The Career Benefits and Missed Parenthood–Penalty of Obtaining Independent Post-doc Funding *

Dirk Czarnitzki Wytse Joosten Maikel Pellens Otto Toivanen

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Abstract

Obtaining independent post-doc funding is a crucial step in pursuing an academic career. Receiving it coincides with a period where other important life events like parenthood are timely. Studying 2005–2009 Research Council of Finland post-doc applications, the main form of pursuing an independent academic career in Finland, we find that obtaining post-doc funding that allows independent research i) improves quantity of academic output and income, and, ii) decreases the probability of having a(nother) child. iii) Especially childless men and women with children pay a missed parenthood penalty through a (starkly) reduced probability of getting a child. iv) Academic outcomes improve only for males, and v) the positive income effects are very heterogenous, with childless males and females with children benefiting the most.

NONE OF THE AUTHORS HAS ANY CONFLICTS OF INTEREST REGARDING THIS RESEARCH.

*Czarnitzki: MSI, KU Leuven and ZEW (dirk.czarnitzki@kuleuven.be). Joosten: National Bank of Belgium (wytsejoosten@gmail.com). Pellens: ECOOM, KU Leuven and ZEW (maikel.pellens@kuleuven.be) Toivanen: Aalto University School of Business, Helsinki Graduate School of Economics and CEPR (otto.toivanen@aalto.fi). We would like to thank the Competition and Innovation Summer School (2018) for helpful comments on an early draft, XXX for excellent research assistance, the Research Council of Finland (formerly Academy of Finland) for granting access to applicant data and Dienst Onderwijscoördinatie of KU Leuven for financial support. All errors are ours.

1 Introduction

For those who obtain a PhD, an academic career is a potentially enticing opportunity. However, the career structure in academia has a steep "up or out" structure where individuals need to compete for a smaller and smaller number of positions as they climb up the academic career ladder. In many, if not most, countries and fields of science, a post-doc position with independent funding is the first step towards establishing oneself as an independent researcher. Given that a PhD is usually obtained in the late 20s or early 30s, such funding is received in a period of a person's life when other important potential life events, like parenthood, are timely. This may be one reason why women are still underrepresented at the top levels of academia (e.g. Kim and Moser 2022). Our objective in this paper is to shed light on career and parenthood effects of the chance to pursue an academic career obtained through an independent prestigious post-doc grant. We deepen the analysis to shed light on how the career and parenthood effects vary by gender and parenthood status at the time of application.

There is extensive evidence that women are still underrepresented at the top of the scientific community (e.g. Kim and Moser 2022) and that women publish less than men (e.g. Huang et al. 2020; Iaria et al. 2022). One potential explanation for these observed differences is the unequal career burden imposed by parenthood. The so-called child penalty is by now well established: Mothers worldwide experience a sharp and permanent decline in income after parenthood (Kleven et al. 2023; see also Ganguli et al. 2014). Regarding scientists, Kim and Moser (2022) show that mothers in science experience a decline in the publication productivity in their early 30s – the age when other researchers are at their most productive. One would expect that women and men of the same (child-bearing) age who have, through a post-doc grant, obtained an option to advance an intensive, interesting and time-consuming career, will react differently to such a career option if (when) the cost of parenthood is asymmetric.

We construct a data set comprising all individuals applying for Research Council of Finland (former Academy of Finland) post-doc grants 2005-2009. These grants are the most prestigious independent Finnish funding available to young researchers who want to take the first step in their careers as independent researchers. Typically, such a grant forms the stepping stone to one's own research group in the lab sciences, and the possibility to boost one's research in social sciences unencumbered by the financing challenges that less fortunate early stage colleagues face. Similar grants are widely used in other developed countries. Our data include information on the year of application, grades the applications received, the panel and committee (see section 2 below) handling the application and whether or not the applicant was awarded a grant. We collect publication information of these individuals and use (pseudonymized) individual identifiers to match publication and application data to registry data containing information on biological children and income in particular. For our main results, we use a restricted sample of accepted and rejected applicants with the same or almost the same grade. We repeat the analysis with a larger but invariably more heterogenous sample of applicants. As we document below, our results hold qualitatively in the larger sample, giving us confidence that they are not statistical flukes of the smaller sample.

A growing literature studies the causal impact of research funding on academic output. Results vary from no effects (e.g. Jacob and Lefgren 2011 who study NIH grants) to positive (e.g. Oliboni et al. 2023 who study Norwegian Research Council grants) and heterogenous (e.g. Ghirelli et al. 2023, studying ERC grants, find positive output effects in chemistry, universe and earth sciences, institutions and behaviours, human mind studies and medicine).[1] We complement the existing literature by adding to

[1] Ganguli (2017) studies grants to Soviet scientists by the International Science Foundation. Though much smaller in absolute

the body of results on the effects of funding on academic output. We extend this literature by studying the effect of post-doc grants on income, and find, using a difference-in-differences setup where the control group consists of applicants with grades at or just below the acceptance threshold, that in the 8 years following the application, grantees publish 20-30% more, potentially at the cost of fewer citations per article, and have 12-20% higher income due to the grant. The publication effects materialize after the grant period whereas the income effects are immediate and long-lasting (i.e., they last beyond the funding period). These grants thus seem to be a career-changer for the successful applicants.

Our work is also directly related to the research on the gender gap in science (Huang et al. 2020; Iaria et al. 2022) and the work of Kim and Moser (2022) on the impact of motherhood on scientific output and careers. We add to this literature by being to our knowledge the first to study the causal effect of independent post-doc funding on parenthood outcomes. Using a regression discontinuity design, comparing applicants at the threshold (or very close to it), we find that obtaining a post-doc grant decreases the probability of obtaining a child by 10 percentage points. This is a large effect given an average probability of 31-34% of obtaining a child in the 8 years after application. This *missed-parenthood penalty* turns out to be heterogenous: Women with children and especially men without children are less likely to get a (further) child. The estimated effects are, at -15 (women with children) and -28 (men without children) percentage points, large both in absolute and in relative terms. In contrast, the probability of childless women and men with children getting a (further) child is not affected. Thus, childless men and women with children bear a cost in terms of family building as a result of obtaining a post-doc grant. We call this the *missed parenthood–penalty* of obtaining an independent post-doc grant.

We then revisit our career outcome regressions by conditioning the treatment effect on gender and parenthood at the time of application. We find that men who did not have children at the time of application are the main beneficiaries career-wise: They publish more (40%) and earn more (70%). The estimated publication and citation effects for women with children – the other group paying the parenthood penalty – are noisy, albeit negative, but the estimated wage impact is large at 20% and statistically significant. They thus seem to pay the parenthood penalty without other career benefits but an increase in income. Men with children publish more, but of lower quality; the point estimate on income is positive, but noisily estimated. Childless successful female applicants do not publish more, nor does the quality of their research increase, and do not experience an increase in income either. The extant literature has not, as far as we can tell, conditioned the causal effects of grant funding on academic outcomes on gender or parenthood.

The fact that we work with the population of applicants over our observation period unfortunately does not result in a large data set. This becomes an issue especially when we split the applicants by gender and parenthood into subgroups. While the fact that our data is small necessarily should affect the interpretation of our results, we note first, that having a dichotomous outcome variable (getting a child) and dichotomous key explanatory variables means that outliers are not generating our results; second, that when we use panel data covering the post-grant period and a random effects estimator, we find statistically significant childbearing treatment effect estimates in line with our main results; and third, that, small as the data is, the results do suggest that further inquiry into the heterogenous effects of obtaining post-doc grants is warranted in order for policy makers to be able to design a system that enables different types of researchers to benefit from the funding that is made available.

We describe the institutional setting in Section 2. In Section 3 we detail our data, explain our sample

terms (500$), these were still relatively substantial in relative terms (1.6 times average annual Soviet wage). Ganguli (2017) finds large and long-lasting effects of these grants.

construction and provide a descriptive analysis. Section 4 is devoted our econometric models whereas in Section 5 we present and discuss our results. We offer our conclusions in Section 6.

2 Institutional setting

We describe the institutional setting as it was during 2005–2009, the years during which the applications we use were made.[2] We focus on two types of grants of the Research Council of Finland (RCF) (formerly Academy of Finland) for individual researchers: 1) Postdoctoral Researcher; and 2) Academy Research Fellow. The RCF explicitly states that *"The funding supports the Academy Research Fellow so that they can increase their competencies and make significant career progress towards more demanding research positions and achieve an established position in the national and international research community."*

Eligibility. To be eligible, the researcher must be affiliated with a Finnish research institute or university. In addition, she must have obtained the doctoral degree no more than four or nine years ago, for respectively the Postdoctoral Researcher and the Academy Research Fellow grant. Although the grants target a different audience, with the Postdoctoral Researcher grant focused on less senior researchers, the objectives and responsibilities are comparable.[3]

The application process is similar to that employed by corresponding national funding organizations in other countries. The administrative structure handling the applications at the RCF had two tiers during 2005–2009: A *panel*, consisting of international academics with relevant substance knowledge. Each panel reports to a *council*, consisting of (Finnish) representatives of those fields of science that the council covers. During our observation period there were 4 councils: Scientific Council for Biological and the Environmental Sciences, Scientific Council for Health Sciences, Scientific Council for Culture and Society and Scientific Council for Sciences and Technology. Each application is reviewed by a panel of (international) experts, focusing on four criteria: Quality, impact, renewal and multidisciplinary, phenomenon-based and internationally-oriented research. The panel reads and evaluates all applications within its field of expertise and agrees on one report and one grade for each application. This grade is an integer on a Likert scale 1–6 that represents the quality of the application, with 6 being the best grade.[4] Based on the panels' reports, the councils make the final funding decisions. The amount of available funding dictates how many applications receive funding from a given council and there is thus no predetermined cutoff grade. We therefore identify the cutoff grade for every council-year combination.[5]

The site of research must be a research organization in Finland, though international (visiting) mobility is encouraged during the funding period (with extra funding provided for this). The RCF requires that the institution provides *"all necessary basic facilities"*, which vary according to the field of study. The 5-year funding is generous and provides a salary that is roughly commensurate with what an assistant professor in Finland would earn plus compulsory social security payments and similar.[6] Besides salary, the funding covers setting up a research team, research costs, costs of international collaboration and mobility and other research costs.

[2]The details of the structure have changed since the period from which our data emanates.

[3]For special reasons, applicants with more than 4 (Postdoctoral grants) or 9 (Academy Research Fellow grants) years since the doctorate may apply. Special reasons include: Completing a medical speciality, maternity, paternity, parental or childcare leave, military service or nonmilitary service and long-term illness.

[4]In 2005 and 2006, a scale of 0 to 5 was used, with 5 being the highest grade.

[5]We provide a schematic overview of the application process in Figure A-1.

[6]The length of the funding period has changed and is currently 4 years.

Use of the grant. The successful applicants are quite free to use the funding as they see fit; the most binding constraints relate to shifting funding from one year to another. The money is also moveable in that if a successful applicant moves from one research institution to another, the funding follows.

In the Finnish context, the RCF post-doc funding is both prestigious and generous; it is often viewed as a stepping stone towards becoming a professor. The RCF grants are also (see Table 1) usually not the first post-doc grant, but are meant for individuals with some time having passed since obtaining a PhD. As such, it is similar to the US NIH R01 grant, as it represents funding for independent principal investigators to run their own laboratories (Azoulay and Greenblatt, 2025), although the RCF post-doc funding is more aimed at researchers at the brink of independence. The alternative for individuals eligible for RCF's post-doc funding is often to resort to smaller and shorter grants from private foundations, or to work as a post-doc for a more senior researcher.

3 Data and descriptive analysis

3.1 Data sources

We have three main data sources: Research Council of Finland (RCF), Web of Science (WoS) and Statistics Finland (SF).

Research Council of Finland (RCF). The RCF data contain information on all Postdoctoral and Academy Research Fellow applications 2005–2009. For each application we know the applicant's name, gender, year of birth, affiliation, the panel reviewing the application, the final grade and the funding decision of the committee. These data include a personal identifier which allows Statistics Finland to link the application data to registry data.[7]

Web of Science (WoS). We collected publication information from WoS for all applicants that were close to the cut-off grade in the particular application round they participated in. We searched for publications using the applicants' first and last names. We manually check whether the downloaded publication is correctly assigned by comparing the WOS data against the applicant's CV, the publication list at the website of the research institution the applicant is affiliated with and the applicant's profile at researchgate.net. The cleaned publication list is then linked to the application information from RCF using information on the first and last name of the applicant as well as the research institution the applicant is affiliated with. The key variables for us are the number of publications (at individual-year level) and the number of citations those publications have received, divided by the number of publications (for a given individual in a given year). The citations are measured in 2018, and articles published earlier will therefore have had more time to garner citations.[8]

Statistics Finland (SF). We use the following so-called FOLK modules of SF:[9] *Basic data* (standard individual level information such as sex, age, level and field of education, location at birth, nationality, municipality of residence, marital status, socio-economic group etc); *Child-parent* (link between children and biological parents), *Family* (number of children in the household) and *Income* (income subject to state taxation and capital income total in state taxation). All these data are available at individual-year level for us until and including 2019. These data all contain an individual identifier which allows us to link them to each other and to the RCF data.

[7] The merged data at Statistics Finland are pseudonymized.

[8] Publication information is collected between March 14 2018 and April 9 2018.

[9] The SF research data catalogue Taika lists these and all other ready-made data modules available to researchers at SF.

3.2 Sample construction and outcome variables

Selecting individuals. We start from a data set of 3 536 applicants, 431 of which obtain an RCF post-doc grant. Of these, 1 609 applicants (325 successful applicants) received a Finnish encrypted ID code. We manage to merge 1 466 individuals (298 successful applicants) to FOLK files; this is a precondition for including them in the log income and parenthood regressions as the outcome variables come from FOLK.

Since the manual downloading and cleaning of the publication list is a very time-consuming process, we only collect publication information for 830 applicants close to the cutoff grade.[10] We further drop 46 applicants whose name string returns more than 20 publications in a year or more than 600 citations in a given year. The motivation for this is that it is highly unlikely that relatively junior researchers would have that many publications and much more likely that the name search results in a large number of false matches.

To arrive at our **Full Sample**, we further drop individual-year observations with missing data on the outcome variables. Our main data set is the **RDD Sample** which contains those successful and unsuccesful applicants in the Full Sample who obtained the marginal grade. By marginal grade we mean the minimum grade of the successful and the maximum grade of the unsuccessful applicants. There are no cases in the same committee-year sample of an unsuccessful applicant having a higher grade than the lowest graded successful applicants. This approach does not remove any successful applicants because it is always the case that the successful applicants have the highest possible grade, as do often the most highly graded unsuccessful applicants. As a robustness check, to eliminate the possibility that our analysis of parenthood and income is affected by restrictions in the publication data collection, we create another sample that does not require publications to be observed. Table A-1 in the Appendix gives an overview of the number of applicants and granted applicants across the data construction process.

Career outcomes - sample and outcome variables. For career outcomes, a (RDD-) difference-in-differences approach is natural. We follow all applicants from before they apply to well after their application. In practice, we limit the time window to $k \in \{-3, 8\}$, where $k = 0$ is the year of application (see Appendix Figure A-2). A strength of our setting is that we have a natural control group for each year's successful applicants: The unsuccessful applicants from the same year (with the (almost) same grade).

We measure career outcomes using the following variables: Number of publications by individual i in year t; number of citations to the publications of an individual i published in year t and obtained by 2018, divided by the number of publications of individual i in year t; and finally, taxable income of individual i in year t.[11] The first two are by now standard in the literature on the effects of research grants on research output whereas the the third is to our knowledge new to the literature.

An issue we face regarding both publications and citations is that the data contain many zeros. We approach this by following the advice of Chen and Roth (2023) and estimate Poisson models for the number of publications and the number of citations. We use the widely used (natural) log transformation for income as there are very few individuals in our data that ever have zero income.

Parenthood outcomes - sample and outcome variable. In the parenthood analysis the outcome variable

[10] The publication information was collected for these applicants regardless of whether they received a Finnish encrypted ID code.

[11] As an alternative income measure, we add capital income to taxable income. This makes no appreciable difference to our results.

is a dummy indicating whether individual i gets a child in the eight years following the application. As it is well-known that the decision to obtain a second (further) child is different from the first (e.g. Andersson et al. 2006; Jones et al. 2023), the difference-in-difference approach is inappropriate. Instead, we use a regression discontinuity (RD) approach. The data are thus a cross-section of our career outcomes samples, where applicant characteristics are measured at the time of the application.

3.3 Descriptive analysis

We start with descriptive statistics on the applicants, displayed in Table 1. The RDD sample consists of 294, the Full sample of 385 applicants, yielding respectively 3 241 and 4 274 applicant-year observations. Half of the applicants are women; the average age at application is 38; and three quarters of applicants have at least one child at the time of application. The average age is explained by the fact that individuals are eligible for the Academy Research Fellow grants up to 9 years since obtaining their PhD, and by the relatively high average age at which a PhD is obtained in Finland. 13% of applicants are childless women, 14% childless men. The Scientific Council for Culture and Society receives the largest share of applications (44%). Two out of five applications are funded. The normalized application score has a small mean in absolute value as it should; recall that the cutoff varies from council to council and from year to year. A closer look at the distribution of the normalized score reveals that in the RDD sample, the normalized score is zero for all unsuccessful applicants (mean -0.25 in the Full sample, with 10% having a normalized score of -1 or smaller, and 1% a normalized score of at least 1). For successful applicants we find a mean normalized score of 0.39 (0.05 in the Full sample), with the 75th percentile obtaining value 1 (1 in the Full sample) and the 99th value 2 (2 in the Full sample).

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Turning to career outcomes - publications, citations per publication and income - in Table 2, we find that the number of publications per year increases for both funded and unfunded applicants. The number of citations on the other hand shows no such progression for either type of applicants, but that is explained by the simple fact that as we measure citations received by early 2018, those publications produced in the post-period have had less time to accumulate citations than those published in the pre-period. Income increases substantially for both groups, from a pre-application average slightly less than €45 000/year to about €65 000/year in the post-application period, measured in 2023 euros. The RDD and Full samples display very similar features.

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We then turn to descriptive statistics conditioned on the type of the applicant in Table 3. Looking first at the top panel (RDD sample), the number of publications per year in the pre-period is lowest for funded men without children (0.47) and highest for men with children (0.98). In the post-period, the number of publications per year increases for all applicant types irrespective of the funding decisions. Unfunded women with children have the lowest post-period publication output (0.86) and funded men who had a child by the time of application the highest (1.64).

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There are differences in citations per publication, with funded women without a child having the highest level in the pre-period (31.86) and funded men without children the lowest (10.57). Moving

from the pre- to the post-period we record an increase in citations per publication for all other male applicants but those who had a child and received funding, but a drop for female applicants. Male applicants with a child have the highest pre-period average income and men without children the lowest. Incomes increase substantially moving to the post-period for all types of applicants.

Finally, the (weighted) average probability of getting a child over all the subgroups in the 8 years post application is 31% in the RDD sample and 34% in the Full sample. The probability is the highest for the unfunded women who were childless at the time of application - they have a 53% probability of getting a child. Women with children at the time of application who obtain funding have the lowest probability of getting another child (9%). The probability of getting a child in the post-period is lower for funded than unfunded applicants for all applicant types, although the difference for male applicants with a child is very small. When we compare the RDD sample descriptive statistics to those for the Full sample, we find them to be mostly in the same ball park.

4 Econometric models

4.1 Pooled Career Outcomes

For the career outcomes, our estimation equation takes the following form:

$$y_{ik} = \mathbb{E}[f(\delta D_{ik} + \alpha_i + \alpha_k + \alpha_t)] \tag{1}$$

In equation (1), the outcome variables are the number of publications by individual i in treatment (as opposed to calendar) year k, the citations to those publications, and the log of taxable income. For the two count variable outcomes $f(.)$ is the exponential function, i.e., we estimate a Poisson model. For log income, $f(.)$ is the linear function. We follow e.g. Jäger et al. (2024) and link treatment time k with calendar time t through $k = t - d$ where t is the calendar year of the observation and d is the calendar year of the application to RCF. Thus, $k = 0$ is the year of application. D_{ik} is an indicator variable taking value one for individual i if the individual has obtained a grant that year or earlier, i.e., it is our treatment dummy. D_{ik} thus takes value 1 from year $k = 0$ onwards, and is zero for $k < 0$. Given our relatively sparse data, we assume a constant treatment effect: δ is hence the average treatment effect on the treated. We however vary the length of the post-period and operate with two lengths: 4 and 8 years. 4 years is close to the funding period and 8 years is dictated by our observation period relative to the point in time we collected our data. We control for individual (α_i), treatment year (α_k) and calendar year (α_t) fixed effects. Because we include individual fixed effects we do not need to control for grades as would be the norm in a regression discontinuity setting.

Given that different individuals apply for and are denied or given a grant in different years, our set-up is staggered. The literature on the econometrics of staggered difference-in-difference settings has taken great strides recently (e.g. Goodman-Bacon 2021; De Chaisemartin and d'Haultfœuille 2023; Callaway et al. 2022; Borusyak et al. 2024). Our setting deviates from the standard one in that literature in that we can assign treatment time also for the individuals in the control group, i.e., the unsuccessful applicants (and we have outcomes that are naturally measured as counts; see Wooldridge 2023). We follow e.g. Jäger et al. (2024) and use this feature of our data to deal with the staggered take-up of treatment. A further motivation for this approach is that we are interested in heterogenous, group-specific, treatment effects and modeling them with this approach is straightforward (see subsection

4.3).

As is common in difference-in-difference settings, our key identifying assumption is that in the counterfactual case of no treatment, the trends in the outcome variable would have been same in the treatment group as they are in the control group, conditional on the controls.

4.2 Parenthood Outcomes

For the parenthood outcome we employ the following RDD specification:

$$y_i = \beta_0 + \gamma_D D_i + \gamma_{DG} D_i G_i + \gamma_{DP} D_i P_i + \gamma_{DGP} D_i G_i P_i + \boldsymbol{\beta X_i} + g(Gr_i) + \omega_i \tag{2}$$

The outcome variable y_i in equation (2) is a dummy taking value one if individual i gets at least one child in the 8 years after receiving a post-doc RCF grant and is zero otherwise. The most interesting variables on the right hand side are D_i and its interactions with G_i and P_i. In this triple interaction, D_i is the treatment dummy taking value one if individual i obtained a RCF post-doc grant and value zero otherwise; G_i is a gender dummy taking value one for women; and P_i is a dummy taking value one for those individuals who are parents at the time of submitting the application. The γ_m's ($m \in \{D,\ DG,\ DP,\ DGP\}$) are the average treatment effect parameters associated with a particular combination of these dummies. Our base category of individuals is a male applicant who is childless by the time of submitting the application. We include into equation (2) a vector $\boldsymbol{X_i}$ of control variables whose effects are captured by the coefficient vector $\boldsymbol{\beta}$. In particular, $\boldsymbol{X_i}$ contains a full set of G_i-P_i interactions as well as Grant Committee fixed effects and five-year bins of age at application.[12] We control for grades with the function $g(Gr_i)$, where Gr_i is the normalized grade of individual i. Following the advice of Gelman and Imbens (2019) (see Ghirelli et al. 2023 for an application that is relevant for us), we approximate the unknown function $g(Gr_i)$ with a second order polynomial where the coefficients are allowed to differ above and below the cutoff grade. Finally, the error term ω_i completes the specification.

4.3 Conditional Career Outcomes

Our econometric specification for the career outcomes where we condition on gender and parenthood is essentially an amalgam of equations (1) and (2), in that we employ the same difference-in-difference approach that we use for the pooled data (equation (1)), but we introduce that G_i-P_i interactions and the triple-interactions of them and the D_{ik} treatment dummy (from equation (2)), yielding equation 3:

$$y_{ik} = \mathbb{E}[f(\theta_D D_i + \theta_{DG} D_i G_i + \theta_{DP} D_i P_i + \theta_{DGP} D_i G_i P_i + \mu_i + \mu_k + \mu_t)] \tag{3}$$

where, following the discussion above, θ_m are the (elements of) conditional average treatment effects, i.e., the parameters of interest, the μ_j are the calendar and treatment year fixed effects as well as the individual fixed effect.

[12] More precisely, we define the following groups: 24-30 years old at application, 31-35, 36-40, 41-45, 46-50, and 51-63. The first and last group are wider to include the sample minimum and maximum, as the data becomes thinner for these groups.

5 Estimation results

5.1 Pooled Career Outcomes

We report the difference-in-difference estimation results of career outcomes for the RDD and Full samples, pooling all applicant types, in Table 4. The columns are organized by outcome variable. There are two columns for each outcome variable, the first one with a short (4 year) and the second one with a long (8 year) post-treatment period. Starting with the top panel where results using the RDD sample are reported, we find, we find (columns (1) and (2)) that there is no statistically significant impact on the number of publications in the short run, but a sizeable positive average treatment effect of roughly 25% in the long (8 year) run (coefficient 0.224). Thus, getting a prestigious post-doc grant does boost a researcher's career in terms of the number of publications, but the gains seem to come mostly only after the funding period has ended. This is not necessarily a huge surprise given the time it takes to establish a research group and/or to navigate the refereeing process. In contrast to this positive result, coefficients in columns (3) and (4) suggest no significant treatment effects on the number of citations per paper at conventional significance levels. We thus find no evidence of an increase in quality due to receiving a grant. Finally, turning to the financial implications of getting a grant, we find in column (5) that successful applicants experience a sizeable, approximately 25%, gain in income already during the grant and that this effect continues and even slightly increases after the grant for at least another 4 years (column (6)). When we switch to the Full sample (lower panel of Table 4), the average treatment effects are smaller than when using the RDD sample, but qualitatively and in terms of statistical significance similar. We conclude that obtaining an RCF post-doc grant gives a career boost to successful applicants in terms of research quantity, without clearly affecting research quality, and has an economically significant positive effect on income.

Our results are in line with Oliboni et al. (2023) who find positive treatment effects on scientific output from Research Council Norway grants, but stand in contrast to Jacob and Lefgren (2011); Ghirelli et al. (2023) who, studying NIH and ERC grants, find no such effects. As far as we are aware, our results on the income effects of grants are new to the literature.

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5.2 Parenthood Outcomes

Main parenthood results. We now turn to the question of whether getting a post-doc grant has an impact on the probability of getting a(nother) child. We show results using the RDD sample in Table 5 and results using the Full sample in Table 6. We first estimate the average treatment effect for all applicants, and then condition the treatment effect on the gender and parenthood status of the applicant.

In column (1) of Tables 5 and 6 we report the average treatment effect when we do not condition on applicant type. We find negative coefficients of roughly -0.09 with the RDD sample and -0.11 with the Full sample, with the coefficient using the Full sample obtaining statistical significance at the 5% level. There is thus evidence that obtaining a post-doc grant decreases the probability of getting a child for the average applicant. Recalling that the average probability of obtaining a(nother) child post application is a little over 30%, a reduction of 8-11 percentage points strikes us as large. We condition on gender in column (2) and find a negative average treatment effect for male applicants of -0.10 in the RDD sample and -0.12 in the full sample, the latter being statistically significant at 10% level. The

coefficient of the *Grant* × *Female* - interaction is 0.04 for the RDD sample and 0.03 for the full sample, but statistically imprecise. Taken at face value, these coefficients would suggest that successful female applicants experience a decrease in the probability of obtaining a child, but that this effect is smaller than for successful male applicants. We condition on parenthood (at the time of obtaining the grant) in column (3). The coefficient of the *Grant*-variable is either at the same level as in column (1) or slightly larger in absolute value. The coefficient on the *Grant* × *Parent*-interaction carries a positive albeit statistically imprecise coefficient. These results suggest that the possible negative impact of obtaining a grant on the probability of getting a(nother) child is smaller for those successful applicants who are already parents by the time of application.

In column (4) we display the results from the model with a full set of interactions between *Grant*, *Parent* and *Female*. The *Grant* coefficient is -0.44 in the RDD sample and -0.29 in the Full sample, both statistically significant at least at the 5% level. These coefficients suggest that applicants in our base group, childless men, experience a large decrease in their probability of becoming a parent in response to getting a post-doc grant. The interaction *Grant* × *Female* obtains a coefficient of 0.51 in the RDD sample and 0.34 in the Full sample; both are statistically significant at conventional levels. The average treatment effect on women who do not have children at the time of application is the sum of the *Grant* and *Grant* × *Female* coefficients. We report this treatment effect and its statistical significance in the Treatment effect panel of the table, row "Childless female". The average treatment effect is positive at 0.08 in the RDD sample and 0.05 in the Full sample, but both are statistically insignificant. Childless male and female grantees thus behave differently, with the former decreasing their likelihood of getting a child in response to obtaining a grant, the latter not.

Turning to those applicants with children at time of application, we find that the interaction *Grant* × *Parent* carries a positive coefficient of 0.434 in the RDD sample and 0.230 in the Full sample; only the former is statistically significant at conventional levels. These coefficients allow us to calculate the treatment effect on successful male applicants with children at the time of application - this is given by the sum of the *Grant* and *Grant* × *Parent* coefficients and reported in the row "Male parent". We estimate the average treatment effect to be exactly zero in the RDD sample, and -0.06 in the Full sample. The former estimate is somewhat noisy with a standard error of 0.09; the latter is statistically imprecise. We conclude that our data does not support concluding that obtaining a post-doc grant affects the decision to get another child for male applicants who had a child at the time of application.

The conclusion is different for women with children at the time of application, as now we add to the treatment effect both the (positive) *Grant* × *Female* and the (large in absolute value) negative *Grant* × *Female* × *Parent* coefficients to obtain an estimate of an average treatment effect of -0.15 using the RDD sample, and of -0.17 using the full sample. The RDD sample estimate is statistically significant at the 10%, the Full sample estimate at the 1% level. In column (5) of the tables we add the interaction *Female* × *Parent* into our vector of control variables. We find that the results are very similar to those reported in columns (4).

Our results thus suggest that successful childless male applicants in particular, but also female applicants with children, pay a missed parenthood penalty due to receiving a post-doctoral grant from the RCF. Childless men experience a 29–43 percentage point decrease in the probability of obtaining a child, and women with children a 16–17 percentage point decrease. Comparing these decreases to the probability of obtaining a child in the control groups it is immediate that they are substantial: The probability of a childless unsuccessful male applicant having a child post application is 36%, and that of women with children 25%, using the RDD figures (the Full sample figures are very close; see Table

3).

An obvious concern with these results is that they are drawn from a sample that is not too large in terms of the number of individuals, and in the different subgroups of interest, the number of individuals is low. This being said, we do start from the population of applicants and given that our key explanatory variables are dummy variables, outliers can not be the cause underlying the results. The strong statistical significance suggests that the effects are likely real, though one has to keep in mind that changing the outcome of a few individuals would affect both the size of the estimated treatment effects as well as their statistical significance.

PLACE TABLES 5 AND 6 HERE

5.3 Robustness tests

We perform two distinct robustness tests. The first one addresses the issue that some (female) applicants may have a low probability of childbearing because of an observable biological trait, i.e., age. Although not as much biology-driven, a fact is that also for childless men the probability of parenthood declines with age. The second robustness test addresses the issue of small sample size by estimating linear probability model of obtaining a child using post application date data at an annual level.

Conditioning the sample on applicant age. As childbearing is highly dependent on age (and not only for females), we split the sample into subgroups by applicant age, using 40 years as the threshold. The results, presented in Tables A-2 and A-3 suggest that the negative treatment effects occur for applicants below age 40. The point estimate for the treatment effects for childless male applicants is -0.43 in the RDD and -0.29 in the Full sample, both statistically significant at the 5% level or better, and those for female applicants with children are -0.25 in the RDD and full sample, the former statistically significant at the 10, the latter at the 5% level. Some care must be applied in interpreting these results given that the estimation samples are small. For instance, the sample size does not allow to estimate a treatment effect for female applicants with children who are over 40 years old at application. As an additional finding it is worth reporting that in the sample of applicants aged 40 or more we find a negative treatment effect of close to 30 percentage points for childless female applicants that is statistically significant at the 10% level.

Panel data estimation. Instead of a cross-section, we can also form a panel data where observations are at the individual-year level, using post application-year observations only. With this set-up we increase the sample (roughly) 8-fold. However, this approach has two issues: First, we cannot use individual fixed effects as our key explanatory variables (*Grant*, *Female*, *Parent*) are time-invariant. Second, getting a child in a given year (our outcome variable) is known to exhibit (negative) autocorrelation. We can however continue to include our controls (*Grant*, *Score* in particular), introduce a time-invariant individual-specific random effect and allow for first-order autocorrelation.

We present the results in Tables A-4 and A-5. Using the RDD sample, with this approach we find that the annual probability of obtaining a child is reduced by 8 percentage points for successful childless male applicants (coefficient of *Grant*); this effect is statistically significant at better than 1% level. The treatment effect for successful male applicants who had at least one child at the time of application is -0.009 (s.e. 0.016). The treatment effects for childless female applicants and female applicants with at least one child are 0.011 (s.e. 0.026) and -0.017 (s.e. 0.017). The results using the Full sample are quite similar, although the point estimate for the treatment effect of childless male applicants is lower in absolute value at -0.041, though it also is statistically significant at the 1% level. In comparing these

treatment effects to those in Tables 5 and 5 one has to keep in mind that the interpretation in those tables was a change in the probability of getting a child over an 8 year period whereas here, the coefficient gives the change in the annual probability of getting a child. As an illustration, a 7.96% decrease in the annual probability yields a decrease of 49 percentage points over a period of 8 years. We find autocorrelation coefficients of the order of -0.02.

5.4 Conditional Career Outcomes

Given the above parenthood outcomes it is important to return to the career outcomes to see whether they also differ by gender and parenthood. For that purpose, we rerun our difference-in-difference regressions for career outcomes, but now condition the treatment effect on gender and parenthood at time of application. We display the results in Tables 7, 8 and 9 for the RDD sample and in Tables A-6, A-7 and A-8 for the Full sample. The top part of each table displays the important coefficients, the bottom part the group-specific treatment effects and their standard errors.

PLACE TABLES 7, 8 AND 9 HERE

Starting with the number of publications (Table 7), we find that when we condition on gender only (column 2), our results suggest that it is successful male applicants who increase their number of publications: the point estimate for males is close to 0.4 and statistically significant, whereas the point estimate for treated females is 0.018, with a relatively large standard error. Results in column (3) show that conditioning on parenthood yields only statistically insignificant coefficients. Finally, in column (4) we condition on both gender and parenthood. These results strongly suggest that the career benefits, in terms of an increase in the number of publications, go to men, and in particular, men without children at the time of application: The treatment effect for male applicant who did not have a child at the time of application is 0.76 whereas that for fathers is somewhat less than half of this. The point estimates for women are either negative (childless women) or small and positive (mothers), both noisily estimated.

Turning then to the number of citations per publication in Table 8, we find in column (2) a statistically significant coefficient at 10% level for the $Grant \times Post \times Female$ - interaction term which carries a large positive coefficient. This suggests that successful female applicants experience an increase in the number citations per publication whereas successful male applicants experience a decline. These treatment effects are however noisily estimated. Interacting the treatment effect with parenthood in column (3) does not yield new insights. When we condition on both gender and parenthood in column (4) the results suggest that two groups of successful applicants - childless men and women with children - may experience an increase in the quality of their publications, though these treatment effects are again noisily estimated. In contrast, successful male applicants who had a child by the time of application seem to experience a large statistically significant decline in the quality of their research.

Finally, in Table 9 the outcome variable is (log) income. Results in column (2) suggest that both successful male and female candidates experience an economically significant increase in their incomes. The estimated treatment effect is 0.26 for successful male applicants and 0.19 for successful female applicants; both are highly statistically significant, but the difference between the treatment effects is not. When we condition on parenthood only (column (3)) we find that successful applicants who had a child by the time of application experience a 24 percentage points lower increase in income than those successful applicants who were childless. The latter group's income treatment effect is over 40%. When we condition on both gender and parenthood in column (4) we get a more nuanced picture: All

applicant types benefit financially from obtaining a grant, but there are large differences. The estimated treatment effect is over 70% for childless male applicants, 20% for female applicants with children, 18% for childless female applicants and 13% for male applicants with children. The two first ones are statistically significant at 5% level or better and that for male applicants with children at 10% level while the treatment effect for childless female applicants is noisy.

6 Discussion and Conclusions

Using a difference-in-differences framework of marginally accepted and rejected applicants for prestigious Research Council of Finland post-doc grants 2005–2009, we first establish that obtaining independent post-doc funding has a large impact both on academic output and income on average. The number of publications increases, though the increase mostly takes place after the funding period; however, we find an initial negative effect on the quality of publications. The successful applicants experience large wage increases that start during the funding period, but continue well past it.

We then study parenthood outcomes using a regression discontinuity design and that successful applicants pay a *missed parenthood*-penalty: The probability of getting a child decreases on average by some 10 percentage points which, relative to the sample average of a circa 30% probability of obtaining a child in the 8 years after the application year strikes us as large.

When we condition the effect of getting a grant on gender and parenthood at the time of application, we find that men without children react to obtaining a grant by drastically reducing the probability of parenthood over the following 8 years, but find no such effect for women without children. Looking at applicants who already have at least one child at the time of application, the gender-specific results are reversed albeit the negative treatment effect on mothers is smaller than that on childless men. The results suggest that men without children and women who already have children pay a missed parenthood penalty in that they get fewer children than they would in the counterfactual case of not receiving the grant or, in the case of childless male applicants, even forego parenthood entirely.

When we condition career outcomes on gender and parenthood, we find that only successful male applicants increase their scientific output, but those with children at the time of application do so at the cost of quality. Also income effects vary widely, with childless male applicants benefiting the most, female applicants with children being the group with the second-highest gains.

Our results suggest that the career benefits that an RCF grant offers come at the cost of (missed) parenthood. The increased scientific output and large income increases we find for childless males who receive the funding come at a cost: They sacrifice parenthood to make the most out of a (large) career opportunity. While childless men pay the missed parenthood penalty, childless women benefit less from the same career opportunity, possibly because they do not delay parenthood. We can only speculate what the reason behind this gender difference in behavior is: A potential explanation is that most of the applicants are individuals in an age where parenthood decisions are made, and women are more cognizant of the fact that the probability of parenthood (i.e., probability of getting the first child) declines quickly with age. It could be that childless men overestimate the probability of being able to delay parenthood. The decline in the probability of parenthood as a function of age is large for both sexes. To illustrate, using registry data on all individuals in Finland for 2011-2019 who were 30 or 40 in 2011 and have an MSc degree by 2011, i.e., individuals who are quite comparable to the applicants in our data (three quarters of the both male and female applicants in our main estimation sample are younger than 42 at time of application and less than 10% are younger than 30), we find that women

who were childless at age 30 in 2011 became parents by 2019 with 67% probability and similar men with 65% probability. The probability to become a parent by 2019 for those women who are otherwise similar, but childless at age 40 in 2011, is only 11%, a decrease of 56 percentage points or 84% and for the respective men 26%, a decrease of 39 percentage points or 60%.

Given the limitations of our data, we caution against putting too much weight on the (policy) conclusions. Our results do however suggest that the scientific enterprise faces serious challenges in providing early career (post-doc) researchers a level-playing field, even in a country that ranks high on various equality indices.[13] It seems that funding that is designed to give a career boost to promising post-doc researchers does so only for some - childless males - and even for them, at the cost of a drastic reduction in the probability of getting a child. The twin facts that applicants in our data are (towards the end of) child-bearing age and that those successful female applicants who had a child at the time of application also have a lower probability of obtaining another child suggest that a possible explanation for the finding that childless females do not benefit career-wise from these prestigious grants is due to them not being able or willing to defer childbearing further into the future. Our results do not yield answers on how to redesign this important part of science funding, but certainly call for more work on both the design of such funding schemes as well as on their heterogenous effects on the careers and lives of academic researchers. Without such information we are at risk of losing potentially promising researchers through no fault of theirs.

[13] As an example, Finland ranked 2nd in 2009 and 3rd in 2006–2008 according to the Global Gender Gap Index (Hausmann et al. 2009).

References

Andersson, G., K. Hank, M. Rønsen, and A. Vikat: 2006, 'Gendering family composition: Sex preferences for children and childbearing behavior in the Nordic countries'. *Demography* **43**, 255–267.

Azoulay, P. and W. H. Greenblatt: 2025, 'Does Peer Review Penalize Scientific Risk Taking? Evidence from NIH Grant Renewals'. Technical report, National Bureau of Economic Research.

Borusyak, K., X. Jaravel, and J. Spiess: 2024, 'Revisiting Event-Study Designs: Robust and Efficient Estimation'. *The Review of Economic Studies* **91**(6), 3253–3285.

Callaway, B., A. Goodman-Bacon, and P. Sant'Anna: 2022, 'Difference-in-Differences with a Continuous Treatment'. *Working paper*.

Chen, J. and J. Roth: 2023, 'Logs with Zeros? Some Problems and Solutions'. *The Quarterly Journal of Economics* **139**(2), 891–936.

Correia, S.: 2023, 'REGHDFE: Stata module to perform linear or instrumental-variable regression absorbing any number of high-dimensional fixed effects'.

Correia, S., P. Guimarães, and T. Zylkin: 2019, 'Verifying the existence of maximum likelihood estimates for generalized linear models'.

Correia, S., P. Guimarães, and T. Zylkin: 2020, 'Fast Poisson estimation with high-dimensional fixed effects'. *The Stata Journal* **20**(1), 95–115.

De Chaisemartin, C. and X. d'Haultfœuille: 2023, 'Two-Way Fixed Effects and Differences-in-Differences with Heterogeneous Treatment Effects: A Survey'. *Econometrics Journal*.

Ganguli, I.: 2017, 'Saving Soviet Science: The Impact of Grants When Government RD Funding Disappears'. *American Economic Journal: Applied Economics* **9**(2), 165–201.

Ganguli, I., R. Hausmann, and M. Viarengo: 2014, 'Closing the gender gap in education: What is the state of gaps in labour force participation for women, wives and mothers?'. *International Labour Review* **153**(2), 173–207.

Gelman, A. and G. Imbens: 2019, 'Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs'. *Journal of Business & Economic Statistics* **37**(3), 447–456.

Ghirelli, C., E. Havari, E. Meroni, and S. Verzillo: 2023, 'The Long-Term Causal Effects of Winning an ERC Grant'. IZA DP16108.

Goodman-Bacon, A.: 2021, 'Difference-in-differences with variation in treatment timing'. *Journal of Econometrics* **225**(2).

Hausmann, R., L. D. Tyson, and S. Zahidi: 2009, 'The Global Gender Gap Report'. Technical report, World Economic Forum.

Huang, J., A. J. Gates, R. Sinatra, and B. Albert-László: 2020, 'Historial comparison of gender inequality in scientific careers across countries and disciplines'. *Proceedings of the National Academy of Sciences* **117**(9), 4609–4616.

Iaria, A., C. Schwarz, and F. Waldinger: 2022, 'Gender gaps in academia: Global evidence over the Twentieth century'. Unpublished manuscript.

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

Jäger, S., J. Heining, and N. Lazarus: 2024, 'How substitutable are workers? Evidence from worker deaths.'. Technical report, Working paper.

Jones, T. R., M. J. Millington, and J. Price: 2023, 'Changes in parental gender preference in the USA: evidence from 1850 to 2019'. *Journal of Population Economics* **36**, 3057–3070.

Kim, S. D. and P. Moser: 2022, 'Women in science. Lessons from the baby boom'. Working Paper.

Kleven, H., C. Landais, and G. Leite-Mariante: 2023, 'The Child Penalty Atlas'. Working Paper 31649, National Bureau of Economic Research.

Oliboni, P. A., J. Adda, and M. Ottaviani: 2023, 'The Impact of Research Grants on Publications and Patents Across Disciplines'. working paper.

Wooldridge, J. M.: 2023, 'Simple approaches to nonlinear difference-in-differences with panel data'. *The Econometrics Journal* **26**(3), C31–C66.

Figures and Tables

Table 1: Descriptive statistics: Applicants

	RDD Sample		Full Sample	
	mean	sd	mean	sd
Female	0.50	0.50	0.51	0.50
Parent	0.73	0.44	0.72	0.45
Woman, no children	0.13	0.34	0.13	0.34
Woman, children	0.36	0.48	0.38	0.49
Man, no children	0.14	0.34	0.15	0.36
Woman, children	0.37	0.48	0.34	0.48
Age	37.71	6.68	37.57	6.56
Field: Biological and environmental sci.	0.16	0.37	0.19	0.39
Field: Culture and society	0.44	0.50	0.42	0.49
Field: Health sciences	0.15	0.36	0.15	0.36
Field: Sciences and technology	0.25	0.43	0.25	0.43
Funded	0.40	0.49	0.39	0.49
Normalized application score	0.16	0.40	-0.14	0.76
Applicant-years	3241		4274	
Applicants	294		385	

Notes: Normalized application score is calculated as the grade of applicant i minus the threshold grade, i.e., the lowest grade of a successful applicant in a given panel in a given year (application round).

Table 2: Descriptive statistics: Outcomes, pooled sample

	RDD Sample		Full Sample	
	Unfunded mean	Funded mean	Unfunded mean	Funded mean
Publications Pre	0.75	0.74	0.82	0.74
Publications Post	1.15	1.26	1.23	1.28
Citations Pre	25.00	27.50	28.21	27.15
Citations Post	23.66	23.01	26.75	22.84
Income Pre	44.97	42.85	44.30	42.70
Income Post	61.52	65.56	62.03	65.04
Applicant-years	1923	1318	2599	1675
Applicants	175	119	235	150

Notes: Publications are measured as the number of publications per year in the pre-period $\tau = -4, .., 0$ and the post-period $\tau = 1, ..., 8$. Citations are the citations per article by 2018. Income is measured in year 2023 thousands of Euro.

Table 3: Descriptive statistics: Outcomes, conditional on applicant type

RDD Sample								
	Woman No Child		Woman Child		Man No Child		Man Child	
	Unfunded mean	Funded mean	Unfunded mean	Funded mean	Unfunded mean	Funded mean	Unfunded mean	Funded mean
Publications Pre	0.58	0.62	0.60	0.66	0.63	0.47	0.98	0.98
Publications Post	1.22	1.13	0.86	0.91	1.34	1.37	1.34	1.64
Citations Pre	23.69	31.86	25.06	29.18	27.24	10.57	24.50	29.82
Citations Post	14.55	22.21	18.50	19.17	33.95	23.45	27.34	27.27
Income Pre	43.93	38.48	43.27	41.96	38.84	34.09	49.04	49.14
Income Post	56.86	62.48	61.12	64.85	52.84	65.99	66.45	67.64
Birth Post	0.53	0.40	0.25	0.09	0.36	0.20	0.40	0.39
Applicant-years	203	205	733	494	220	143	767	476
Applicants	19	20	64	43	25	15	67	41
Full Sample								
	Woman No Child		Woman Child		Man No Child		Man Child	
	Unfunded mean	Funded mean	Unfunded mean	Funded mean	Unfunded mean	Funded mean	Unfunded mean	Funded mean
Publications Pre	0.83	0.54	0.70	0.64	0.82	0.77	0.96	0.93
Publications Post	1.45	1.15	0.95	0.88	1.52	1.46	1.36	1.69
Citations Pre	28.51	26.62	26.85	28.17	33.30	20.95	27.44	28.91
Citations Post	20.40	20.72	22.20	18.23	42.36	23.12	27.01	28.62
Income Pre	42.66	35.65	43.59	44.33	38.06	35.29	48.30	47.44
Income Post	57.99	60.73	61.17	65.53	54.17	63.45	67.80	67.20
Birth Post	0.50	0.46	0.27	0.13	0.36	0.33	0.40	0.33
Applicant-years	287	251	1048	622	332	212	932	590
Applicants	26	24	92	54	36	21	81	51

Notes: "No Child" and "Child" refer to whether the individual has a child at the time of grant application. Publications are measured as the number of publications per year in the pre-period $\tau = -4, .., 0$ and the post-period $\tau = 1, ..., 8$. Citations are the citations per article by 2018. Income is measured in year 2023 thousands of Euro. Birth is an indicator variable taking value 1 if the individual got a(n additional) biological child and 0 otherwise.

Table 4: Career outcomes

RDD Sample						
	Publications		Citations/Publ		Ln(Income)	
	(1) Short	(2) Long	(3) Short	(4) Long	(5) Short	(6) Long
Post x Grant	0.076	0.224**	-0.100	-0.084	0.222***	0.227***
	(0.104)	(0.097)	(0.135)	(0.117)	(0.053)	(0.051)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Treatment year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1594	2647	837	1362	2138	3241
Individuals	216	237	180	204	292	294
(Pseudo) R-Squared	0.296	0.354	0.683	0.686	0.504	0.468
Full Sample						
	Publications		Citations/Publ		Ln(Income)	
	(1) Short	(2) Long	(3) Short	(4) Long	(5) Short	(6) Long
Post x Grant	0.033	0.183**	-0.072	-0.051	0.143***	0.155***
	(0.091)	(0.086)	(0.114)	(0.099)	(0.048)	(0.046)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Treatment year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2152	3555	1117	1824	2826	4274
Individuals	290	317	239	274	383	385
(Pseudo) R-Squared	0.314	0.369	0.685	0.69	0.501	0.458

Notes: Short = post-period 4 years; *Long* = post-period 8 years. Columns (1)-(4): Poisson pseudo-likelihood regression (Correia et al., 2019, 2020). Columns (3)-(4) include exposure on publication count. Columns (5)-(6): Linear regression with fixed effects (Correia, 2023). The number of observation varies across columns because i) the long post-period has 4 more observations / individual; ii) the Poisson regressions exclude observations where there is no variation in the LHS variable over time. Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Parenthood outcomes: RDD sample

	(1)	(2)	(3)	(4)	(5)
Grant	-0.089	-0.108	-0.137	-0.439***	-0.369***
	(0.058)	(0.081)	(0.110)	(0.124)	(0.136)
Grant × Female		0.039		0.514***	0.348*
		(0.104)		(0.144)	(0.200)
Grant × Parent			0.065	0.434***	0.336**
			(0.120)	(0.139)	(0.158)
Grant × Female × Parent				-0.664***	-0.443*
				(0.154)	(0.230)
Female × Parent					-0.220
					(0.165)
Gender	Yes	Yes	Yes	Yes	Yes
Parent	Yes	Yes	Yes	Yes	Yes
Gender X Parent	No	No	No	No	Yes
Grant Score	Yes	Yes	Yes	Yes	Yes
Grant Committee FE	Yes	Yes	Yes	Yes	Yes
Age bins	Yes	Yes	Yes	Yes	Yes
Application year FE	Yes	Yes	Yes	Yes	Yes
Observations	294	294	294	294	294
R-Squared	0.231	0.231	0.232	0.272	0.278
Treatment Effects					
Male		-0.108 (0.081)			
Female		-0.069 (0.076)			
Childless			-0.137 (0.110)		
Parent			-0.072 (0.064)		
Childless male				-0.439 (0.124)***	-0.369 (0.136)***
Male parent				-0.005 (0.087)	-0.033 (0.090)
Childless female				0.076 (0.126)	-0.021 (0.150)
Female parent				-0.154 (0.079)*	-0.128 (0.079)

Notes: Linear regression. The post-period is 8 years. Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1. Treatment effects are calculated as the sum of the appropriate coefficients. The numbers in parenthesis in the Treatment effect rows are standard errors of the reported treatment effects.

Table 6: Parenthood outcomes: Full sample

	(1)	(2)	(3)	(4)	(5)
Grant	-0.114**	-0.128*	-0.111	-0.294**	-0.228*
	(0.047)	(0.070)	(0.094)	(0.121)	(0.130)
Grant × Female		0.029		0.342**	0.182
		(0.091)		(0.142)	(0.181)
Grant × Parent			-0.003	0.230*	0.134
			(0.106)	(0.138)	(0.152)
Grant × Female × Parent				-0.447***	-0.233
				(0.152)	(0.208)
Female × Parent					-0.215
					(0.139)
Gender	Yes	Yes	Yes	Yes	Yes
Parent	Yes	Yes	Yes	Yes	Yes
Gender X Parent					
Grant Score	Yes	Yes	Yes	Yes	Yes
Grant Committee FE	Yes	Yes	Yes	Yes	Yes
Age bins	Yes	Yes	Yes	Yes	Yes
Application year FE	Yes	Yes	Yes	Yes	Yes
Observations	385	385	385	385	385
R-Squared	0.216	0.216	0.216	0.234	0.240
Treatment Effects					
Male		-0.128 (0.070)*			
Female		-0.099 (0.061)			
Childless			-0.111 (0.094)		
Parent			-0.114 (0.052)**		
Childless male				-0.294 (0.121)**	-0.228 (0.130)*
Male parent				-0.064 (0.079)	-0.094 (0.081)
Childless female				0.048 (0.112)	-0.046 (0.129)
Female parent				-0.169 (0.064)***	-0.144 (0.065)**

Notes: Linear regression. The post-period is 8 years. Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1. Treatment effects are calculated as the sum of the appropriate coefficients. The numbers in parenthesis in the Treatment effect rows are standard errors of the reported treatment effects.

Table 7: Career outcomes: Publications, RDD sample

	(1)	(2)	(3)	(4)
Grant × Post	0.224**	0.378***	0.244	0.762**
	(0.097)	(0.123)	(0.238)	(0.310)
Grant × Post × Female		-0.360*		-0.938**
		(0.193)		(0.452)
Grant × Post × Parent			-0.034	-0.459
			(0.262)	(0.337)
Grant × Post × Female × Parent				0.708
				(0.499)
Individual FE	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes
Treatment year FE	Yes	Yes	Yes	Yes
Observations	2647	2647	2647	2647
Individuals	237	237	237	237
Pseudo R-Squared	0.354	0.354	0.355	0.355
Treatment Effects				
Male		0.378 (0.123)***		
Female		0.018 (0.152)		
Childless			0.244 (0.238)	
Parent			0.210 (0.106)**	
Childless male				0.762 (0.310)**
Male parent				0.302 (0.132)**
Childless female				-0.177 (0.329)
Female parent				0.072 (0.170)

Notes: Poisson pseudo-likelihood regression (Correia et al., 2019, 2020). Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Career outcomes: Citations/publications, RDD sample

	(1)	(2)	(3)	(4)
Grant × Post	-0.084	-0.257	0.109	0.476
	(0.117)	(0.170)	(0.200)	(0.398)
Grant × Post × Female		0.391*		-0.566
		(0.236)		(0.476)
Grant × Post × Parent			-0.236	-0.855*
			(0.244)	(0.443)
Grant × Post × Female × Parent				1.165**
				(0.555)
Individual FE	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes
Treatment year FE	Yes	Yes	Yes	Yes
Observations	1362	1362	1362	1362
Individuals	204	204	204	204
Pseudo R-Squared	0.686	0.690	0.687	0.692
Treatment Effects				
Male		-0.257 (0.170)		
Female		0.134 (0.160)		
Childless			0.109 (0.200)	
Parent			-0.127 (0.138)	
Childless male				0.476 (0.398)
Male parent				-0.379 (0.187)**
Childless female				-0.090 (0.246)
Female parent				0.220 (0.205)

Notes: Poisson pseudo-likelihood regression (Correia et al., 2019, 2020) with exposure on publication count. Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Career outcomes: Income, RDD sample

	(1)	(2)	(3)	(4)
Grant × Post	0.227***	0.258***	0.413***	0.705***
	(0.051)	(0.076)	(0.129)	(0.234)
Grant × Post × Female		-0.067		-0.528**
		(0.102)		(0.265)
Grant × Post × Parent			-0.244*	-0.571**
			(0.140)	(0.245)
Grant × Post × Female × Parent				0.595**
				(0.287)
Individual FE	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes
Treatment year FE	Yes	Yes	Yes	Yes
Observations	3241	3241	3241	3241
Individuals	294	294	294	294
Within R-Squared	0.468	0.469	0.469	0.473
Treatment Effects				
Male		0.258 (0.076)***		
Female		0.191 (0.068)***		
Childless			0.413 (0.129)***	
Parent			0.169 (0.054)***	
Childless male				0.705 (0.234)***
Male parent				0.133 (0.071)*
Childless female				0.177 (0.124)
Female parent				0.200 (0.082)**

Notes: Linear regression with fixed effects (Correia, 2023). Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix

A-1 Institutional setting

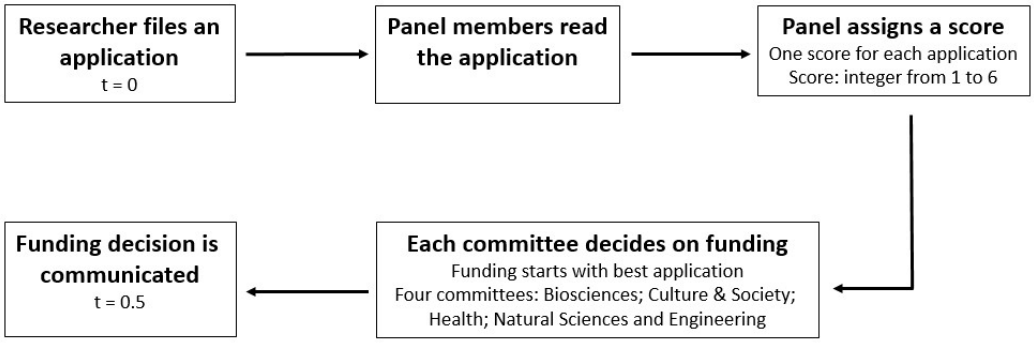


Figure A-1: The Decision-making process

A-2 Data

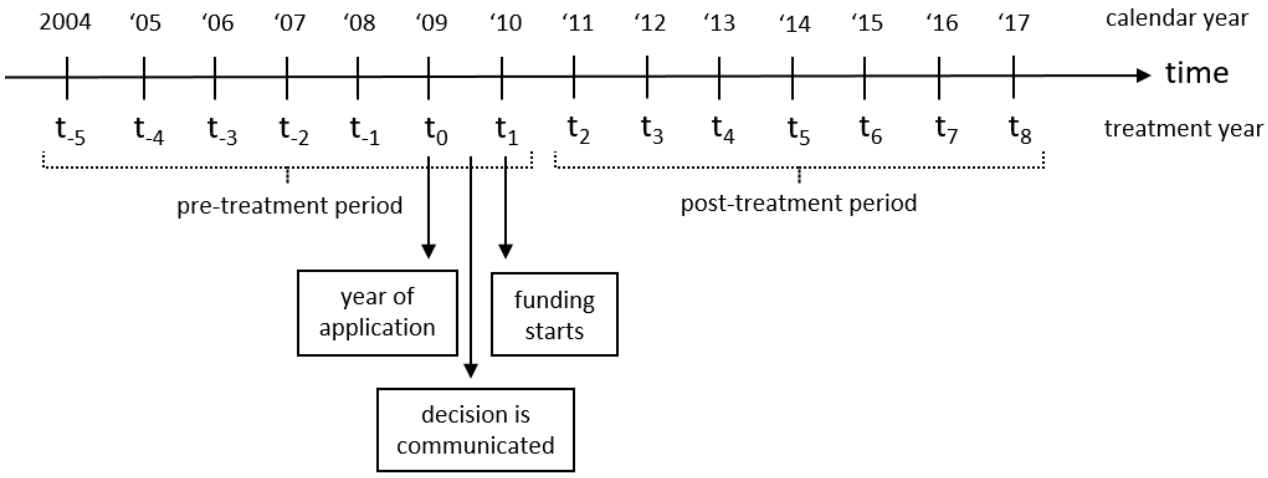


Figure A-2: Timeline

Table A-1: Sample preparation

Data cleaning stage	Applicants	Granted
All applicants	3536	431
With Finnish ID code	1609	325
With records in FOLK files	1466	298
With publications collected	551	229
After cleaning and outlier removal	1169	267
Final sample		
Full sample	385	150
RDD sample	294	119
Robustness: Only career outcomes		
Full sample	1012	217
RDD sample	306	126

A-3 Robustness tests

A-3.1 Samples split by age

Table A-2: Parenthood outcomes: By age of parent, RDD sample

	Under 40				Over 40			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grant	-0.119	-0.176	-0.095	-0.430***	-0.023	0.052	-0.282	-0.210
	(0.084)	(0.107)	(0.137)	(0.136)	(0.065)	(0.107)	(0.173)	(0.194)
Grant × Female		0.123		0.696***		-0.139		-0.091
		(0.148)		(0.174)		(0.115)		(0.108)
Grant × Parent			-0.034	0.384**			0.309*	0.282*
			(0.153)	(0.160)			(0.174)	(0.169)
Grant × Female × Parent				-0.895***				0.000
				(0.194)				(.)
Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grant Score	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grant Committee FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Application year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197	197	197	197	97	97	97	97
R-Squared	0.116	0.120	0.117	0.191	0.109	0.124	0.153	0.159
Treatment Effects								
Male		-0.176 (0.107)				0.052 (0.107)		
Female		-0.053 (0.118)				-0.087 (0.065)		
Childless			-0.095 (0.137)				-0.282 (0.173)	
Parent			-0.129 (0.096)				0.027 (0.062)	
Childless male				-0.430 (0.136)***				-0.210 (0.194)
Male parent				-0.046 (0.119)				0.072 (0.107)
Childless female				0.266 (0.162)				-0.301 (0.175)*
Female parent				-0.245 (0.125)*				-0.019 (0.042)

Notes: Linear regression. The post-period is 8 years. Age of parent: age at application. Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1. Treatment effects are calculated as the sum of the appropriate coefficients. The numbers in parenthesis in the Treatment effect rows are standard errors of the reported treatment effects.

Table A-3: Parenthood outcomes: By age of parent, Full sample

	Under 40				Over 40			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grant	-0.142**	-0.188**	-0.086	-0.290**	-0.037	0.053	-0.254*	-0.158
	(0.067)	(0.088)	(0.112)	(0.131)	(0.047)	(0.089)	(0.146)	(0.157)
Grant × Female		0.101		0.454***		-0.142		-0.119
		(0.127)		(0.165)		(0.097)		(0.093)
Grant × Parent			-0.086	0.165			0.252*	0.228
			(0.133)	(0.157)			(0.148)	(0.144)
Grant × Female × Parent				-0.575***				0.000
				(0.190)				(.)
Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grant Score	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grant Committee FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Application year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	264	264	264	264	121	121	121	121
R-Squared	0.089	0.091	0.090	0.121	0.111	0.130	0.140	0.153
Treatment Effects								
Male		-0.188 (0.088)**				0.053 (0.089)		
Female		-0.087 (0.098)				-0.089 (0.048)*		
Childless			-0.086 (0.112)				-0.254 (0.146)*	
Parent			-0.171 (0.080)**				-0.002 (0.045)	
Childless male				-0.290 (0.131)**				-0.158 (0.157)
Male parent				-0.125 (0.105)				0.070 (0.091)
Childless female				0.164 (0.141)				-0.277 (0.149)*
Female parent				-0.246 (0.112)**				-0.049 (0.037)

Notes: Linear regression. The post-period is 8 years. Age of parent: age at application. Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1. Treatment effects are calculated as the sum of the appropriate coefficients. The numbers in parenthesis in the Treatment effect rows are standard errors of the reported treatment effects.

Table A-4: Parenthood outcomes: RE Panel regression, RDD sample

	(1)	(2)	(3)	(4)
Grant	-0.014	-0.025*	-0.024	-0.079***
	(0.011)	(0.014)	(0.019)	(0.028)
Grant × Female		0.023		0.090**
		(0.019)		(0.038)
Grant × Parent			0.011	0.070**
			(0.021)	(0.031)
Grant × Female × Parent				-0.098**
				(0.044)
Individual RE	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes
Observations	2292	2292	2292	2292
Individuals	306	306	306	306
Pseudo R-Squared	0.035	0.036	0.040	0.048
Treatment Effects				
Male		-0.025 (0.014)*		
Female		-0.001 (0.015)		
Childless			-0.024 (0.019)	
Parent			-0.013 (0.012)	
Childless male				-0.079 (0.028)***
Male parent				-0.009 (0.016)
Childless female				0.011 (0.026)
Female parent				-0.017 (0.017)

Notes: Random-effects linear model with AR(1) disturbance. Standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A-5: Parenthood outcomes: RE Panel regression, Full sample

	(1)	(2)	(3)	(4)
Grant	-0.008	-0.007	-0.023**	-0.041***
	(0.007)	(0.009)	(0.011)	(0.016)
Grant × Female		-0.003		0.036
		(0.012)		(0.022)
Grant × Parent			0.019	0.047***
			(0.013)	(0.018)
Grant × Female × Parent				-0.057**
				(0.026)
Individual RE	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes
Observations	7686	7686	7686	7686
Individuals	1012	1012	1012	1012
Pseudo R-Squared	0.037	0.037	0.043	0.044
Treatment Effects				
Male		-0.007 (0.009)		
Female		-0.010 (0.009)		
Childless			-0.023 (0.011)**	
Parent			-0.004 (0.008)	
Childless male				-0.041 (0.016)***
Male parent				0.005 (0.010)
Childless female				-0.006 (0.016)
Female parent				-0.016 (0.011)

Notes: Random-effects linear model with AR(1) disturbance. Standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A-6: Career outcomes: Publications, Full sample

	(1)	(2)	(3)	(4)
Grant × Post	0.183**	0.266**	0.160	0.138
	(0.086)	(0.110)	(0.180)	(0.234)
Grant × Post × Female		-0.198		0.058
		(0.172)		(0.361)
Grant × Post × Parent			0.028	0.168
			(0.203)	(0.263)
Grant × Post × Female × Parent				-0.352
				(0.407)
Individual FE	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes
Treatment year FE	Yes	Yes	Yes	Yes
Observations	3555	3555	3555	3555
Individuals	317	317	317	317
Pseudo R-Squared	0.369	0.369	0.369	0.370
Treatment Effects				
Male		0.266 (0.110)**		
Female		0.067 (0.135)		
Childless			0.160 (0.180)	
Parent			0.188 (0.097)*	
Childless male				0.138 (0.234)
Male parent				0.306 (0.122)**
Childless female				0.196 (0.278)
Female parent				0.012 (0.151)

Notes: Poisson pseudo-likelihood regression (Correia et al., 2019, 2020). Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A-7: Career outcomes: Citations/publications, Full sample

	(1)	(2)	(3)	(4)
Grant × Post	-0.051	-0.131	-0.043	0.130
	(0.099)	(0.144)	(0.179)	(0.284)
Grant × Post × Female		0.171		-0.347
		(0.200)		(0.365)
Grant × Post × Parent			-0.011	-0.348
			(0.216)	(0.334)
Grant × Post × Female × Parent				0.698
				(0.444)
Individual FE	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes
Treatment year FE	Yes	Yes	Yes	Yes
Observations	1824	1824	1824	1824
Individuals	274	274	274	274
Pseudo R-Squared	0.690	0.690	0.690	0.691
Treatment Effects				
Male		-0.131 (0.144)		
Female		0.041 (0.137)		
Childless			-0.043 (0.179)	
Parent			-0.054 (0.119)	
Childless male				0.130 (0.284)
Male parent				-0.218 (0.168)
Childless female				-0.218 (0.220)
Female parent				0.133 (0.169)

Notes: Poisson pseudo-likelihood regression (Correia et al., 2019, 2020) with exposure on publication count. Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A-8: Career outcomes: Income, Full sample

	(1)	(2)	(3)	(4)
Grant × Post	0.155***	0.168**	0.271**	0.371**
	(0.046)	(0.068)	(0.111)	(0.178)
Grant × Post × Female		-0.025		-0.204
		(0.092)		(0.222)
Grant × Post × Parent			-0.158	-0.273
			(0.122)	(0.191)
Grant × Post × Female × Parent				0.235
				(0.243)
Individual FE	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes
Treatment year FE	Yes	Yes	Yes	Yes
Observations	4274	4274	4274	4274
Individuals	385	385	385	385
Within R-Squared	0.458	0.458	0.459	0.460
Treatment Effects				
Male		0.168 (0.068)**		
Female		0.143 (0.062)**		
Childless			0.271 (0.111)**	
Parent			0.113 (0.049)**	
Childless male				0.371 (0.178)**
Male parent				0.097 (0.067)
Childless female				0.167 (0.132)
Female parent				0.129 (0.071)*

Notes: Linear regression with fixed effects (Correia, 2023). Robust standard errors in parentheses. Stars indicate significance levels: *** p<0.01, ** p<0.05, * p<0.1.