintegration grants. In more detail, they show that China's Young Thousand Talents (YTT) program has been successful in recruiting and nurturing high-caliber scientists and that YTT scientists outperform their overseas peers in post-return publication, mainly owing to their access to greater funding and larger research teams. These results show the potential of talent programs as a policy tool for countries to attract expatriate scientists and promote their productivity.

Non et al. (2022) examine the impact of a Dutch competitive mobility grant, known as the Rubicon grant, on the quantity and quality of a researcher's publications, the number of co-authors, and the probability of leaving academia. Using regression discontinuity design (RDD), the authors find no significant effect of the grant on any of the scientific outcomes studied. The authors explain the lack of effect by several specific features of the Dutch fellowship, including the fact that such fellowships are mostly used to fund the first postdoctoral job and that the duration of funding is limited to two years, compared to longer periods funded by other programs.

Finally, relevant to our study is the small strand of studies that have examined the impact of Marie Curie in the past. Examples are Fraunhofer et al. (2014), Avramov (2015), Franke et al. (2017), Jonkers et al. (2018). These generally find positive effects on a number of outcomes such as publication quantity and quality, employability, career progression. However, these studies have in common the use of online surveys directed at some funded researchers and at a control group of observationally similar researchers. This has a series of limitations, notably, the lack of a causal identification strategy and data on the universe of applicants. One exception is the recent work by Yildiz et al. (2024), who use Horizon 2020 data (2014-2020) and adopt a RDD. Contrary to our study, which allows for a much longer post-treatment period, this paper limits the analysis to study whether grants help researchers diversifying into new topics, whereas we provide a more comprehensive account of the effects of the policy on a wider range of outcomes. Results from this study document that grantees indeed increase the share of publications with new topics, though only in the aftermath of receiving the grant.

Overall, the existing literature provides mixed evidence on the effectiveness of mobility grants for researchers' careers and more research is needed to identify the factors and mechanisms through which researchers benefit from mobility. An additional explanation for such mixed results could be that the objectives of funding agencies go beyond individual career benefits for the grantees. Such objectives may include international knowledge transfer and the creation of links between research communities in different countries (Non et al., 2022).

# 3 Validity of the Research Design

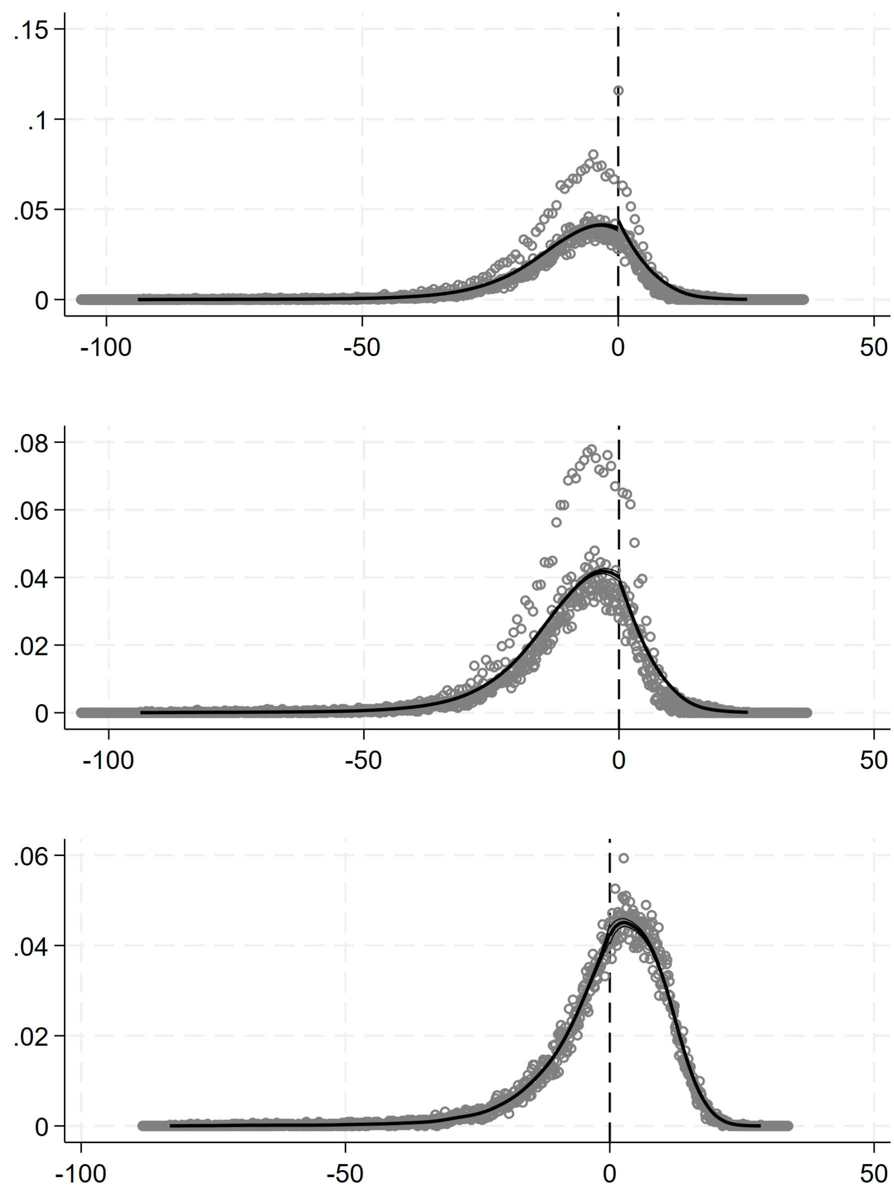
In this section we report additional tests concerning the validity of our research design. In particular, we focus on potential manipulation of the running variable, and discontinuity in predetermined covariates.

## 3.1 Manipulation of the running variable

The key assumption for the validity of a RDD is that units cannot precisely manipulate the value of the covariate that determines their treatment status. If units can manipulate their position relative to the cutoff, this might be visible as a discontinuity in the density of the running variable at the cutoff. Such a discontinuity would suggest potential issues with the design's validity, as it implies systematic sorting around the cutoff.

McCrary (2008) provides a formal test to assess the continuity assumption. Figure A9 reports the plot obtained via the McCrary (2008) manipulation test showing the actual density estimate. The McCrary (2008) test yields a log difference in height of 0.11 and standard error of 0.0223, thus failing to reject the null hypothesis of no difference in the density of treated and control observations at the cutoff. However, the presence of discontinuity in the density of the running variable does not come as a surprise. Indeed, in our setting each competition has its own specific threshold and the running variable is centered on the score of the last researcher to whom a mobility grant is offered. This creates an artificial accumulation at the cut-off (Fort et al., 2022), as it can be observed in the top panel of Figure A9, which in turn can lead to detecting discontinuity in the density function. Excluding observations with centered running variable equal to 0, leads to the plot in the middle panel in Figure A9 which shows stronger overlap of the two fitted lines. Statistical tests provide further confirmation on the absence of discontinuities in the running variable with a log difference in height of -0.022 and standard error of 0.0225. A similar approach consists of using residuals from a regression with centered scored as dependent variable and competition fixed effects on the right hand side (Granato et al., 2024). The bottom panel of Figure A9 plots the residuals and provides further confirmation on the absence of discontinuity in the running variable around the threshold. The test yields a log difference in height of -0.028 with standard error of 0.0329.

Figure A9: Manipulation tests



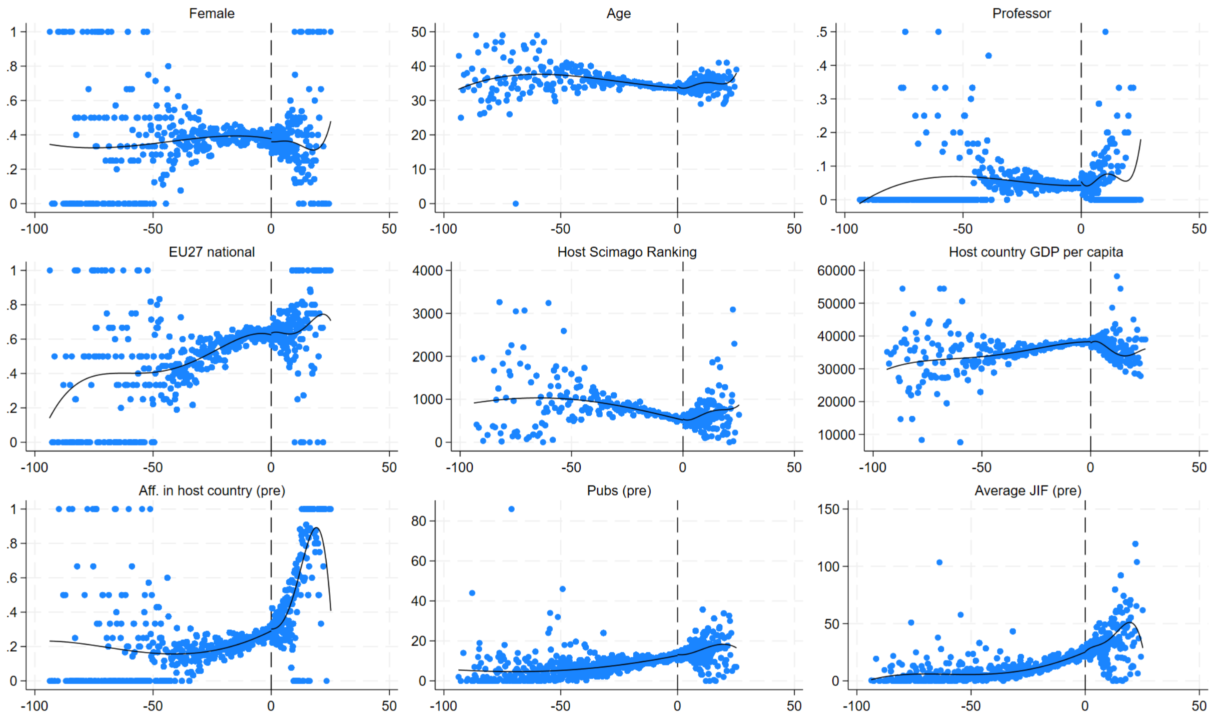

Notes: the plots report the density of the running variable following McCrary (2008). The top panel uses all observations. The middle panel discards observations located exactly at the threshold based on Fort et al. (2022). The bottom panel uses residuals obtained by regressing the running variable against competition fixed effects.

### 3.2 Continuity of pre-determined covariates

Another key assumption for our estimates to be valid requires that pre-determined covariates do not present discontinuity around the competition-specific threshold. Indeed, a RDD framework assumes that units just above and below the threshold are similar in all respects except for the treatment assignment. The absence of discontinuity in covariates around the threshold suggests that individuals could not manipulate their position relative to the cutoff, which helps to rule out the possibility that the subjects have some control over treatment assignment. Smoothness in covariates lends support to the idea that the design mimics a randomized experiment near the cutoff. In this section we provide additional graphical and statistical evidence on the smoothness of pre-determined covariates around the cut-off, extending the one presented in the main text. As discussed in Cattaneo et al. (2024), in a Fuzzy RDD setting the estimation of balancing tests regarding pree-determined covariates should focus on *intention-to-treat* effects. As the goal of such falsification tests is to check whether units just above the threshold are comparable to those just below the cut-off, the effects of interest are those of the treatment assignment on the covariates.

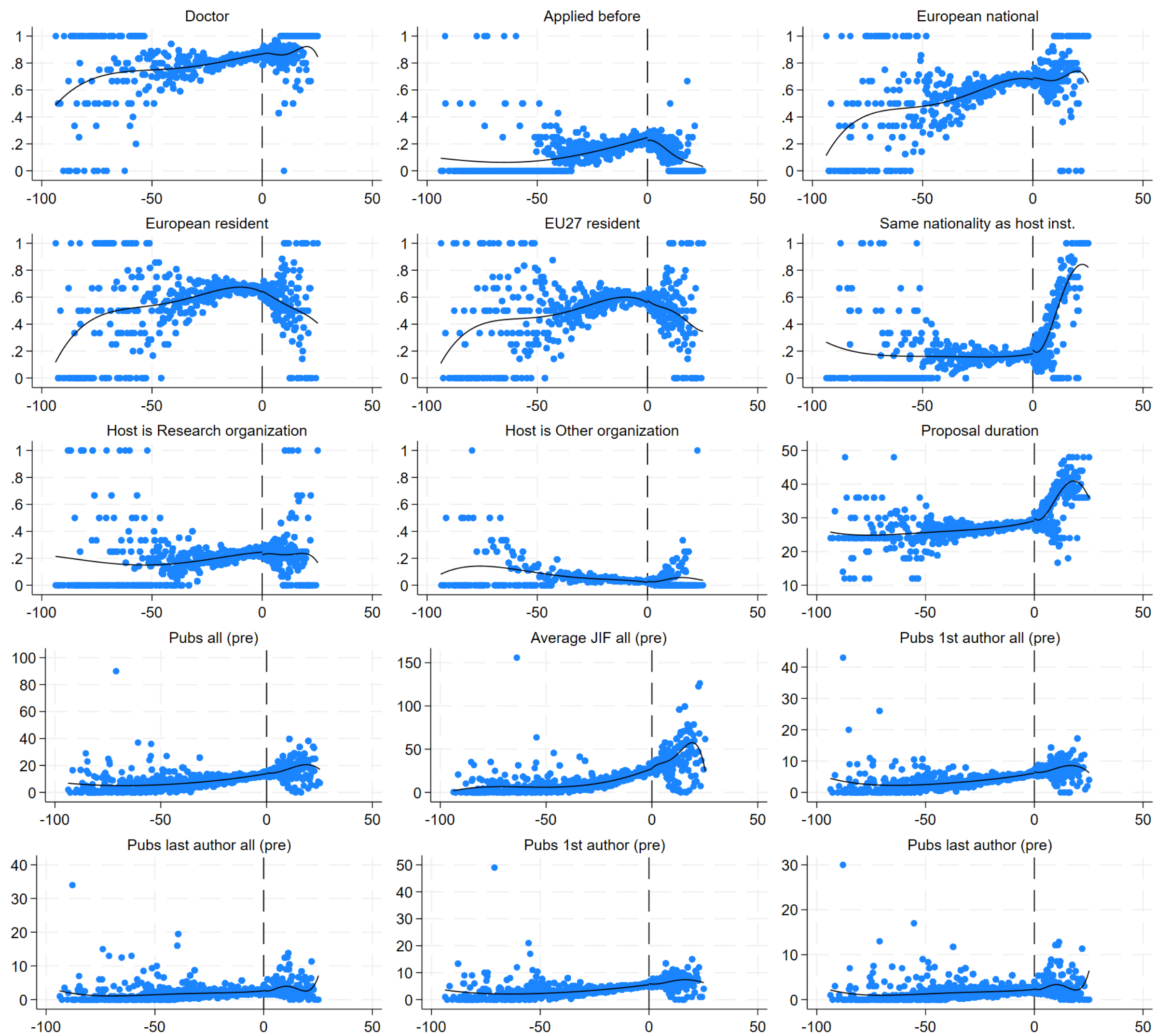
In what follows, we report global balancing graphs (see Figures A10 and A11) which plot covariates using the entire sample (i.e. infinite bandwidth). These do not show clear-cut jumps around the threshold. Table A3 takes this further and reports global balancing tests using either a linear or a quadratic polynomial of the running variable. Even when using the entire sample of applicants, most covariates are fairly balanced. We also report additional local RDD plots using MSE-optimal bandwidths (see Figure A12), as well as tests using a quadratic running variable in Table A4. These show no sings of discontinuity, thus further reassuring on the validity of the research design.

Figure A10: Global RDD pre-treatment plots (i)




Notes: plots show smoothness around the threshold for a number of pre-determined variables. Fitted lines are polynomials of order four.

Figure A11: Global RDD pre-treatment plots (ii)




Notes: plots show smoothness around the threshold for a number of pre-determined variables. Fitted lines are polynomials of order four.

Table A3: Global balancing tests for pre-determined covariates

| | Linear | | | Quadratic | | | |
|---|---|---|---|---|---|---|---|
| | Diff. | SE | *p-value* | Diff. | SE | *p-value* | N |
| Female | -0.024 | 0.009 | 0.006 | -0.017 | 0.010 | 0.091 | 41024 |
| Age | 0.022 | 0.113 | 0.846 | 0.235 | 0.138 | 0.089 | 41024 |
| Professor | 0.001 | 0.004 | 0.901 | 0.004 | 0.005 | 0.360 | 41002 |
| Doctor | 0.002 | 0.007 | 0.804 | -0.000 | 0.008 | 0.987 | 41002 |
| Applied before | -0.013 | 0.007 | 0.089 | -0.030 | 0.009 | 0.001 | 41024 |
| European National | -0.019 | 0.009 | 0.034 | -0.009 | 0.010 | 0.354 | 41024 |
| EU27 National | -0.014 | 0.009 | 0.132 | -0.009 | 0.010 | 0.384 | 41024 |
| European resident | -0.030 | 0.008 | 0.000 | -0.007 | 0.010 | 0.462 | 41024 |
| EU27 resident | -0.030 | 0.009 | 0.001 | -0.016 | 0.010 | 0.129 | 41024 |
| Same nationality as host inst. | 0.002 | 0.006 | 0.757 | 0.005 | 0.007 | 0.490 | 40853 |
| Host is Higher ed institution | 0.009 | 0.009 | 0.280 | 0.012 | 0.010 | 0.217 | 41024 |
| Host is Research organization | -0.010 | 0.008 | 0.216 | -0.010 | 0.010 | 0.285 | 41024 |
| Host is other organization | 0.001 | 0.004 | 0.834 | -0.002 | 0.004 | 0.546 | 41024 |
| Proposal duration | -0.072 | 0.085 | 0.403 | -0.063 | 0.095 | 0.507 | 41024 |
| Host Scimago Institution Ranking | -1.722 | 15.735 | 0.913 | 12.557 | 17.803 | 0.481 | 30009 |
| Host country GDP per capita | -386.743 | 150.343 | 0.011 | -352.246 | 176.365 | 0.047 | 40836 |
| Distance | -83.411 | 52.981 | 0.117 | -27.003 | 62.434 | 0.666 | 40836 |
| Aff. in host country (pre) | 0.018 | 0.007 | 0.007 | 0.014 | 0.008 | 0.111 | 40985 |
| Pubs all (pre) | 0.729 | 0.305 | 0.018 | 0.369 | 0.350 | 0.293 | 40985 |
| Average JIF all (pre) | 3.166 | 1.028 | 0.002 | 1.427 | 0.939 | 0.130 | 40985 |
| Pubs 1st author all (pre) | 0.469 | 0.147 | 0.002 | 0.263 | 0.169 | 0.120 | 40985 |
| Pubs last author all (pre) | 0.245 | 0.172 | 0.155 | 0.078 | 0.197 | 0.691 | 40985 |
| Pubs(pre) | 0.664 | 0.281 | 0.019 | 0.315 | 0.322 | 0.328 | 40985 |
| Average JIF (pre) | 2.794 | 0.898 | 0.002 | 1.253 | 0.847 | 0.140 | 40985 |
| Pubs 1st author (pre) | 0.434 | 0.134 | 0.001 | 0.238 | 0.151 | 0.116 | 40985 |
| Pubs last author (pre) | 0.233 | 0.154 | 0.132 | 0.100 | 0.177 | 0.572 | 40985 |
| Co-authors (pre) | 1.321 | 0.841 | 0.118 | 0.622 | 0.864 | 0.472 | 40985 |

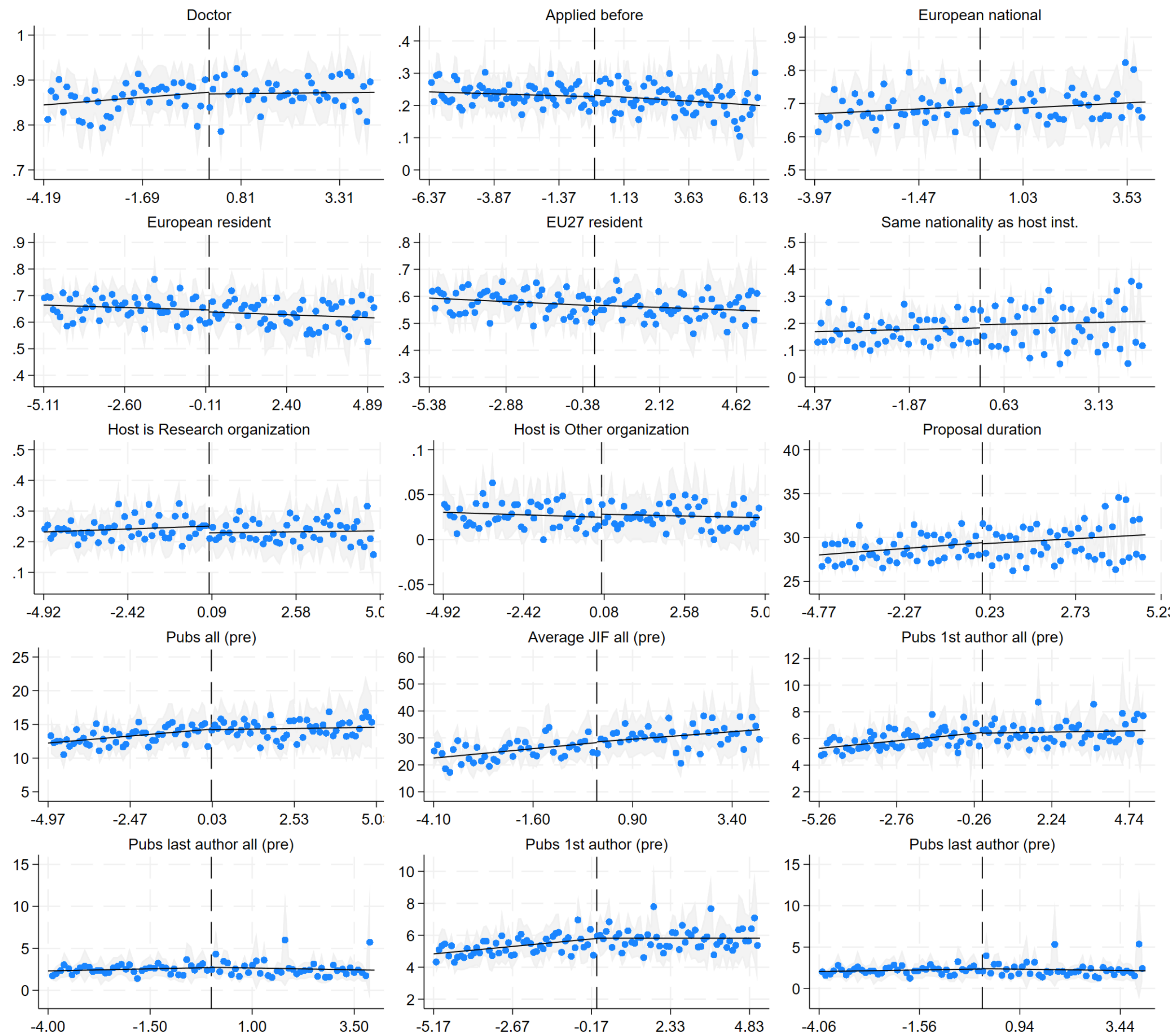
Notes: the table reports global balancing tests for pre-determined covariates using the entire sample, that is, without restricting the bandwidth to observations close to the cut-off. Results are obtained using a Sharp RDD specification including a linear (or quadratic) polynomial of the running variable on each side of the threshold and competition fixed effects. Standard errors are robust and clustered at the competition-level.

Table A4: Balancing tests for pre-determined covariates

| | Diff. | P-value | N left | N right | N |
|---|---|---|---|---|---|
| Female | -0.007 | 0.711 | 14419 | 7913 | 41024 |
| Age | 0.328 | 0.160 | 9751 | 6885 | 41024 |
| Professor | 0.006 | 0.420 | 12109 | 7531 | 41002 |
| Doctor | 0.002 | 0.940 | 13598 | 7791 | 41002 |
| Applied before | -0.001 | 0.993 | 14564 | 7926 | 41024 |
| European National | 0.003 | 0.885 | 10335 | 7054 | 41024 |
| EU27 National | 0.010 | 0.605 | 10492 | 7096 | 41024 |
| European resident | 0.014 | 0.389 | 10136 | 6984 | 41024 |
| EU27 resident | 0.025 | 0.186 | 9751 | 6885 | 41024 |
| Same nationality as host inst. | 0.019 | 0.291 | 8492 | 6440 | 40853 |
| Host is Higher ed institution | 0.011 | 0.561 | 11413 | 7365 | 41024 |
| Host is Research organization | -0.020 | 0.277 | 11929 | 7483 | 41024 |
| Host is other organization | 0.009 | 0.146 | 11580 | 7400 | 41024 |
| Proposal duration | 0.160 | 0.238 | 8522 | 6460 | 41024 |
| Host Scimago Institution Ranking | -35.385 | 0.219 | 8244 | 5481 | 30009 |
| Host country GDP per capita | -307.076 | 0.275 | 12549 | 7585 | 40836 |
| Distance | 55.913 | 0.506 | 14839 | 7947 | 40836 |
| Aff. in host country (pre) | -0.007 | 0.538 | 14731 | 7951 | 40985 |
| Pubs all (pre) | -0.011 | 0.916 | 10330 | 7050 | 40985 |
| Average JIF all (pre) | -0.193 | 0.885 | 9028 | 6650 | 40985 |
| Pubs 1st author all (pre) | -0.133 | 0.678 | 15206 | 8015 | 40985 |
| Pubs last author all (pre) | -0.195 | 0.664 | 13592 | 7788 | 40985 |
| Pubs(pre) | -0.025 | 0.952 | 10866 | 7204 | 40985 |
| Average JIF (pre) | -0.243 | 0.855 | 9578 | 6837 | 40985 |
| Pubs 1st author (pre) | -0.108 | 0.734 | 12437 | 7582 | 40985 |
| Pubs last author (pre) | -0.194 | 0.576 | 12255 | 7545 | 40985 |
| Co-authors (pre) | 0.483 | 0.714 | 9578 | 6837 | 40985 |

Notes: the table reports balancing tests for pre-determined covariates around the threshold. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a quadratic polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level.

Figure A12: Local RDD pre-treatment plots



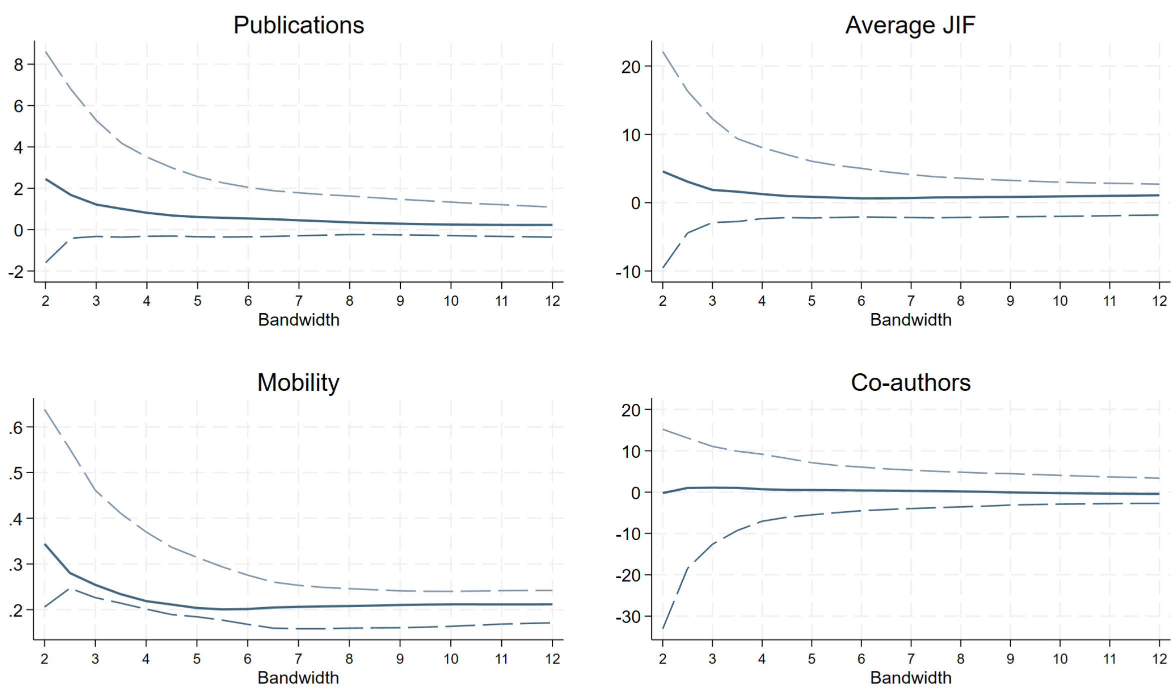

Notes: plots show smoothness around the threshold for a number of pre-determined variables. MSE-optimal bandwidths computed following Calonico et al. (2017). Fitted lines are polynomials of order one. Shaded area represents 95% confidence intervals.

# 4 Additional Results

## 4.1 Alternative bandwidths

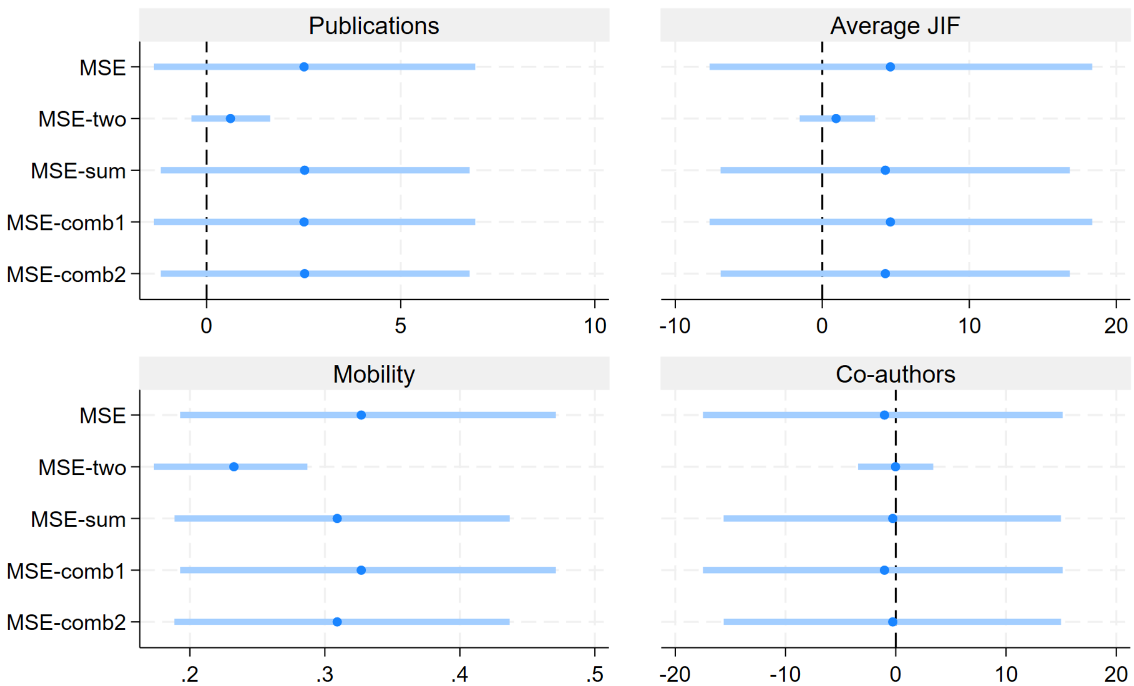
In our baseline estimates, we employed the standard MSE-optimal bandwidths (Calonico et al., 2017). In this section we test the sensitivity of the results to alternative bandwidths around the threshold. A consistent treatment effect across a range of bandwidths provides strong evidence that the observed relationships reflect the causal impact. We report estimates using symmetrical bandwidths going from 2 to 12 centered scores. We see that varying the bandwidths around the threshold generally does not imply any sensible variation in point estimates across all outcomes, thus reinforcing the validity of the conclusions drawn from baseline RDD analyses. Additionally, for all our main outcomes, we repeat the analysis using alternative optimal bandwidths computed following Calonico et al. (2017). In particular, Figure A14 shows our baseline results with a variety of optimal bandwidth selectors. It is worth noting that optimal bandwidth selectors using more observations and producing more precise estimates though introducing more bias (e.g. MSE-two), still confirm that effects are indistinguishable from zero for publication outcomes, whereas the confirm the positive and statisticaly significant effects on mobility.

Figure A13: Estimates by bandwidths




Notes: plots report point estimates and confidence intervals obtained by using a variety of bandwidths around the threshold, going from [-2;2] up to [-12,12] centered scores. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Shaded area represents 95% confidence intervals.

Figure A14: Estimates using a variety of optimal bandwidth selectors

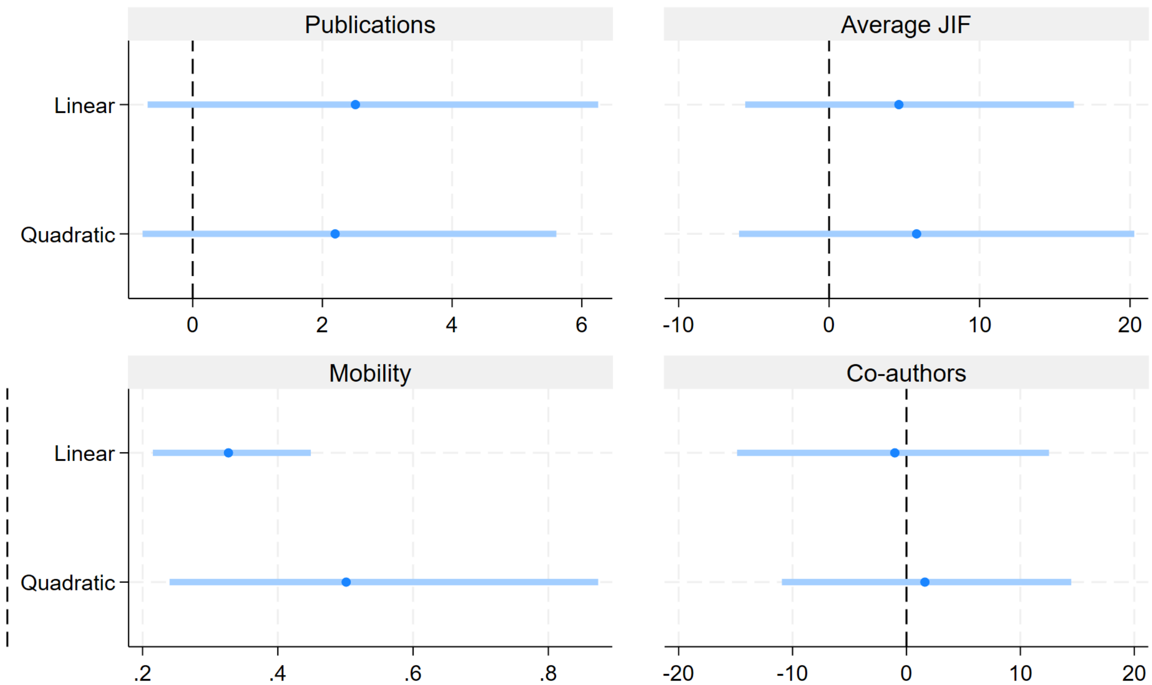



Notes: plots Fuzzy RDD estimates using a variety of optimal bandwidth selectors based on Calonico et al. (2017). These are MSE (Mean Squared Error-optimal bandwidth selector), MSE-two (two different (MSE-optimal bandwidth selectors below and above the cutoff) MSE-sum (MSE-optimal bandwidth selector for the sum of regression estimates), MSE-comb1 (minimum between MSE and MSE-sum), MSE-comb2 (median bweteen MSE-two, MSE, MSE-sum, for each side of the cut-off separately). Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 95% confidence intervals.

## 4.2 Alternative adjustment of the running variable

We test the sensitivity of our results to an alternative adjustment of the running variable. As suggested by Gelman and Imbens (2019) we limit the polynomial order to second-order polynomials. Figure A15 reports both our baseline results using a linear polynomial as well as those using a second order one. Point estimates and confidence intervals tend to be largely in line with our baseline estimates.

Figure A15: Estimates using quadratic running variable




Notes: the figure plots our Fuzzy RDD estimates using a linear adjustment of the running variable as in our baseline results, and a quadratic one. Specifications include the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level.

### 4.3 Mobility

In our baseline specifications we use a proxy for mobility within five years of the funding call. We also test whether results change when using a shorter (longer) time window. Results in Tables A5 and A6 show that point estimates are comparable with the baseline ones irrespective of whether we choose a shorter time span (i.e. three years) or longer (i.e. 10 years).

Table A5: Fuzzy RDD estimates on mobility (3 years)

| | Mobility | Mobility | Mobility |
|---|---|---|---|
| RD Estimate | 0.324*** | 0.324*** | 0.346*** |
| | [0.088] | [0.088] | [0.094] |
| Mean dep var | 0.55 | 0.55 | 0.55 |
| Pol. order | 1 | 1 | 1 |
| BW | 1.9 | 1.9 | 1.8 |
| N (left) | 3063 | 3063 | 2899 |
| N (right) | 3187 | 3187 | 3060 |
| N | 41024 | 41024 | 40985 |
| p-value | 0.000 | 0.000 | 0.000 |
| Robust p-value | 0.000 | 0.000 | 0.000 |
| F-stat 1st stage | 31.827 | 31.827 | 28.555 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.0

Our estimates on mobility are based on measures derived from affiliations reported in scholarly publications. As already discussed in the main text of the paper, this approach has some limitations. One possible concern with this is that our results could be merely driven by a differential increase in the post-competition number of affiliations across treated and control researchers. Indeed, there is evidence suggesting that high-quality researchers exhibit multiple affiliations (Hottenrott et al., 2021). To rule out that our findings are simply reflecting this, we re-run our baseline models using as dependent variable a dummy indicating with 1 if a researcher has at least one publication in a new affiliation with respect to the pre-competition period, and 0 otherwise. Results displayed in Table A7 show that point estimates are relatively small and indistinguishable from zero, thus providing support for the validity of our findings.

Table A6: Fuzzy RDD estimates on mobility (10 years)

| | Mobility | Mobility | Mobility |
|---|---|---|---|
| RD Estimate | 0.326*** | 0.326*** | 0.353*** |
| | [0.099] | [0.099] | [0.102] |
| Mean dep var | 0.66 | 0.66 | 0.66 |
| Pol. order | 1 | 1 | 1 |
| BW | 1.7 | 1.7 | 1.7 |
| N (left) | 2726 | 2726 | 2584 |
| N (right) | 2908 | 2908 | 2799 |
| N | 41024 | 41024 | 40985 |
| p-value | 0.001 | 0.001 | 0.001 |
| Robust p-value | 0.002 | 0.002 | 0.001 |
| F-stat 1st stage | 20.464 | 20.464 | 19.512 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.0

Table A7: Fuzzy RDD estimates on new affiliation (5 years)

| | Mobility | Mobility | Mobility |
|---|---|---|---|
| RD Estimate | 0.134 | 0.134 | 0.176 |
| | [0.138] | [0.138] | [0.140] |
| Mean dep var | 0.74 | 0.74 | 0.74 |
| Pol. order | 1 | 1 | 1 |
| BW | 1.5 | 1.5 | 1.5 |
| N (left) | 2397 | 2397 | 2243 |
| N (right) | 2628 | 2628 | 2497 |
| N | 40985 | 40985 | 40985 |
| p-value | 0.331 | 0.331 | 0.207 |
| Robust p-value | 0.303 | 0.303 | 0.179 |
| F-stat 1st stage | 11.715 | 11.715 | 11.357 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Our main proxy for mobility is based on affiliations reported in publications, in line with extant literature in the field. One shortcoming of this approach is that bibliometric data can under-report mobility. For instance, we would not have information on affiliations if researchers do not publish (or do not do so in the period examined here). Likewise, if researchers move but do not report the affiliation of the host institution in their publications, they will not be considered as movers in our sample.

To address this potential issue, we conducted a robustness check by linking our dataset to external CV-based information from LinkedIn (via Revelio), ORCID, and manual search. Specifically, we focus on a subsample of researchers around the funding threshold (approximately 10,000 observations) and compare the mobility status inferred from publication data with that inferred from CV sources. Notably, CV information is not immune from problems, as it is often impossible to find or incomplete (in about 20% cases in our sample).

Accordingly, we combine both sources of information, and redefine our mobility variable as follows: if a researcher is classified as non-mobile based on publication affiliations but is identified as mobile based on CV data, we correct the dependent variable to reflect a mobility event (i.e., set it to 1). In all other cases, the mobility status remains unchanged. This adjustment allows us to account for under-reporting in bibliometric sources and test whether our main results are robust to an alternative, CV-augmented definition of mobility. The results of this exercise are reported in Table A8 and show that our main findings remain substantively unchanged.

Table A8: Fuzzy RDD estimates on mobility corrected (5 years)

| | Mobility | Mobility | Mobility |
|---|---|---|---|
| RD Estimate | 0.300*** | 0.314*** | 0.337*** |
| | [0.087] | [0.074] | [0.081] |
| Mean dep var | 0.69 | 0.69 | 0.68 |
| Pol. order | 1 | 1 | 1 |
| BW | 1.8 | 1.9 | 1.8 |
| N (left) | 2899 | 2899 | 2725 |
| N (right) | 3060 | 3060 | 2908 |
| N | 40985 | 40985 | 40985 |
| p-value | 0.001 | 0.000 | 0.000 |
| Robust p-value | 0.002 | 0.000 | 0.000 |
| F-stat 1st stage | 26.087 | 30.329 | 26.402 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

### 4.4 Alternative outcomes

We test the sensitivity of our results concerning the effects of MSCA grants on publication output in three ways. First, we re-run our models using as dependent variable the number of first-authored publications. This is done to tease out potential effects concerning the prominence of grantees vis-à-vis their co-authors which cannot be detected using a simple publication count. Tables A9 and A10 yield no statistically significant results. Second, instead of considering journal articles and conference proceedings as done in our main analysis, we include all publications. No substantial differences are detected (see Tables A11 and A12). Third, in the main analysis we use the average JIF to proxy for publication quality. We provide additional evidence on this by using alternative proxies that are not journal-based, but articles-based. In particular, we use citations and field-weighted citations (FWCI) both winsorized at the 99% to reduce the potential influence of extreme outliers. Results are reported in Tables A13 and A14 for citations count and Tables A15 and A16 for FWCI and are consistent with our baseline findings. To sum up, in all cases point estimates keep being indistinguishable from zero, thus aligning with the findings derived from our baseline models.

Table A9: Fuzzy RDD estimates on first-authored publications (5 years)

| | Pubs | Pubs | Pubs | Pubs (log) | Pubs (log) | Pubs (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 0.194 | 0.186 | 0.169 | -0.114 | -0.141 | -0.094 |
| | [0.652] | [0.599] | [0.910] | [0.231] | [0.168] | [0.166] |
| Mean dep var | 3.16 | 3.16 | 3.18 | 1.14 | 1.15 | 1.15 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 2.2 | 2.2 | 1.7 | 1.6 | 1.8 | 1.7 |
| N (left) | 3385 | 3385 | 2725 | 2397 | 2725 | 2725 |
| N (right) | 3470 | 3470 | 2908 | 2628 | 2908 | 2908 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.766 | 0.756 | 0.853 | 0.620 | 0.403 | 0.573 |
| Robust p-value | 0.772 | 0.767 | 0.861 | 0.555 | 0.335 | 0.513 |
| F-stat 1st stage | 47.612 | 49.820 | 22.500 | 14.487 | 23.856 | 23.123 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table A10: Fuzzy RDD estimates on first-authored publications (10 years)

| | Pubs | Pubs | Pubs | Pubs (log) | Pubs (log) | Pubs (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 0.276 | 0.232 | 0.471 | 0.250 | 0.147 | 0.238 |
| | [1.354] | [1.116] | [1.190] | [0.316] | [0.252] | [0.252] |
| Mean dep var | 4.89 | 4.90 | 4.89 | 1.43 | 1.43 | 1.43 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.8 | 2.0 | 1.9 | 1.4 | 1.5 | 1.5 |
| N (left) | 2900 | 3062 | 2899 | 2244 | 2397 | 2397 |
| N (right) | 3060 | 3186 | 3060 | 2497 | 2628 | 2628 |
| N | 41024 | 40985 | 40985 | 41024 | 40985 | 40985 |
| p-value | 0.838 | 0.836 | 0.692 | 0.429 | 0.560 | 0.346 |
| Robust p-value | 0.840 | 0.846 | 0.677 | 0.386 | 0.544 | 0.317 |
| F-stat 1st stage | 27.736 | 35.449 | 30.273 | 9.569 | 12.709 | 11.943 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table A11: Fuzzy RDD estimates on scientific productivity (5 years) - all publications

| | Pubs | Pubs | Pubs | Pubs (log) | Pubs (log) | Pubs (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 1.978 | 1.590 | 2.454 | 0.212 | 0.080 | 0.171 |
| | [2.560] | [2.022] | [1.898] | [0.313] | [0.234] | [0.230] |
| Mean dep var | 12.55 | 12.55 | 12.53 | 2.21 | 2.21 | 2.21 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.9 | 1.9 | 2.0 | 1.5 | 1.5 | 1.5 |
| N (left) | 3062 | 3062 | 3217 | 2397 | 2397 | 2397 |
| N (right) | 3186 | 3186 | 3347 | 2628 | 2628 | 2628 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.440 | 0.432 | 0.196 | 0.498 | 0.734 | 0.458 |
| Robust p-value | 0.412 | 0.403 | 0.170 | 0.446 | 0.718 | 0.416 |
| F-stat 1st stage | 31.992 | 34.955 | 39.502 | 11.340 | 12.353 | 12.544 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table A12: Fuzzy RDD estimates on scientific productivity (10 years) - all publications

| | Pubs | Pubs | Pubs | Pubs (log) | Pubs (log) | Pubs (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 5.824 | 4.484 | 7.450 | 0.390 | 0.244 | 0.371 |
| | [6.916] | [5.288] | [7.036] | [0.420] | [0.306] | [0.294] |
| Mean dep var | 26.36 | 26.57 | 26.40 | 2.84 | 2.84 | 2.84 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.7 | 1.8 | 1.6 | 1.4 | 1.5 | 1.5 |
| N (left) | 2725 | 2899 | 2584 | 2243 | 2243 | 2243 |
| N (right) | 2908 | 3060 | 2799 | 2497 | 2497 | 2497 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.400 | 0.396 | 0.290 | 0.353 | 0.425 | 0.207 |
| Robust p-value | 0.362 | 0.361 | 0.249 | 0.285 | 0.371 | 0.160 |
| F-stat 1st stage | 22.929 | 28.394 | 16.258 | 8.625 | 10.485 | 11.020 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table A13: Fuzzy RDD estimates on citations (5 years)

| | Citations | Citations | Citations | Citations (log) | Citations (log) | Citations (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 95.690 | 61.038 | 112.059 | 0.231 | -0.253 | -0.064 |
| | [91.362] | [68.498] | [93.406] | [0.709] | [0.464] | [0.460] |
| Mean dep var | 283.99 | 289.49 | 284.67 | 4.63 | 4.63 | 4.63 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.8 | 1.9 | 1.7 | 1.4 | 1.5 | 1.5 |
| N (left) | 2725 | 3062 | 2584 | 2243 | 2243 | 2243 |
| N (right) | 2908 | 3186 | 2799 | 2497 | 2497 | 2497 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.295 | 0.373 | 0.230 | 0.745 | 0.586 | 0.889 |
| Robust p-value | 0.265 | 0.349 | 0.201 | 0.703 | 0.528 | 0.858 |
| F-stat 1st stage | 25.075 | 32.598 | 18.706 | 8.247 | 11.173 | 10.855 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table A14: Fuzzy RDD estimates on citations (10 years)

| | Citations | Citations | Citations | Citations (log) | Citations (log) | Citations (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 82.952 | 39.866 | 89.498 | 0.856 | 0.288 | 0.518 |
| | [172.530] | [126.019] | [181.773] | [0.758] | [0.504] | [0.497] |
| Mean dep var | 568.03 | 566.33 | 563.42 | 5.31 | 5.31 | 5.31 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.8 | 2.0 | 1.7 | 1.4 | 1.5 | 1.5 |
| N (left) | 2899 | 3217 | 2584 | 2243 | 2243 | 2243 |
| N (right) | 3060 | 3347 | 2799 | 2497 | 2497 | 2497 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.631 | 0.752 | 0.622 | 0.259 | 0.568 | 0.297 |
| Robust p-value | 0.612 | 0.762 | 0.609 | 0.203 | 0.521 | 0.245 |
| F-stat 1st stage | 27.872 | 38.243 | 19.595 | 8.084 | 10.140 | 10.188 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table A15: Fuzzy RDD estimates on FWCI (5 years)

| | Citations | Citations | Citations | Citations (log) | Citations (log) | Citations (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 2.186 | 0.921 | 2.963 | -0.025 | -0.204 | -0.076 |
| | [4.528] | [3.666] | [4.877] | [0.385] | [0.289] | [0.306] |
| Mean dep var | 12.55 | 12.52 | 12.56 | 2.03 | 2.03 | 2.03 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.7 | 1.7 | 1.5 | 1.5 | 1.5 | 1.4 |
| N (left) | 2584 | 2725 | 2397 | 2243 | 2397 | 2243 |
| N (right) | 2799 | 2908 | 2628 | 2497 | 2628 | 2497 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.629 | 0.802 | 0.543 | 0.948 | 0.482 | 0.803 |
| Robust p-value | 0.609 | 0.809 | 0.518 | 0.935 | 0.400 | 0.741 |
| F-stat 1st stage | 20.245 | 22.215 | 13.257 | 10.603 | 11.418 | 9.629 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

Table A16: Fuzzy RDD estimates on FWCI (10 years)

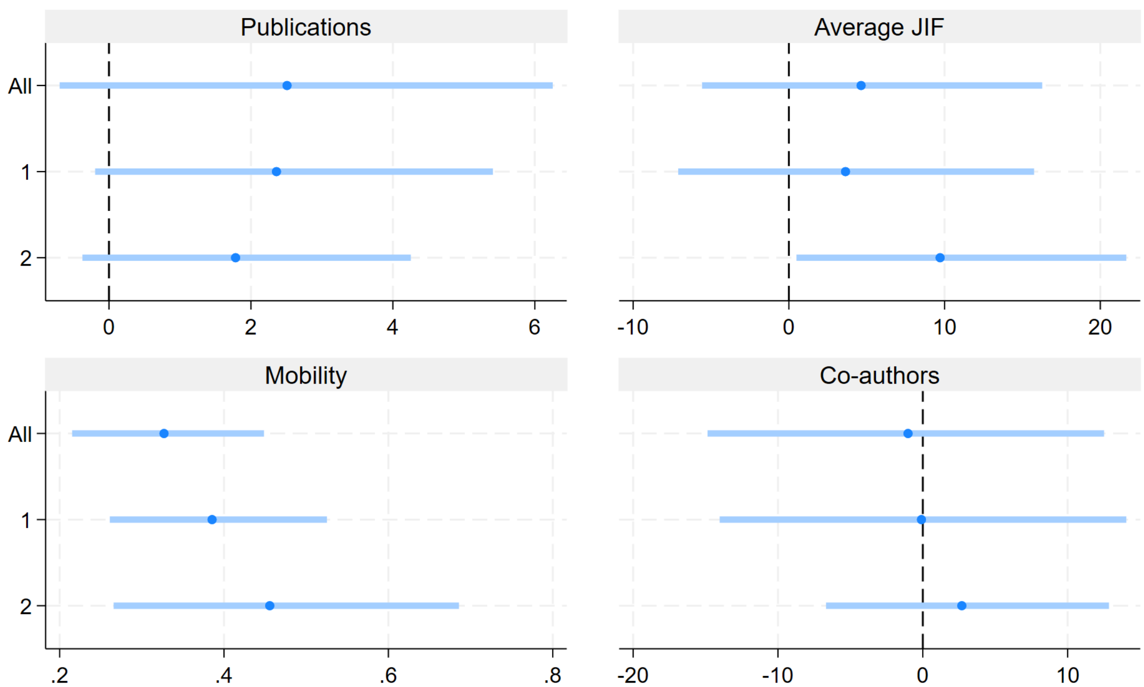
| | Citations | Citations | Citations | Citations (log) | Citations (log) | Citations (log) |
|---|---|---|---|---|---|---|
| RD Estimate | 2.389 | 1.040 | 2.972 | -0.003 | -0.177 | -0.014 |
| | [8.997] | [6.407] | [10.013] | [0.487] | [0.354] | [0.351] |
| Mean dep var | 26.03 | 26.31 | 26.01 | 2.61 | 2.61 | 2.61 |
| Pol. order | 1 | 1 | 1 | 1 | 1 | 1 |
| BW | 1.8 | 1.9 | 1.6 | 1.4 | 1.5 | 1.5 |
| N (left) | 2725 | 3062 | 2397 | 2243 | 2243 | 2243 |
| N (right) | 2908 | 3186 | 2628 | 2497 | 2497 | 2497 |
| N | 40985 | 40985 | 40985 | 40985 | 40985 | 40985 |
| p-value | 0.791 | 0.871 | 0.767 | 0.995 | 0.616 | 0.967 |
| Robust p-value | 0.787 | 0.901 | 0.766 | 0.998 | 0.563 | 0.947 |
| F-stat 1st stage | 24.384 | 34.628 | 14.994 | 9.347 | 10.885 | 9.964 |

Notes: the table reports Fuzzy RDD estimates. Results are obtained following Calonico et al. (2017), with MSE-optimal bandwidths, a triangular kernel and a linear polynomial of the running variable on each side of the threshold. Standard errors are robust and clustered at the competition-level. The mean dependent variable reported in the table refers to the mean of untreated units within the optimal bandwidths. For each dependent variable, the first column includes competition fixed effects, the second adds the pre-competition dependent variable, the third adds the following controls: sex, age, the number of publications before the competition, and host institution type fixed effects. * 0.10 ** 0.05 *** 0.01

### 4.5 Multiple applicants

One potential concern regarding our baseline RDD results is the presence in our sample of researchers who may apply to the program multiple times, eventually securing a grant. On average, around 20% of applying researchers to a given competition have submitted at least one proposal to one of MSCA Individual Fellowships during FP7. In such scenario, researchers who marginally fail to receive the grant, serving as controls in one competition, might marginally win the grant in a subsequent application. This situation could lead to a comparison between researchers who are treated earlier versus others who are simply treated later, potentially biasing our results. To address this, we re-run our models using two approaches: i) for researchers applying multiple times and eventually winning a grant, we include only the application associated with their successful grant and discard applicants that are awarded more than one grant; ii) for researchers applying multiple times, we include only those who have never received the grant, which allows us to have controls that are never contaminated by treatment. In what follows, we report the baseline results (All) and the estimates obtained using the above samples (1 and 2). Estimates reported in Figure A16 show no sign of sensible variation with respect to the baseline, indicating that multiple applicants do not present a challenge for our main results.

Figure A16: Estimates accounting for multiple applicants

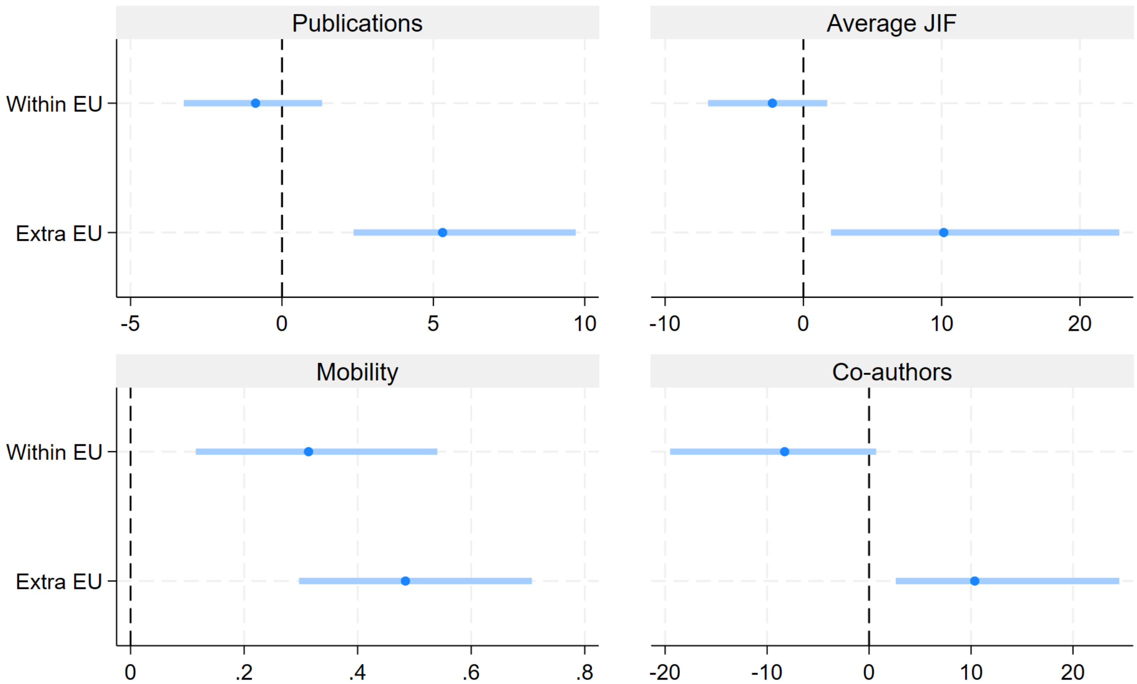



Notes: the figure plots our Fuzzy RDD estimates for the following three samples: i) our original sample including all applicants; ii) for multiple applicants, the last winning application; iii) serial applicants that never won. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

### 4.6 Additional heterogeneity results

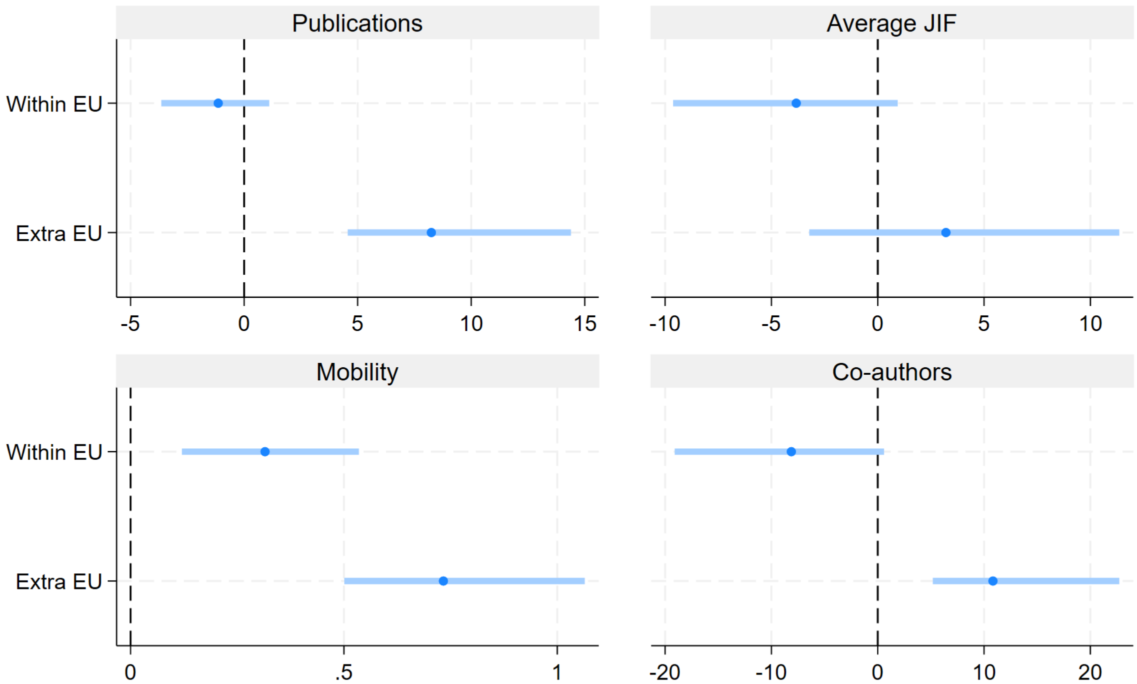
We report additional tests concerning potential differential effects across a set of observable characteristics. In particular, we reports results by splitting the sample into intra-European or extra-European based on the origin and host countries reported in each individual application. This allows to consider applications submitted to CIG which since 2011 can support both intra- and extra-European reintegration. Results reported in Figure A17 corroborate the findings displayed in the main text. Additionally, we test whether effects vary depending on applicant-level characteristics such as sex (Figure A20) and age (Figure A21). We also report split-sample results across GDP per capita levels of origin (Figure A24) and host countries (Figure A23). We do not find clear-cut effects across this battery of tests. We do observe some evidence that researchers' outcomes are somewhat more positively affected by grants for relatively older scientists, and that female researchers may benefit from grants in landing more prestigious affiliations while not improving publication outcomes, which could suggest the presence of certification effects.

Figure A17: Heterogeneous effects across type of mobility



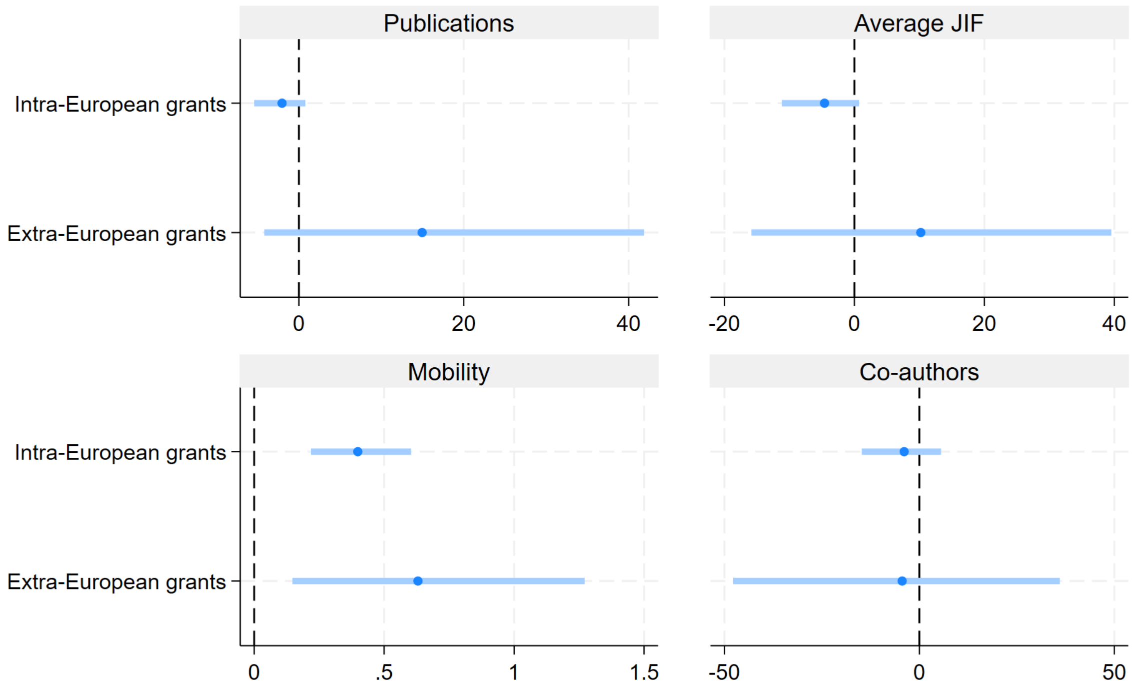

Notes: plots reports Fuzzy RDD estimates by splitting sample across types of mobility: within-EU (i.e. mobility from a EU28 country to another EU28 country) and extra-EU (i.e. from or to a EU28 country). Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A18: Heterogeneous effects across type of mobility (no US)



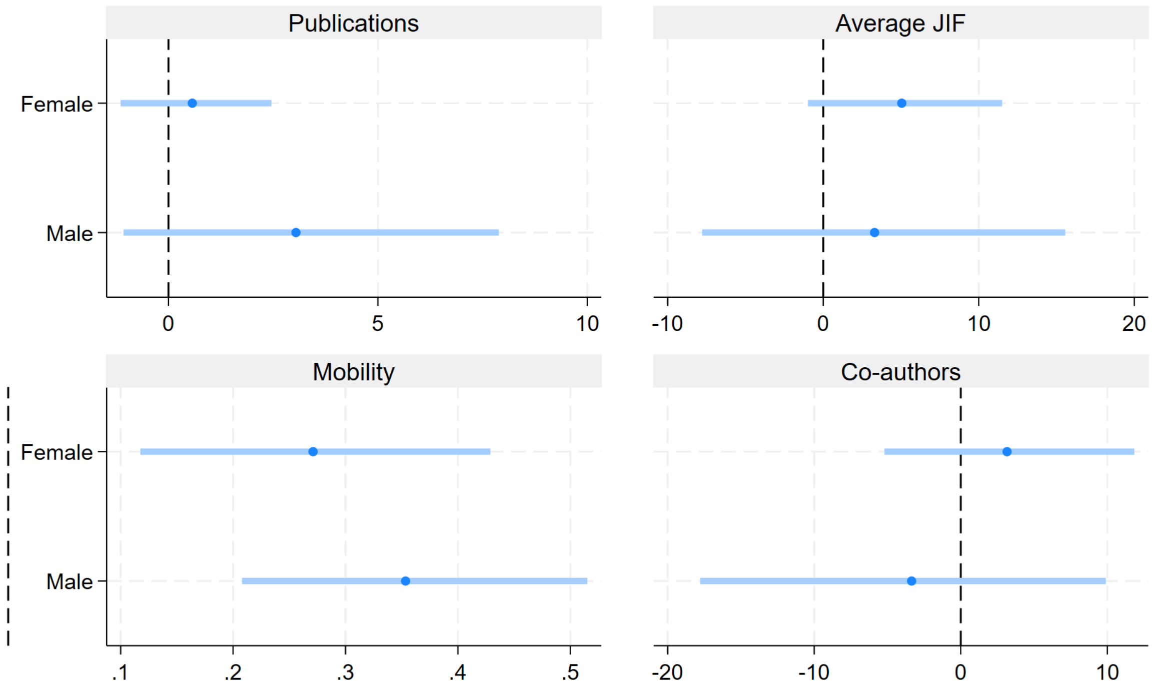

Notes: plots reports Fuzzy RDD estimates by splitting sample across types of mobility: within-EU (i.e. mobility from a EU28 country to another EU28 country) and extra-EU (i.e. from or to a EU28 country). Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A19: Heterogeneous effects across type of mobility grants (no US)



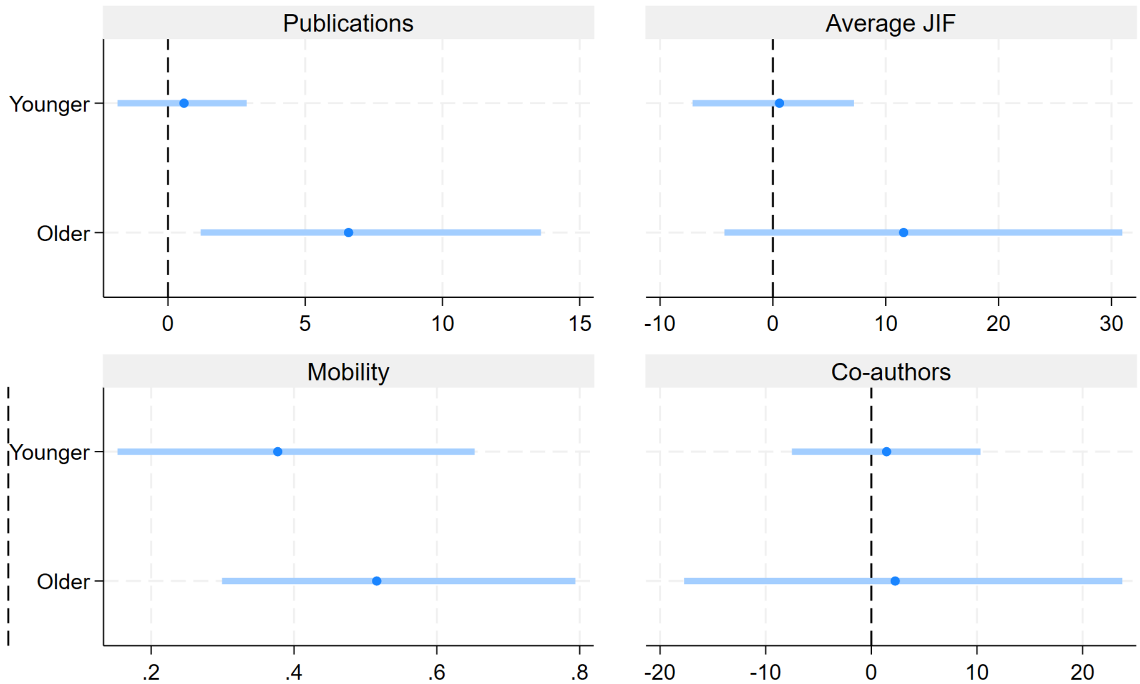

Notes: plots reports Fuzzy RDD estimates by splitting sample across types of mobility grants: intra-European (i.e. IEF) and extra-European mobility grants (i.e. IIF, IOF). Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A20: Heterogeneous effects across researchers' sex



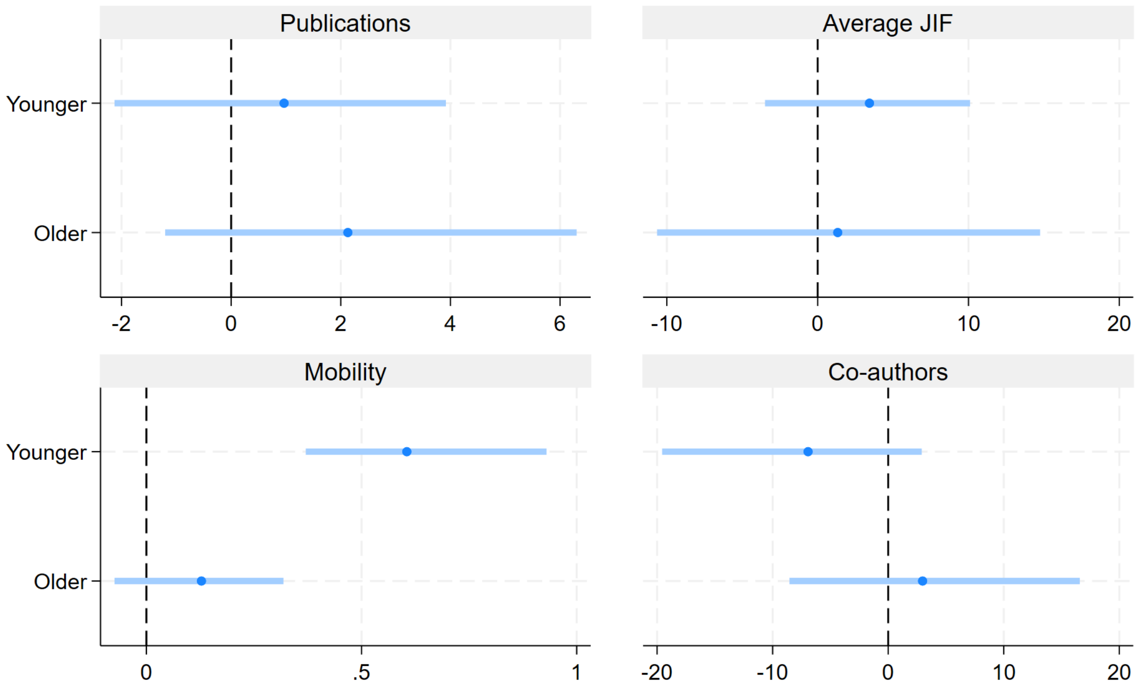

Notes: plots reports Fuzzy RDD estimates by splitting sample across researchers' sex. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A21: Heterogeneous effects across researchers' age



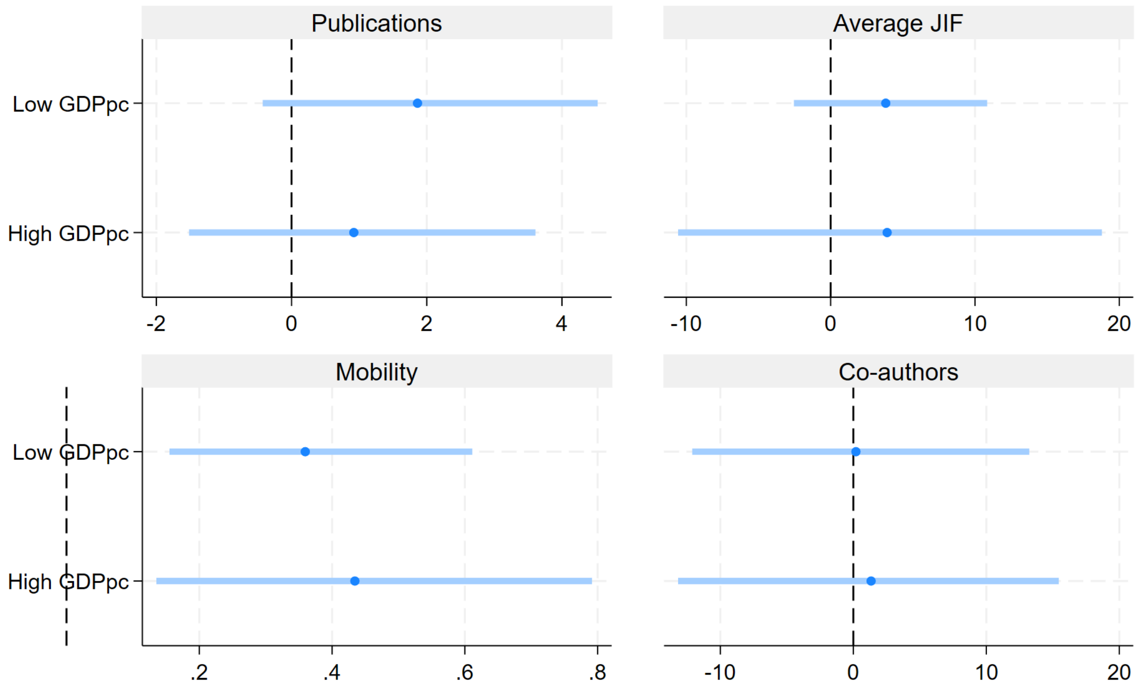

Notes: plots reports Fuzzy RDD estimates by splitting sample across above and below median researchers' age. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A22: Heterogeneous effects across researchers' scientific age



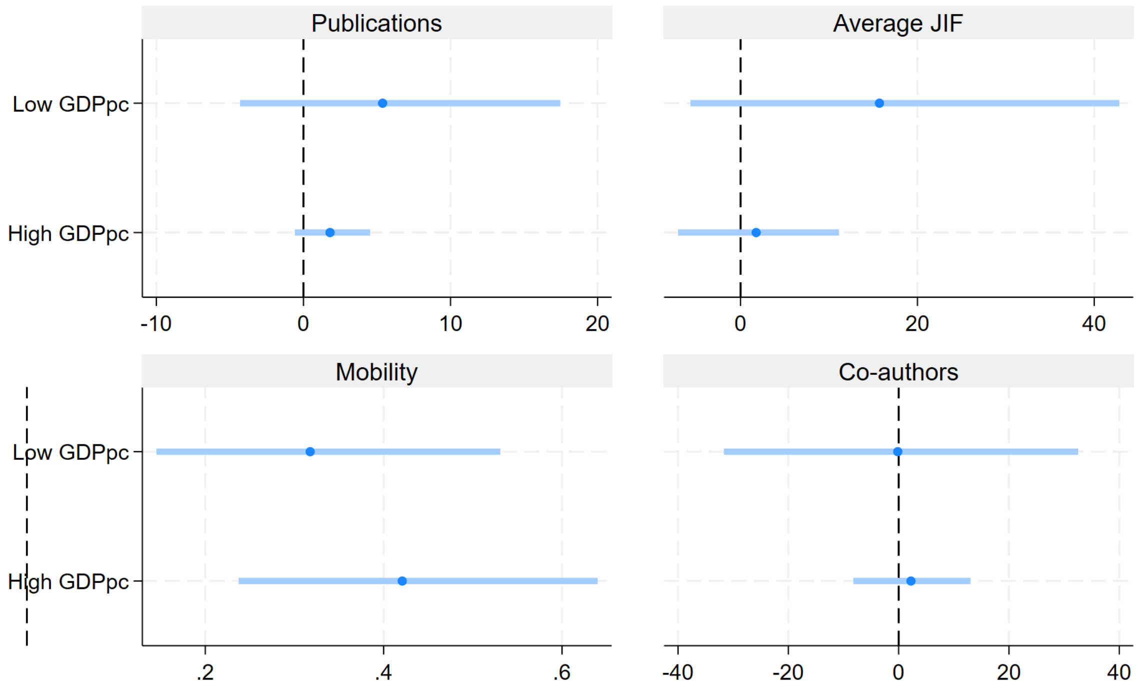

Notes: plots reports Fuzzy RDD estimates by splitting sample across above and below median researchers' scientific age. Scientific age is defined as the years elapsed from the researcher first publication and it is not defined for researchers without pre-competition publications. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A23: Heterogeneous effects across economic development of host country



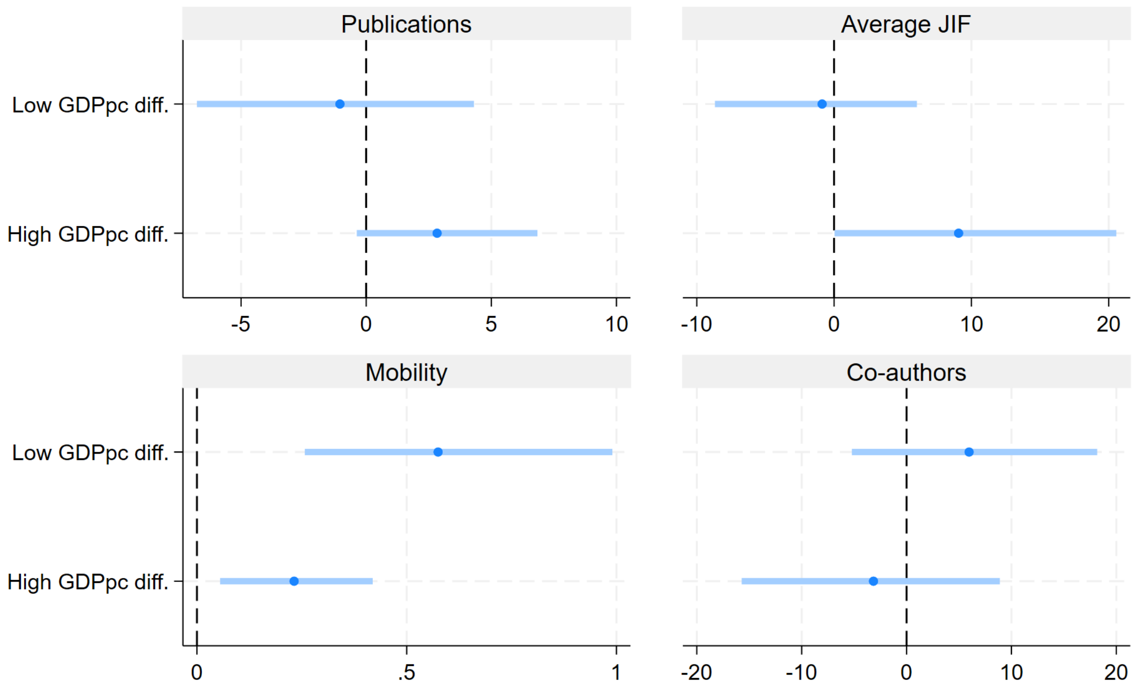

Notes: plots reports Fuzzy RDD estimates by splitting sample across above and below GDP per capita of host countries. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A24: Heterogeneous effects across economic development of origin country



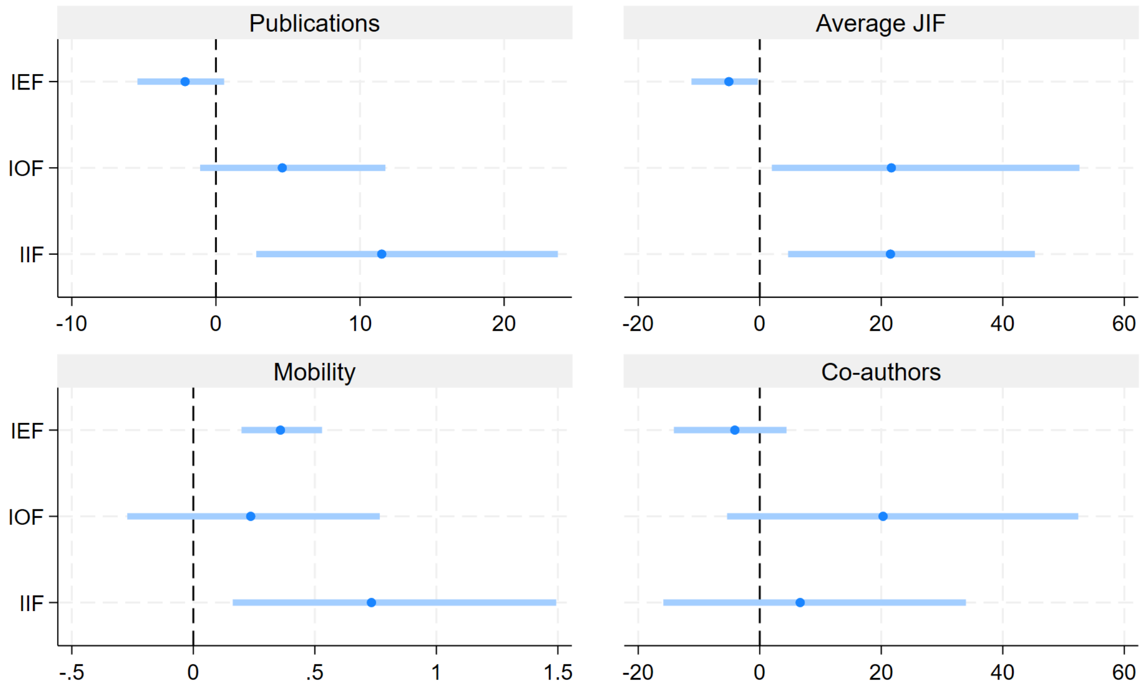

Notes: plots reports Fuzzy RDD estimates by splitting sample across above and below GDP per capita of origin countries. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A25: Heterogeneous effects across difference in economic development of origin and host country



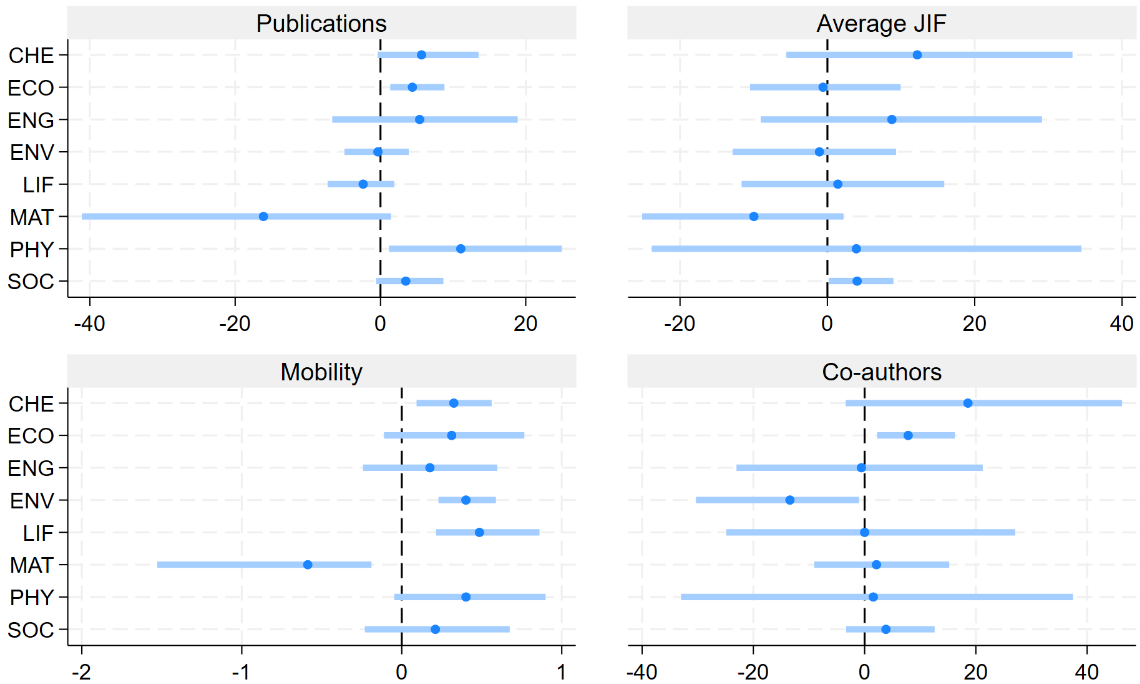

Notes: plots reports Fuzzy RDD estimates by splitting sample across above and below difference in the GDP per capita of origin and host countries. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A26: Heterogeneous effects across subprograms



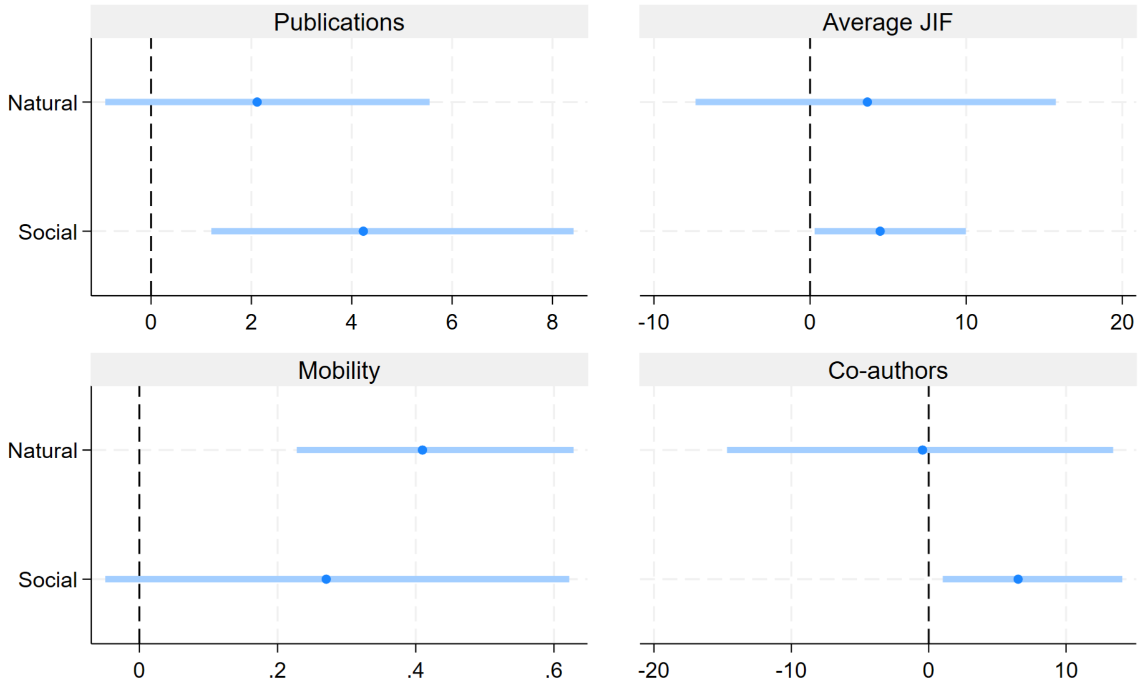

Notes: plots reports Fuzzy RDD estimates by splitting sample across subprograms (IEF: Intra-European Fellowships, IIF: International Incoming Fellowships; IOF: International Outgoing Fellowships; and CIG: Career Integration Grants). Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A27: Heterogeneous effects across panels



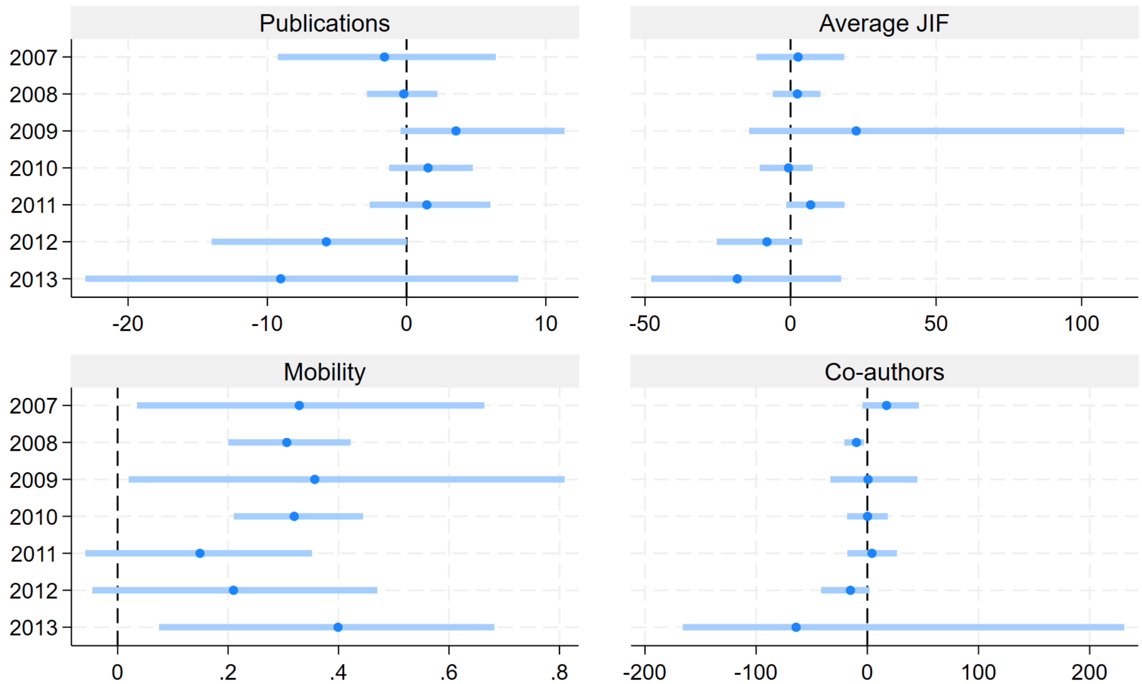

Notes: plots reports Fuzzy RDD estimates by splitting sample across panels. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A28: Heterogeneous effects across Natural vs Social Sciences




Notes: plots reports Fuzzy RDD estimates by splitting sample across Natural vs Social Sciences. Panels in Natural Sciences are CHE, ENG, ENV, LIF MAT, PHY. Panels in Social Sciences are ECO, SOC. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A29: Heterogeneous effects across program cohorts




Notes: plots reports Fuzzy RDD estimates by splitting sample across competition years. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

## 5 Applicant and Author Disambiguation and Matching

In this section, we provide a detailed account of the process used to disambiguate and match applicants with author profiles in bibliographic databases. This task is complex but crucial for ensuring the accuracy and robustness of the econometric analysis. Several challenges arise during this process.

First, homonyms are common, especially in bibliographic data, complicating the accurate identification of individual researchers. Second, we dispose of limited information available on applicants—there are no unique identifiers such as ORCID IDs, nor is there explicit data on the applicants' affiliations at the time of application. Affiliation data can only be inferred indirectly from other sources. Third, applicants lack unique identifiers within the dataset, making it difficult to track individuals who have submitted multiple applications. Finally, although Scopus provides relatively accurate author identifiers, these are generally precise—one identifier rarely corresponds to more than one individual—but not always comprehensive, as many researchers have multiple Scopus profiles (Baas et al., 2020; Moed et al., 2013). As a result, we face two primary issues: identifying the correct person in Scopus and ensuring that all of their Scopus IDs are linked accurately.[3]

### 5.1 Data Enhancement

To address these challenges, we first enriched the dataset with key affiliation information at the time of application. Affiliation data is available for a subset of applicants, depending on the type of grant application (IOF and IIF). For those without direct affiliation information, we inferred it from institutional email addresses or addresses provided by the applicants. When only a physical address was available, we cross-referenced it with the host individual's address data (for which we have affiliation names) and assigned an affiliation where there was a perfect match. This method allowed us to recover affiliation information for approximately 90% of the sample with a precision rate exceeding 99%.

Additionally, we created a unique identifier for each applicant based on name and date of birth. Given the variability in how applicants report their names across applications, we standardized the names and manually inspected groups of individuals with the same birth date to correct any

[3] We assume Scopus identifiers are generally precise and avoid correcting possible errors within individual profiles. At the scale of our dataset, it is unfeasible to match publications manually, bypassing Scopus identifiers.

discrepancies (e.g., spelling errors or variations in middle names).

### 5.2 Pool of Potential Matches

We first match applicants with the largest possible set of Scopus author profiles, initially prioritizing recall over precision. We employ both name- and email-based matching. We included all Scopus profiles with names compatible with the applicants', allowing for variations such as typographical errors, inversions of first and last names, different transliterations (e.g., "ü," "u," "ue"), middle names, or initials.[4] We further utilized the Scopus RESTful API to retrieve author profiles linked to the applicant's email address as recorded in publications. This required identifying the relevant author from the co-authorship list, which is generally accurate but can produce false positives for common names. We refined this pool by removing profiles incompatible by age, retaining only those where the individual would have been at least 20 years old at their first publication and no older than 90 at their last. This yielded an initial set of 3,011,859 applicant-author pairs.

We developed a text similarity measure to both narrow the sample of potential matches and serve, at a later stage, as a key predictor of match probability. The measure compares the titles and abstracts of applicants' proposals with those of potential matches' papers from Scopus. After normalizing the text (removing special characters, converting to lowercase, and eliminating stopwords), we applied n-grams to capture meaningful word sequences. Using the TF-IDF (Term Frequency-Inverse Document Frequency) method, we vectorized the text and calculated cosine similarity to assess the closeness between each applicant's proposal and the potential matches. To ensure feasibility, we limited the comparison to a maximum of 20 randomly selected papers per candidate, enabling efficient processing without compromising accuracy.

Based on the text similarity measure, we restricted the sample of potential matches in two ways: (1) for author profiles matched to multiple applicants, we retained only the pair with the highest text similarity score, and (2) when more than 20 potential matches were available for an applicant, we retained only the top 20 profiles by similarity score. The distribution of potential matches was highly skewed, with 5% of the most common names, such as "John Smith," "Li Chen," and "Hans Muller," accounting for 80% of the potential matches. Manual inspection, as well as

[4]For example, "J. Smith" was considered a potential match for "John Smith," and profiles with partial surname overlaps, such as "Juan Garcia" and "Juan Garcia-Marquez," were also included. However, profiles with incompatible initials or name components (e.g., "J. W. Smith" for "John K. Smith") were excluded.

later extensive manual classification, ensured that this selection process remained conservative, with virtually no correct matches being discarded on the basis of text similarity. At this stage, 248,920 pairs of applicants and potential matches remained.

### 5.3 Feature Engineering

We then constructed a set of features to predict the probability that a match is correct. Table A17 lists all features used and their description. The first set of features derive from the previously built measures, such as "matches_name" for profiles identified by name and "matches_email" for those identified by email. We also considered the implied age at the time of first and last publication ("first_pub_age" and "last_pub_age"). Additionally, we incorporated the text similarity measure as both a continuous variable ("text_similarity") and a ranking within the applicant's pool of potential matches ("text_rank"). We also maintain the number of author profiles originally matched to applicant ("count_ids"), as proxy for their name frequency in the population of researchers, and the number of publications associated with the Scopus author ("documents_sco"). The latter is relevant because profiles with only one or few publications tend to be less likely correct matches.

We built further features based on available data, such as (1) the match between the applicant's field of application and the primary research field of Scopus authors ("field_match"),[5] (2) the number of publications where the author was affiliated with the applicant's country of application ("ctry_match"), and (3) the number of publications where the author was affiliated with the applicant's nationality ("nation_match"). Then we added a general name similarity measure ("name_similarity")[6] and indicators on whether first names ("firstname_match"), initials ("inits_match"),

[5]We categorize MSCA panel topics by pairing them with relevant Scopus ASJC codes in the following non-mutually exclusive groupings: Chemistry (Agricultural and Biological Sciences, Chemical Engineering, Chemistry), Economics (Business, Management and Accounting, Decision Sciences, Economics, Econometrics and Finance, Sociology and Political Science), Engineering (Agricultural and Biological Sciences, Chemical Engineering, Computer Science, Earth and Planetary Sciences, Engineering, Materials Science), Environmental Science (Agricultural and Biological Sciences, Earth and Planetary Sciences, Energy, Environmental Science), Life Sciences (Agricultural and Biological Sciences, Biochemistry, Genetics and Molecular Biology, Dentistry, Health Professions, Immunology and Microbiology, Medicine, Multidisciplinary, Neuroscience, Nursing, Pharmacology, Toxicology and Pharmaceutics, Psychology, Veterinary), Mathematics (Mathematics), Physical Sciences (Agricultural and Biological Sciences, Physics and Astronomy), Social Sciences (Arts and Humanities, Business, Management and Accounting, Decision Sciences, Economics, Econometrics and Finance, Psychology, Sociology and Political Science).

[6]To build this we normalize and deconstruct each name into its constituent parts (first, middle, and last names), which are then alphabetically sorted and recombined. This approach ensures that the comparison is insensitive to name order, accommodating variations such as "John Michael Doe" vs. "Michael John Doe." The similarity between names is quantified using Python's difflib.SequenceMatcher, which calculates a similarity score from 0 to 1 based on the fraction of characters that match directly or after adjustments for modifications like insertions or deletions. We

Table A17: Features and Descriptions

| Feature Name | Description |
|---|---|
| count_ids | Number of author profiles originally matched to the applicant, as a proxy for the frequency of the applicant's name among researchers. |
| ctry_match | Number of publications where the author's affiliation country matches the applicant's country of application. |
| documents_sco | Number of publications associated with the Scopus author. |
| field_match | Match between the applicant's field of application and the primary research field of Scopus authors. |
| firstname_match | Indicates whether the first name fully matches between the applicant and the Scopus author. |
| firstname_msca_double | Indicates whether the applicant's first name is composed of two or more parts. |
| firstname_sco_double | Indicates whether the Scopus author's first name is composed of two or more parts. |
| first_pub_age | Age of the potential match at the time of their first publication. |
| inits_match | Indicates whether the initials of the applicant and Scopus author match. |
| last_pub_age | Age of the potential match at the time of their last publication. |
| matches_email | Indicates whether the match is identified based on an email address. |
| matches_name | Indicates whether the match is identified based on name compatibility. |
| name_similarity | Measures the name similarity between the applicant and the Scopus author, based on a combined score of full name and initials match. |
| nation_match | Number of publications where the author's affiliation country matches the applicant's nationality. |
| pubs_address | Number of publications with the same address as the applicant. |
| pubs_postcode | Number of publications with the same postcode as the applicant. |
| surname_match | Indicates whether the surname fully matches between the applicant and the Scopus author. |
| surname_msca_double | Indicates whether the applicant's surname is composed of two or more parts. |
| surname_sco_double | Indicates whether the Scopus author's surname is composed of two or more parts. |
| text_rank | Ranking of text similarity for the potential match compared to other possible matches for the applicant. |
| text_similarity | Cosine similarity between the applicant's proposal and the Scopus author's papers based on titles and abstracts. |
| urls_similarity | Measures the similarity of URLs retrieved from web searches for the applicant and the Scopus author. |
| url_valid | Indicates whether any valid URL was returned by the web search. |

Notes: The table describes the features used in the model for matching applicants with Scopus author profiles, along with brief descriptions. Each feature is key to establishing the credibility of the match between the dataset entries and the Scopus author identities.

or surnames (“surname_match”) matched exactly. Alongside these, we flag double first or surnames for applicants (“firstname_msca_double,” “surname_msca_double,”) and Scopus authors (“firstname_sco_double,” and “surname_sco_double”).[7]

We then developed a highly informative feature based on search engine results for pairs of applicants and authors. A similar method, albeit for companies, is adopted in Autor et al. (2020) and Baruffaldi and Poege (2024). For each pair (consisting of "applicant name, affiliation" and "author name, Scopus affiliation"), we retrieved the top three Google search results and measured the similarity based on matching URLs ("urls_similarity"). This feature proved highly predictive, as well as complementary to other features, as it leverages information embedded in URLs from personal pages, CVs, and institutional websites. It is also robust to variations in individual and affiliation names. However, it remains a noisy indicator, as both false positive and false negative may emerge. Alongside this indicator, we consider whether any valid result was returned by the web search ("url_valid""), to account for a small number of cases where the web search returned no results.

Finally, we utilized address information from applicants. Using the Scopus RESTful API, we verified whether a specific address was associated with a given author. We created the feature "pubs_address" to count the number of publications matching the applicant’s address. Similarly, but less restrictively, "pubs_postcode" counts publications matching the applicant’s postcode. While this feature may occasionally introduce errors when other coauthors share the same address, manual inspection confirmed that profiles with at least one matching publication were generally correct matches; more frequently, however, correct matches were not associated with positive values of these features.

### 5.4 Data Classification and Match Prediction

We manually processed and labeled 8,810 applicants near the acceptance cutoff to ensure precision within the most relevant bandwidth for the RDD estimation. The features we built, along with proposal titles and representative author publication titles, as well as affiliation information,

adjust the measure to provide greater weigth to similarity in the initials of each name component.

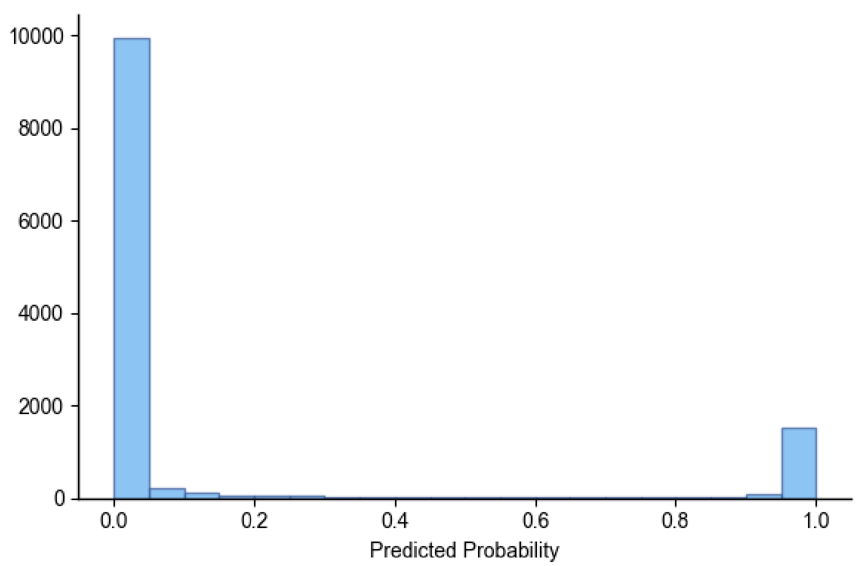
[7] For example, “firstname_match” would indicate a match between "John K" and "John K" but not "John"; “inits_match” would indicate a match between "J K" and "John K"; and “surname_match” would indicate a match between "Garcia-Marques" and "Garcia-Marques," but not "Garcia".

facilitated efficient classification. A large number of cases could be assessed with the information already available. Ambiguous cases were further investigated using CVs and online resources. In 203 cases, the ambiguity was too high, and the applicants were dropped.

To match the remaining applicants, we trained a machine learning (ML) model using the manually labeled data. Following prior literature, we selected a random forest classifier due to its robustness and ability to handle numerous predictors, reducing overfitting through the aggregation of multiple decision trees (Donner, 2022; Heinisch et al., 2020). We train the model on all features, transforming into logarithm all approximately continuous variable, and and adding main interactions between features (respectively indicated with "log_*" and "*_x_*", when reported in Figure A31). After training, we extended the model predictions to the entire restricted pool of candidates. The final matches consisted of both manually curated pairs and model-predicted pairs, resulting in 40,273 Scopus identifiers for 30,993 applicants.

### 5.5 Match Quality

Figure A30: Frequency of prediction probabilities




Notes: The histogram illustrates the distribution of prediction probabilities generated by the Random Forest classification model. The concentration near the values of 0 and 1 suggests a high degree of confidence in the model's classifications.

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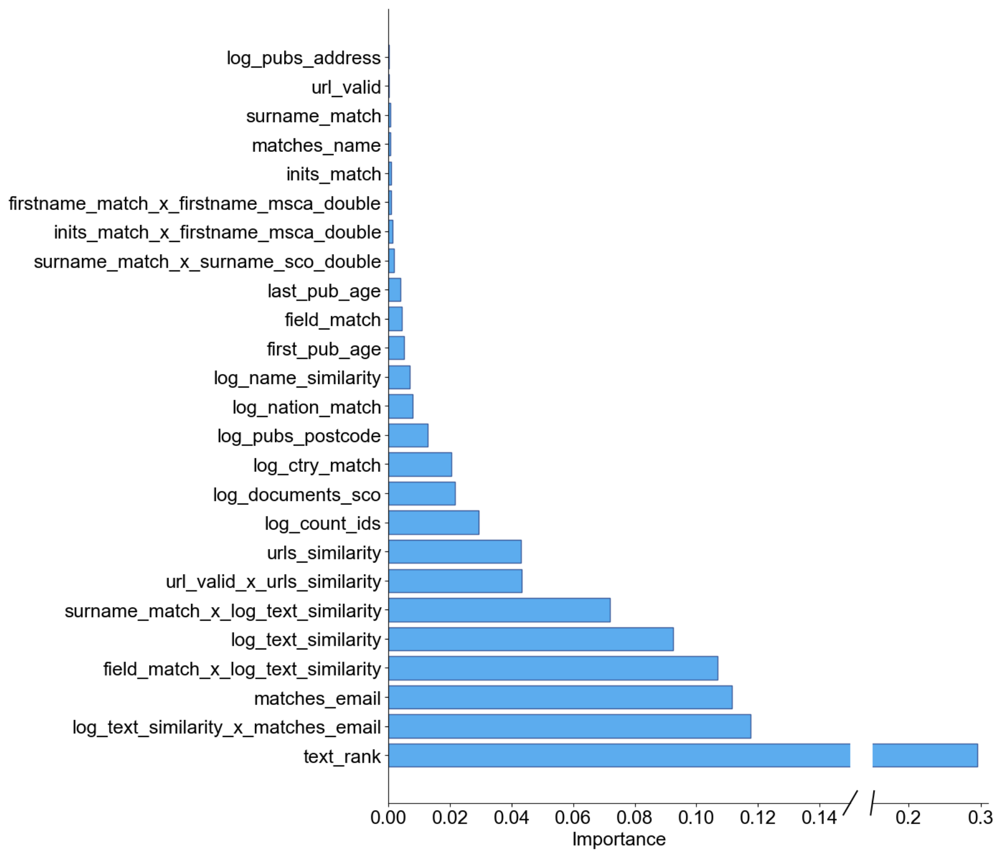
The model performed exceptionally well. We first assessed performance using an 80/20 train-test split and retrained the model on the full dataset before extending it to the general sample. In this test, we achieve 98% precision and approximately 95% recall compared to manually classified cases.[8] When training and assessing precision and recall on the entire training set we reach 99% and 97%, respectively. To further test the model behavior, we conducted two additional evaluations. First, we analyzed the distribution of predicted probabilities, reported in Figure A30, which showed that the model classified most cases with high confidence, with the majority of predictions near 0 or 1. Second, we plotted feature importance, displayed in Figure A31, revealing that text similarity, email match, and URL similarity, as expected, were the most influential, but other variables also contributed.

The overall precision and recall of the final dataset are likely even higher. The model was eventually trained on the entire training set, and the final dataset combined manually curated cases with model-predicted cases. Most evidently, approximately one third of the sample was manually curated. Accordingly, manually curated cases are exclusively subject to human error while the indication about precision and recall applies to the remaining part of the sample, relative to the same cases as training set. We also manually inspected all cases with no match and corrected approximately 60 false negatives caused by idiosyncratic issues (e.g., name changes, use of nicknames in publications, etc.).

[8] By means of comparison, a more naive approach based exclusively on name similarity, email information, and basic information on field and country match features would achieve about 90% precision and 80% recall, or less.

Figure A31: Features importance




Notes: The graph displays the relative importance of each feature used in the Random Forest classification model. Feature importance is measured by the decrease in model accuracy when the feature's values are permuted, indicating how much the model relies on the feature for making accurate predictions.

## References


Aman, V. (2018). A new bibliometric approach to measure knowledge transfer of internationally mobile scientists. *Scientometrics*, 117(1):227–247.

Arora, A. and Gambardella, A. (2005). The impact of nsf support for basic research in economics. *Annales d'Economie et de Statistique*, pages 91–117.

Autor, D., Dorn, D., Hanson, G. H., Pisano, G., and Shu, P. (2020). Foreign competition and domestic innovation: Evidence from us patents. *American Economic Review: Insights*, 2(3):357–374.

Avramov, D. (2015). Fp7 ex-post evaluation people specific programme (2007-2013): Rationale, implementation and achievements.

Aykac, G. (2021). The value of an overseas research trip. *Scientometrics*, 126(8):7097–7122.

Ayoubi, C., Pezzoni, M., and Visentin, F. (2021). Does it pay to do novel science? the selectivity patterns in science funding. *Science and Public Policy*, 48(5):635–648.

Baas, J., Schotten, M., Plume, A., Côté, G., and Karimi, R. (2020). Scopus as a curated, high-quality bibliometric data source for academic research in quantitative science studies. *Quantitative Science Studies*, 1(1):377–386.

Barnett, A., Blakely, T., Liu, M., Garland, L., and Clarke, P. (2024). The impact of winning funding on researcher productivity, results from a randomized trial. *Science and Public Policy*, page scae045.

Baruffaldi, S. and Poege, F. (2024). Like stars: How firms learn at scientific conferences. *Management Science*.

Baruffaldi, S. H., Marino, M., and Visentin, F. (2020). Money to move: The effect on researchers of an international mobility grant. *Research Policy*, 49(8):104077.

Benavente, J. M., Crespi, G., Garone, L. F., and Maffioli, A. (2012). The impact of national research funds: A regression discontinuity approach to the chilean fondecyt. *Research Policy*, 41(8):1461–1475.

Calonico, S., Cattaneo, M. D., Farrell, M. H., and Titiunik, R. (2017). rdrobust: Software for regression-discontinuity designs. *The Stata Journal*, 17(2):372–404.

Carayol, N. and Lanoë, M. (2017). The impact of project-based funding in science:\r\nlessons from the anr experience. Technical report, Groupe de Recherche en Economie Théorique et Appliquée (GREThA).

Cattaneo, M. D., Idrobo, N., and Titiunik, R. (2024). *A practical introduction to regression discontinuity designs: Extensions*. Cambridge University Press.

Chudnovsky, D., López, A., Rossi, M. A., and Ubfal, D. (2008). Money for science? the impact of research grants on academic output. *Fiscal Studies*, 29(1):75–87.

De Benedetto, M. A., De Paola, M., Scoppa, V., and Smirnova, J. (2023). Erasmus program and labor market outcomes: Evidence from a fuzzy regression discontinuity design.

Donner, P. (2022). Algorithmic identification of ph. d. thesis-related publications: a proof-of-concept study. *Scientometrics*, 127(10):5863–5877.

Dubois, P., Rochet, J.-C., and Schlenker, J.-M. (2014). Productivity and mobility in academic research: Evidence from mathematicians. *Scientometrics*, 98:1669–1701.

Fangmeng, T. (2016). Brain circulation, diaspora and scientific progress: A study of the international migration of chinese scientists, 1998–2006. *Asian and Pacific migration journal*, 25(3):296–319.

Fort, M., Ichino, A., Rettore, E., and Zanella, G. (2022). Multi-cutoff rd designs with observations located at each cutoff: problems and solutions.

Franke, J., Humburg, M., and Souto-Otero, M. (2017). Fp7 ex post and h2020 interim evaluation of marie skłodowska-curie actions (msca).

Franzoni, C., Scellato, G., and Stephan, P. (2014). The mover's advantage: The superior performance of migrant scientists. *Economics Letters*, 122(1):89–93.

Fraunhofer, I., Associati, E., GfK, E., et al. (2014). Marie curie researchers and their long-term career development: a comparative study.

Ganguli, I. (2017). Saving soviet science: The impact of grants when government r&d funding disappears. *American Economic Journal: Applied Economics*, 9(2):165–201.

Gelman, A. and Imbens, G. (2019). Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business & Economic Statistics*, 37(3):447–456.

Ghirelli, C., Havari, E., Meroni, E. C., and Verzillo, S. (2023). The long-term causal effects of winning an erc grant. *Banco de Espana Working Paper No. 2213*.

Granato, S., Havari, E., Mazzarella, G., and Schnepf, S. V. (2024). Study abroad programmes and student outcomes: Evidence from erasmus. *Economics of Education Review*, 99:102510.

Gu, J., Pan, X., Zhang, S., and Chen, J. (2024). International mobility matters: Research collaboration and scientific productivity. *Journal of Informetrics*, 18(2):101522.

Heinisch, D. P., Koenig, J., and Otto, A. (2020). A supervised machine learning approach to trace doctorate recipients' employment trajectories. *Quantitative Science Studies*, 1(1):94–116.

Heyard, R. and Hottenrott, H. (2021). The value of research funding for knowledge creation and dissemination: A study of snsf research grants. *Humanities and Social Sciences Communications*, 8(1):1–16.

Horta, H., Jung, J., and Santos, J. M. (2018). Effects of mobilities on the research output and its multidisciplinarity of academics in hong kong and macau: An exploratory study. *Higher Education Quarterly*, 72(3):250–265.

Horta, H., Jung, J., and Santos, J. M. (2020). Mobility and research performance of academics in city-based higher education systems. *Higher Education Policy*, 33:437–458.

Hottenrott, H., Rose, M. E., and Lawson, C. (2021). The rise of multiple institutional affiliations in academia. *Journal of the Association for Information Science and Technology*, 72(8):1039–1058.

Hussinger, K. and Carvalho, J. N. (2022). The long-term effect of research grants on the scientific output of university professors. *Industry and Innovation*, 29(4):463–487.

Jacob, B. A. and Lefgren, L. (2011). The impact of research grant funding on scientific productivity. *Journal of public economics*, 95(9-10):1168–1177.

Jonkers, K., Fako, P., Isella, L., Zacharewicz, T., Del Rio, J., Sandstrom, U., and van den Besselaar, P. (2018). A comparative analysis of the publication behaviour of msca fellows.

Langfeldt, L., Bloch, C. W., and Sivertsen, G. (2015). Options and limitations in measuring the impact of research grants—evidence from denmark and norway. *Research Evaluation*, 24(3):256–270.

Lawson, C. and Shibayama, S. (2015). International research visits and careers: An analysis of bioscience academics in japan. *Science and Public Policy*, 42(5):690–710.

Liu, M. and Hu, X. (2022). Movers' advantages: The effect of mobility on scientists' productivity and collaboration. *Journal of Informetrics*, 16(3):101311.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of econometrics*, 142(2):698–714.

Moed, H. F., Aisati, M., and Plume, A. (2013). Studying scientific migration in scopus. *Scientometrics*, 94:929–942.

Momeni, F., Karimi, F., Mayr, P., Peters, I., and Dietze, S. (2022). The many facets of academic mobility and its impact on scholars' career. *Journal of Informetrics*, 16(2):101280.

Netz, N., Hampel, S., and Aman, V. (2020). What effects does international mobility have on scientists' careers? a systematic review. *Research evaluation*, 29(3):327–351.

Non, M., van Honk, J., van Houten, V., van der Weijden, I., and van Leeuwen, T. (2022). Getting off to a flying start? the effects of an early-career international mobility grant on scientific performance. Technical report, CPB Netherlands Bureau for Economic Policy Analysis.

Oyer, P. (2006). Initial labor market conditions and long-term outcomes for economists. *Journal of Economic Perspectives*, 20(3):143–160.

Robinson-Garcia, N., Sugimoto, C. R., Murray, D., Yegros-Yegros, A., Larivière, V., and Costas, R. (2019). The many faces of mobility: Using bibliometric data to measure the movement of scientists. *Journal of informetrics*, 13(1):50–63.

Shen, W., Xu, X., and Wang, X. (2022). Reconceptualising international academic mobility in the global knowledge system: towards a new research agenda. *Higher Education*, 84(6):1317–1342.

Shen, W.-Q., Liu, D., and Chen, H. (2017). Chinese ph. d. students on exchange in european union countries: Experiences and benefits. *European Journal of Higher Education*, 7(3):322–335.

Shi, D., Liu, W., and Wang, Y. (2023). Has china's young thousand talents program been successful in recruiting and nurturing top-caliber scientists? *Science*, 379(6627):62–65.

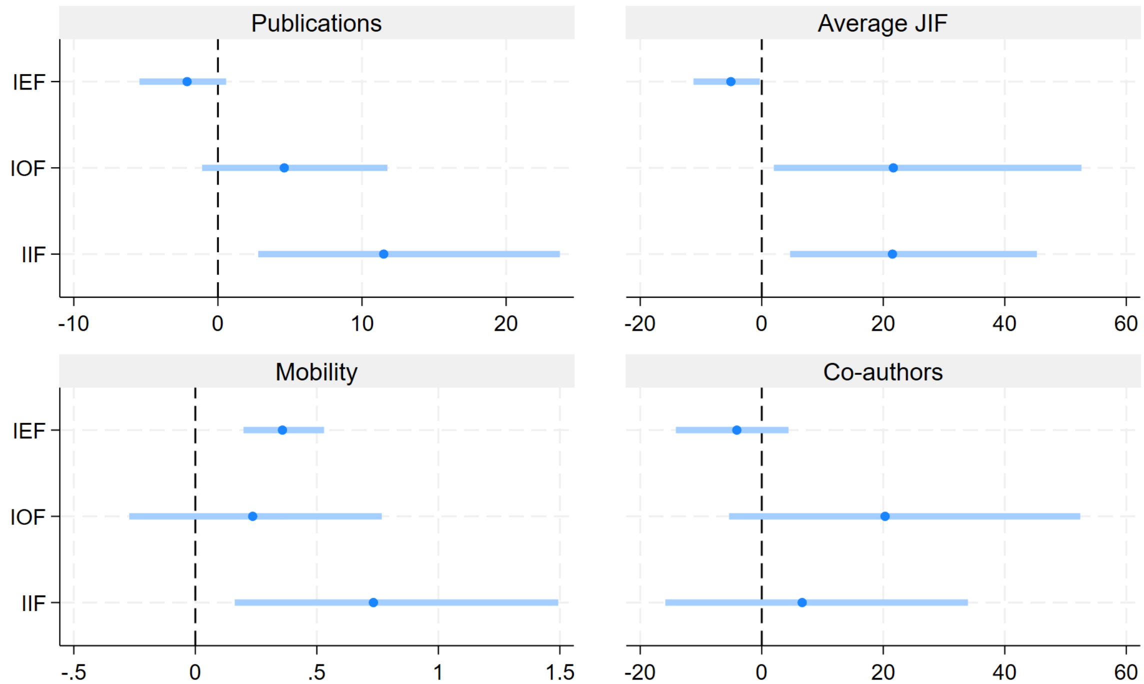
Shin, J. C., Jung, J., Postiglione, G. A., and Azman, N. (2014). Research productivity of returnees from study abroad in korea, hong kong, and malaysia. *Minerva*, 52:467–487.

Stephan, P. (2012). *How economics shapes science*. Harvard University Press.

Wang, Y., Jones, B. F., and Wang, D. (2019). Early-career setback and future career impact. *Nature communications*, 10(1):4331.

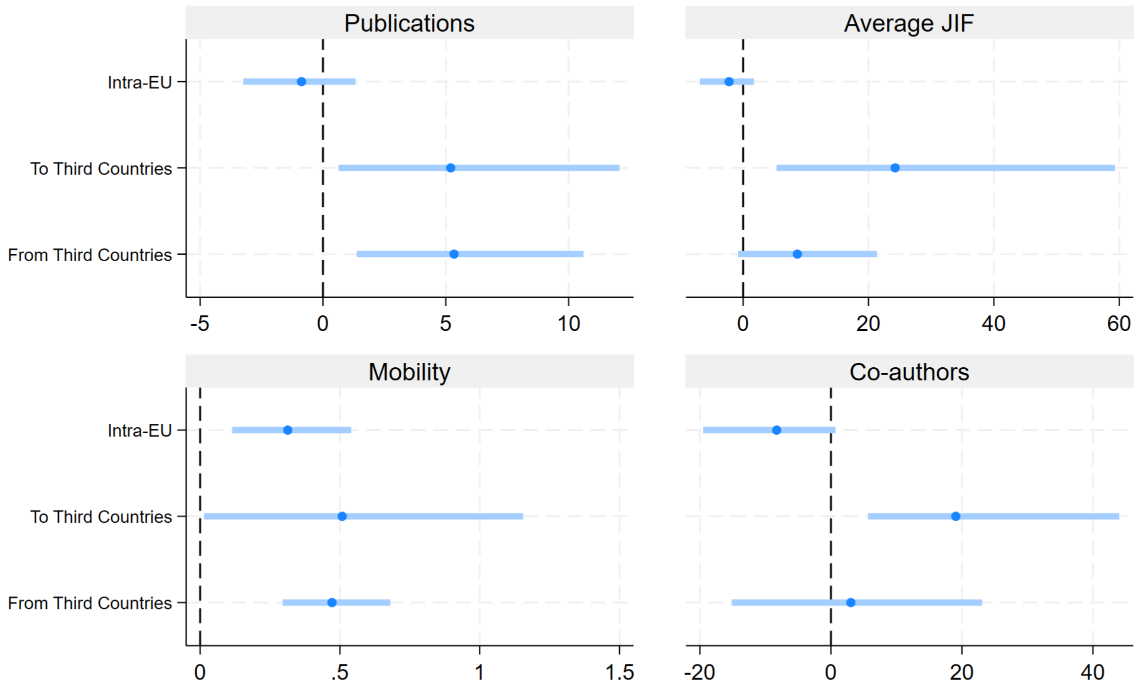
Yildiz, Y., Bohorquez, D. C., Visentin, F., and Ciarli, T. (2024). Expanding horizons: The impact of postdoctoral mobility grants on research diversification.

Figure A32: Heterogeneous effects across sub-programs



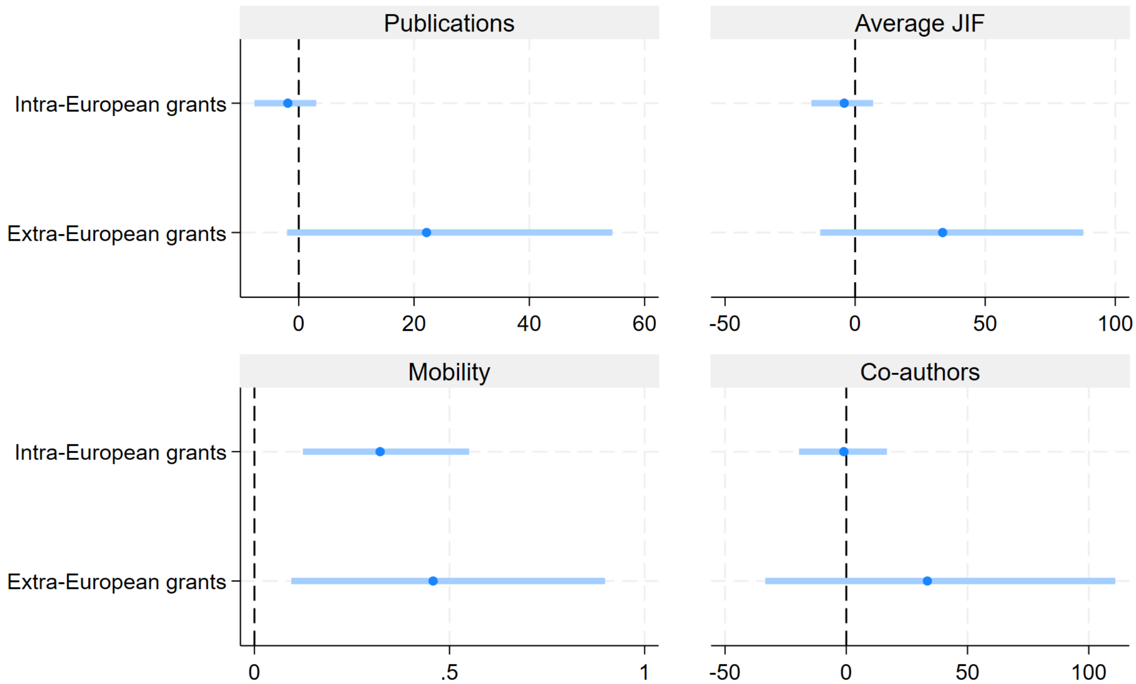

Notes: plots reports Fuzzy RDD estimates by splitting sample across the different sub-programs. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A33: Heterogeneous effects across main directions of mobility



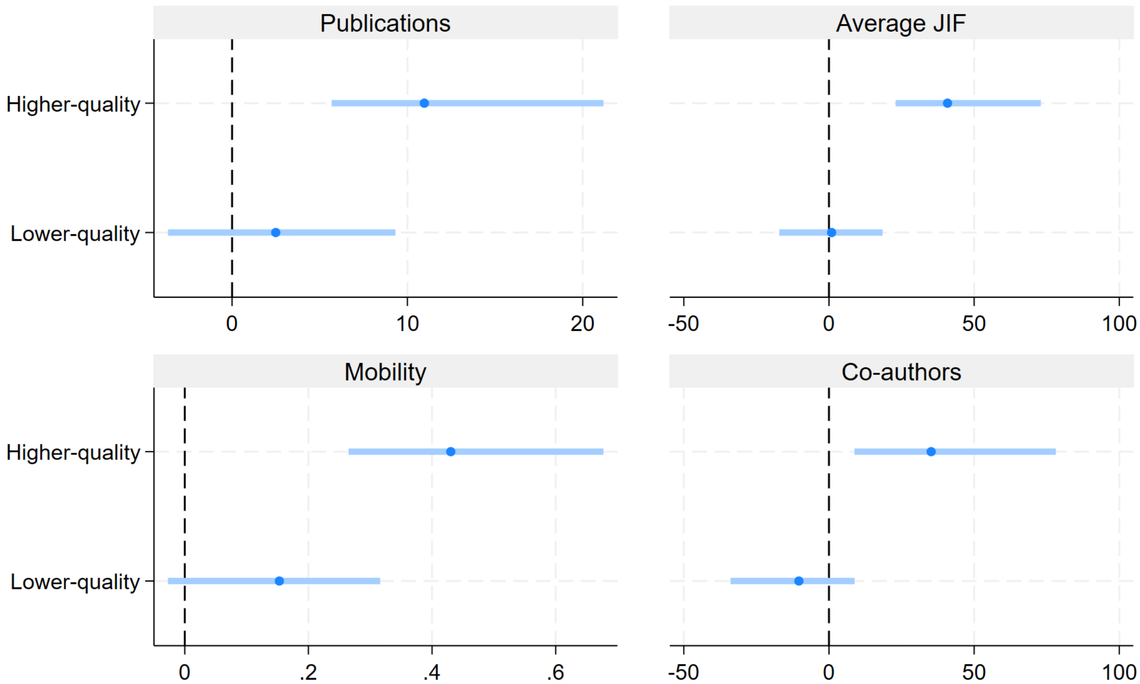

Notes: plots reports Fuzzy RDD estimates by splitting sample in three groups depending on the origin and host country (i.e. within-EU mobility, from the EU to Third Countries, from Third Countries to the EU. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A34: Heterogeneous effects across type of mobility grants (10 years)



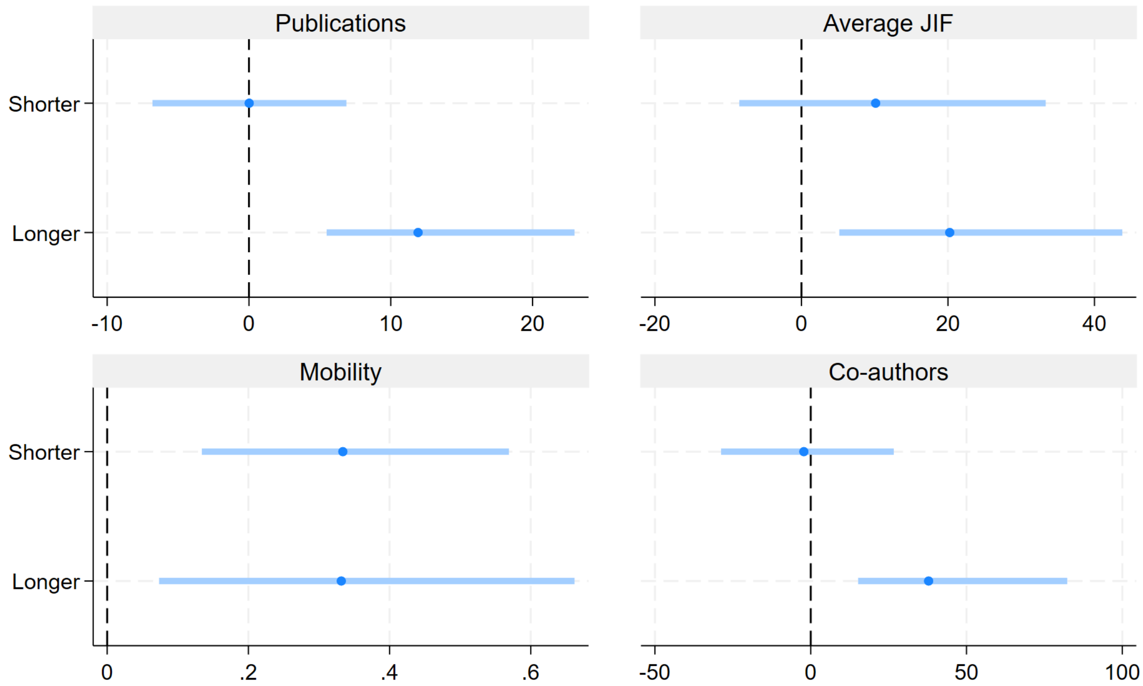

Notes: plots reports Fuzzy RDD estimates by splitting sample across types of mobility grants: intra-European (i.e. IEF) and extra-European mobility grants (i.e. IIF, IOF). Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A35: Heterogeneous effects across quality of host institutions (10 years)



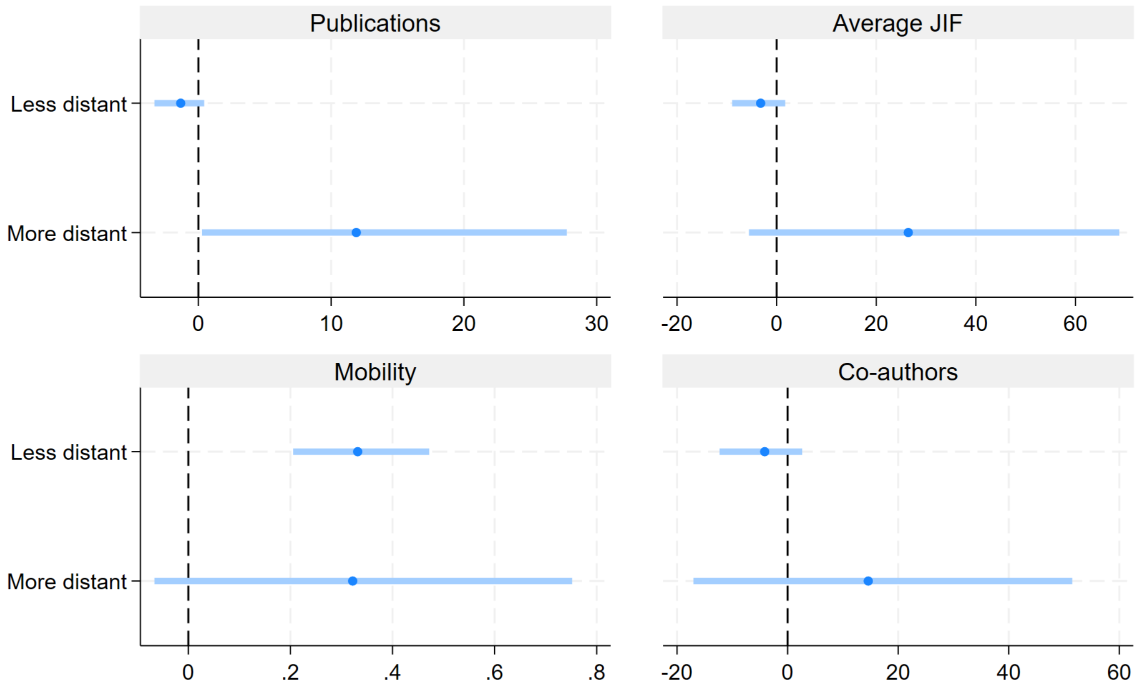

Notes: plots reports Fuzzy RDD estimates by splitting sample across research institutions ranked within the first 50 positions of the 2013 Scimago Institutions Rankings (higher-quality) versus the rest (lower quality). Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A36: Heterogeneous effects across duration of research stay (10 years)



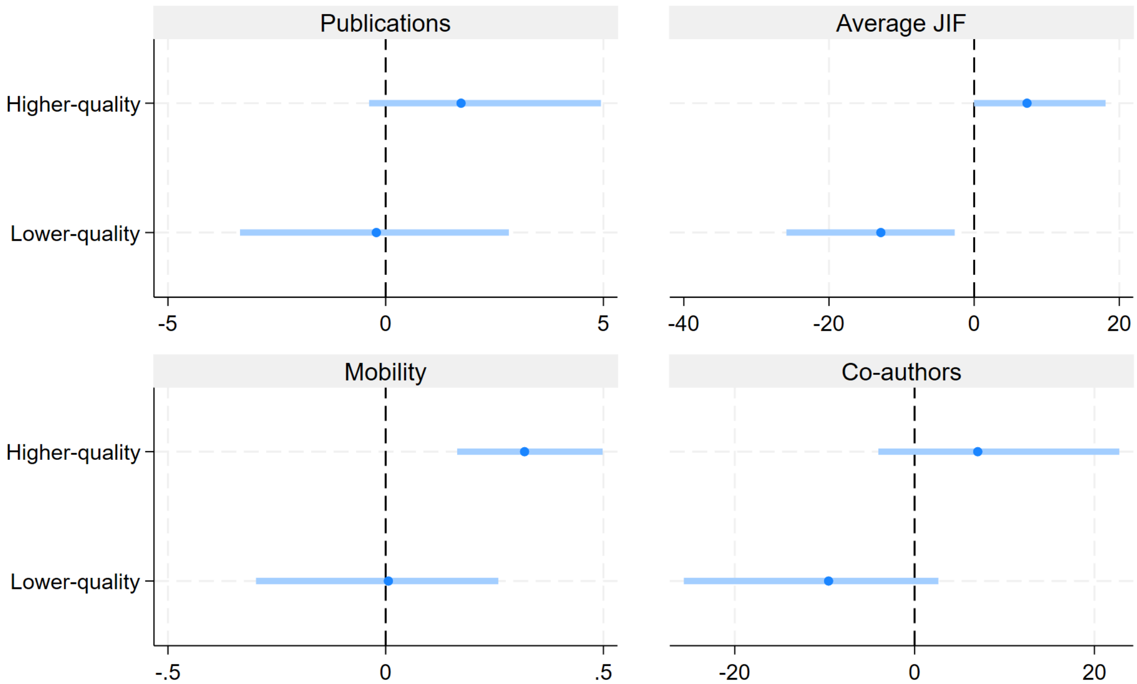

Notes: plots reports Fuzzy RDD estimates by splitting sample across above and below median duration of research stay abroad. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A37: Heterogeneous effects across km distance




Notes: plots reports Fuzzy RDD estimates by splitting sample across km distance between host and destination countries. Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.

Figure A38: Heterogeneous effects across quality of host institutions (only intra-EU)




Notes: plots reports Fuzzy RDD estimates by splitting sample across research institutions ranked within the first 50 positions of the 2013 Scimago Institutions Rankings (higher-quality) versus the rest (lower quality). Specifications include linear polynomials of the running variable on each side of the threshold, the pre-competition dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition-level. Lines represents 90% confidence intervals.