CPB Netherlands Bureau for
Economic Policy Analysis

Getting off to a flying start? The effects of an early-career international mobility grant on scientific performance

We investigate the effects on scientific performance of an international mobility grant that is aimed at early career researchers. Our data contain information on grant applicants as well as bibliographic/ bibliometric data. The data allow us to use a sharp Regression Discontinuity Design because applicants are ranked by an independent scientific committee and are awarded based on their rank until the budget is depleted.

We find no significant effects of the grant on the probability of leaving academia, the quantity of scientific publications, the citation score and the number of co-authors.

CPB Discussion Paper

Marielle Non (CPB), Jeroen van Honk (CWTS),
Vince van Houten (CPB), Inge van der Weijden (CWTS),
Thed van Leeuwen (CWTS)

December 2022

Doi: https://doi.org/10.34932/3rhz-k449

Getting off to a flying start? The effects of an early-career international mobility grant on scientific performance[1]

Mariëlle Non[2] Jeroen van Honk[3] Vince van Houten[2]
Inge van der Weijden[3] Thed van Leeuwen[3]

December 2022

Abstract

We investigate the effects on scientific performance of an international mobility grant that is provided by the Dutch Research Council NWO and is aimed at early career researchers. Our data contain grant applicants and their demographic information, as well as bibliographic/bibliometric data attached to the applicants oeuvres. The data allow us to use a sharp Regression Discontinuity Design because applicants are ranked by an independent scientific committee and are awarded based on their rank until the budget is depleted. We find no significant effects of the grant on the probability of leaving academia, the quantity of scientific publications, the citation score and the number of co-authors. The finding that the control group of non-awarded applicants is as likely to continue in academia as the awarded applicants suggests that non-awarded applicants find other means of starting a productive academic career.

Keywords: international mobility grant, postdoctoral researchers, academic career, quantity of publications, quality of publications, citation score, co-authors, regression discontinuity design

[1] We thank the Dutch Research Council (NWO) for giving us access to their data. Lisa van Leeuwen provided excellent research assistance. We thank Jonneke Bolhaar, Paul Verstraten and seminar participants at the CPB for their useful comments and suggestions.
[2] CPB Netherlands Bureau for Economic Policy Analysis
[3] CWTS Leiden

1. Introduction

Many research managers and science funding agencies consider international mobility as essential for the professional development of academic researchers and for the circulation and diffusion of knowledge between countries. In a 2017 survey among researchers working in the UK, 79 percent of respondents indicate they believe there is an expectation for good researchers to be internationally mobile (Guthrie et al., 2017b). Many governmental institutions worldwide stimulate international mobility of researchers with grant schemes. Well-known examples are the US Fulbright program and the EU Marie Curie fellowships, but many countries also run smaller national grant schemes funding research stays abroad. For example, the Swedish Research Council offers international postdoc grants for young Swedish researchers and the Flanders Research Foundation runs several schemes financing short or long visits abroad.

Despite this perceived importance of international mobility and the amount of public money spent on mobility schemes, there is to date only very limited evidence on the effect of public support of mobility on the accomplishments of researchers. To our knowledge, only Baruffaldi et al. (2020) study the outcomes of a mobility grant program. Based on data from the Swiss National Science Foundation on a postdoc mobility scholarship, they conclude that, compared to non-awarded applicants, awarded applicants increase their co-author network and improve their output quality as measured by the journal impact factor. However, as also acknowledged by Baruffaldi et al. (2020), those outcomes were obtained within a specific context, based on a single grant in a single country. The benefits and disadvantages of international mobility will likely vary depending on, among other factors, the career stage of the researcher, the length of stay abroad, and the origin and destination country of the mobile researcher (Guthrie et al., 2017a; Netz et al., 2020).

We study a Dutch competitive mobility grant, known as the Rubicon grant, which funds a stay abroad of maximum two years for researchers at the start of their academic career. We combine data from the Dutch Research Council (NWO) on grant applicants with bibliometric data from the in-house version of the Web of Science (WoS) database available at CWTS to analyze the outcomes of awarded and non-awarded applicants. Our data contain a ranking of the proposals by an evaluation committee, which NWO uses to award the most deserving candidates. This allows us to use a Regression Discontinuity Design (RDD), comparing applicants who ‘just were awarded’ with nearly equally deserving applicants who ‘just were not awarded’ (Imbens and Lemieux, 2008). We investigate four different dimensions of scientific performance: leaving academia, the quantity of scientific output, the perceived quality (based on citation measures) of the publications, and the number of co-authors. We hypothesize that a period abroad allows researchers to extend their professional network and form new collaboration ties, which in turn might lead to more publications and citations and a higher probability of building an academic career.

We find no significant effect of the mobility grant on any of the scientific outcomes we study. At first sight, this is in contrast with the results in Baruffaldi et al. (2020), who do find significant positive effects on the co-author network and journal impact factor. However, we note there are several contextual differences between the grant we study and the grant studied by Baruffaldi et al. (2020). For example, researchers need to apply for the Dutch Rubicon grant within one year of obtaining their PhD, hence the grant is mostly used to finance the first job after the PhD. In contrast, applicants for the Swiss grant need to have at least one year of research experience at postdoc level. Also, the Rubicon grant funds a stay of at most two years, while the Swiss grant has a maximum duration of three years.

Our study contributes to two strands of literature: the effects of mobility of academic researchers and the effects of research grants in general.

The literature on mobility of researchers mostly finds that internationally mobile researchers have a larger collaboration network and a higher scientific productivity and impact (Guthrie et al., 2017a; Netz et al., 2020). However, caution is needed in the interpretation of those results. First, many studies compare mobile with non-mobile researchers without being able to correct for differences in personal characteristics or intrinsic motivation (e.g. De Filippo et al., 2009; Jonkers and Cruz-Castro, 2013; Scellato et al., 2015). Therefore, it is uncertain whether the results of those studies can be interpreted as true causal effects. Second, many of those studies cannot distinguish between different types of mobility, even though for instance a postdoc abroad might be very different from a short research stay in a later career stage or a multi-year assistant professorship. Note that studying a mobility grant, as we do, circumvents the abovementioned problems.

Some studies indicate that the relation between mobility and academic performance depends on the academic context. For example, Veugelers and Van Bouwel (2015) find that for European researchers a move to the US has stronger positive effects on scientific productivity than a move within Europe. Part of this effect can be explained by the fact that researchers moving to the US are more strongly career motivated. Contrary to the general finding of a positive effect of mobility, Li and Tang (2019) find that non-mobile Chinese researchers have a quicker career trajectory than their returnee peers. In the Chinese context, local connections seem to play an important role in career advancement. Other studies mention modern communication technologies or a period of adjustment to the new environment as possible explanations for a negative or smaller than expected effect of international mobility (Bolli and Schläpfer, 2015; Halevi et al., 2016).

The literature on the effects of receiving a research grant gives a somewhat mixed picture. Many studies on the topic find that obtaining a grant has a positive effect on career advancement, as measured for instance by obtaining professorship or receiving more grants (Bloch et al., 2014; Bol et al., 2018; Gerritsen et al., 2013; Jacob and Lefgren, 2011a). However, the evidence on scientific output is less clear. For example, Jacob and Lefgren (2011a) find a 20 percent increase in the research productivity of receivers of an NIH postdoctoral fellowship, but Jacob and Lefgren (2011b) find that receipt of an NIH research grant has at most a small effect on research output and Benavente et al. (2012) conclude that while receivers of a Chilean research grant publish significantly more than non-receivers, their citation score is not higher.

Several studies mention reasons why receiving a research grant might not have an effect on scientific output. For example, Jacob and Lefgren (2011b) present some evidence that in the case they studied non-receivers shift to alternative sources of funding. Ayoubi et al. (2019) find that participating in a grant competition per se has a positive effect on the number of publications and average impact factor, independent of whether the grant is obtained or not. The grant studied by Ayoubi et al. (2019) is for multidisciplinary joint research, and the authors suggest that in writing a proposal, applicants already expand their collaboration network and knowledge. Further, Wang et al. (2019) find that although some of the applicants just below an NIH funding threshold disappear from the NIH system, the remaining non-receivers outperform those who are just above the funding threshold in the long run. The authors suggest that early-career setbacks might actually strengthen those who persevere. The net effect of receiving a grant might thus depend on the fraction of non-receivers who persist.

2. Institutional context

NWO is one of the most important science funding bodies in the Netherlands, with a total yearly research funding budget of almost 1 billion euros.[1] The large majority of this budget is provided by the Ministry of Education, Culture and Science and is distributed by NWO by means of competitive research grants. One of the instruments of NWO is the Rubicon grant, an outgoing grant aimed at individual researchers at the start of their academic career. In 2021, the total budget for the Rubicon grant was almost 7 million euros. With the grant, NWO aims to retain young and promising researchers for academia. The Rubicon grant allows young researchers to gain international experience, and it bridges the gap between finishing a PhD and applying for an NWO early career grant. Although NWO aims to strengthen Dutch research, receivers of the Rubicon grant are not obliged to return to the Netherlands after their period abroad.

Researchers can apply for the Rubicon grant within one year of obtaining their PhD. The grant covers the travel costs, salary, and research costs of a stay abroad of maximum two years. The Rubicon grant scheme exists since 2005. Each year, except for 2005, there are three application rounds. In 2005, there was only one round. Until 2011, researchers working abroad could also apply for a Rubicon grant to fund a research stay in the Netherlands. As from 2012, the application is only open for researchers who in the five years prior to application have conducted scientific research at an academic research institute in the Netherlands for at least three years and who want to fund a research stay outside of the Netherlands.[2] Researchers can apply only once for a Rubicon grant, that is, if an application is not granted, the applicant cannot re-apply in a next round.

NWO uses a competitive selection process to determine who will be awarded a Rubicon grant. The applications are divided in three different disciplines (Alpha-Gamma, Beta, and Life Sciences) and in each discipline a scientific committee scores the applications on a scale of 1 to 9, where 1 is the best possible score and 9 the worst. Applicants need a score at or below 3.4 to be considered for funding. In all but one of the round-discipline combinations we consider, the available funding is less than the total amount requested by all applicants with a score at or below 3.4. In those round-discipline combinations, the best rated applicants are awarded, until the available funding for that round-discipline combination has been depleted. In case there is a tie, that is, two or more researchers have the same grade, but there is only funding left for one of them, NWO gives priority to female candidates. If this does not solve the tie, the scientific committee re-assesses the candidates in the tie to determine who will get the grant.

[1] In 2021, the national government provided 2,3 billion euros directly to universities as research funding. The budget of NWO therefore is a significant part of the total research funding in the public sector.

[2] NWO makes an exception on this rule for researchers who study an exclusively Dutch topic, like Dutch literature or Dutch law. Those researchers can use a Rubicon grant for a stay at an institute in the Netherlands, other than the institute that awarded the PhD. In 2012 and 2013 there were in total five applications for a stay in the Netherlands.

3. Data

3.1 Data sources

NWO provided data on the applicants for the Rubicon grant from 2005 until 2013. During this period there have been 25 application rounds, where each round has been split in three different disciplines (Alpha-Gamma, Beta, Life Sciences). Hence, in total we consider 75 round-discipline combinations, each of which has a separate ranking of candidates. The data only contain the applicants that scored at or below 3.4 and are considered for funding. Variables included in the data are the name, gender, date of birth, and destination of the applicant, the committee score, and the final outcome (not awarded, awarded, awarded but not accepted by applicant[3]). In total, there are 2,292 applicants in the NWO dataset, of which 697 were awarded the grant, including 62 applicants who did not accept the grant. Table A1 in Appendix A gives an overview of the number of applicants and the number of awarded grants per round-discipline combination.

We complement the NWO data with bibliographic data from the WoS database, specifically the Science Citation Index Expanded, the Social Sciences Citation Index, and the Arts & Humanities Citation Index. WoS offers a good coverage of the international scientific literature, but, like other bibliographic databases, it is not fully exhaustive. In particular, the main bibliographic databases are known to have insufficient coverage of monographs and non-English language journals, which both are important publishing forms in arts and humanities, law, and some social sciences.

Matching the Rubicon applicants in the NWO data to authors in the WoS database is challenging, as only the name and date of birth of the applicants are known. We use the author-clustering algorithm as described in Caron and Van Eck (2014) to link publications to authors, and we then manually check the results. For 224 applicants in the NWO data no match could be made, either because the name of the applicant does not occur in the WoS database or because the name is so common that it is not possible to distinguish the correct person with certainty. In our matching process, we prioritize quality of data over quantity of data, meaning that for those researchers whose names could not be disambiguated, the matched publication count is more likely to underrepresent than overrepresent their actual publication count.

Table 1 gives the match rate for different disciplines, destinations and final committee decisions. The match rate is relatively low in the Alpha-Gamma discipline. One reason for this is that researchers in arts and humanities tend to publish in monographs, book chapters and locally oriented journals in other languages than English, instead of international journals. This makes it less likely they can be found in the WoS database. Also, non-Dutch researchers who apply for a stay in the Netherlands are relatively often not matched. A fair share of those researchers have a common name (e.g. Brown or Xu) that is hard to uniquely identify in the WoS database. Finally, the match rate is lower for applicants who were not awarded the grant.[4] One reason for this might be that awardees most likely

[3] It is not uncommon for researchers at the end of their PhD track to apply for several grants and research positions at the same time. It might occur that a Rubicon awardee also gets a superior offer.
[4] A partial explanation is that the percentage of awardees is lower in the Alpha-Gamma discipline and among non-Dutch applicants, which are both groups with a relatively low match rate. However, when we control for this, the match rate is still significantly lower for non-awarded applicants.

continue in academia for at least the duration of the grant, while non-awardees might opt to leave academia. This might in theory bias our analysis. However, in Appendix B we show that there is no discontinuity in match rate at the cutoff, that is, there is no discontinuity in match rate between applicants who 'just were awarded' the grant and who 'just were not awarded'. Moreover, when we impute that all non-matched applicants left academia without ever publishing, the main conclusions of our analysis do not change.

		Matched	Not matched
	Total	90.2%	9.8%
Discipline	Alpha-Gamma	84.7%	15.3%
	Beta	91.1%	8.9%
	Life Sciences	95.3%	4.7%
Destination	Abroad	92.6%	7.4%
	Netherlands	84.1%	15.9%
Decision	Not awarded	88.0%	12.0%
	Awarded	95.4%	4.6%
	Awarded, not accepted	95.2%	4.8%

Table 1: Percentage of NWO applicants matched and not matched to WoS data

3.2 Variables

The NWO committee scores cannot be used directly to perform an RDD analysis because the cutoff point at which the grant is awarded varies between rounds and disciplines, and the grading scale might differ between committees and rounds. In general, each committee focusses on constructing a relative ranking ('is candidate A more deserving than candidate B') and not on absolute scores. To reflect this, we construct a ranking of applicants. The applicants who were awarded the grant, including those who rejected the awarded grant, get a rank at or above zero. For each round-discipline combination, the awarded applicant with the weakest committee score (that is, the awardee with the numerically highest score given that 1 is the best possible score and 3.4 the worst score in our dataset) gets rank 0, the awarded applicant with the next-to-weakest score gets rank 1, etcetera. When two applicants have the exact same score, they get the same rank. Non-awarded applicants all get a negative rank, starting at -1. For each round-discipline combination, the non-awarded applicant with the best score (that is, the non-awardee with the numerically lowest score given that 1 is the best possible score and 3.4 the worst score in our dataset) gets rank -1, the applicant with the next-to-best score gets rank -2, etcetera. In round 2006-2, all Beta applicants that scored at or below 3.4 were awarded the grant. We exclude this round-discipline from our analysis.

In our study, we focus on the effect of the grant on leaving academia, quantity and quality of publications, and co-author networks. We operationalize 'leaving academia' by a dummy variable that indicates whether the applicant stopped publishing within five years after the year of application. That is, the dummy variable indicates whether the year of the most recent publication is smaller than the year of application plus five. Although this is a rough proxy of (dis)continuing in academia, it at least gives insight in the scientific activity of the applicant.

We measure the quantity of publications by counting the total number of articles, letters, reviews, and proceedings papers of the applicant in the years up to and including the application year and in the five years following the application year.[5,6] WoS also includes other publications, such as book reviews and editorial material. We leave out those publication types as they do not have a citation score. When we do include those publications in the count, the conclusions of our analysis do not change.

We proxy the quality of publications by the number of times the publication has been cited. Although this proxy has limitations, it is commonly used in the literature. In some scientific fields, the average number of citations is much higher than in other fields. Moreover, the number of citations depends on the year of publication as older publications have had more time to get cited. To correct for this, we use the Mean Normalized Citation Score (MNCS) indicator proposed in Waltman et al. (2011). The indicator divides the number of citations of a publication by the expected number of citations given the field and year of publication. Then, for each applicant, we average over all publications of the applicant in the relevant time period (up to and including the application year or the five years following the application year). If the applicant has no publications in the relevant time period, we insert a missing MNCS. If we insert a 0 instead, our conclusions do not change.

For very recent publications that did not yet have much time to get cited, the number of citations might be a noisy indicator of the quality of the work, even after correcting for field of study and publication year. Therefore, we also study the citation score of the journals the applicant published in, using the Mean Normalized Journal Score (MNJS). This indicator is constructed in the same way as the MNCS, but at journal level instead of publication level. Moreover, we also construct an alternative quality indicator by considering whether a publication belongs to the top 10 percent most frequently cited publications in the same field and publication year, following the method outlined in Waltman and Schreiber (2013). As before, we average this indicator over all publications of the applicant in the relevant time period to construct a variable named high impact share. If the applicant has no publications in the relevant time period, we insert a missing for MNJS and high impact share.

Finally, we construct two variables counting the number of unique co-authors up to and including the application year and the number of new unique co-authors (that is, not counting co-authors with whom the applicant already worked together in the years up to and including the year of application) in the five years after application. We consider all scientific output in the WoS data to construct the co-author variables; hence we include publications such as editorial material and book reviews. Again, if the applicant has no publications in the relevant time period, we insert a missing. Inserting a 0 instead does not change our conclusions.

Table 2 gives an overview of the variables we use in our analysis.

[5] We consider publications until and including the application year as work done prior to the grant. This accounts for delay in publication. Also, after awarding the grant, it usually takes a few months before the applicants move abroad and start the research.

[6] As a robustness check, we also did the analysis tracking applicants for seven years after the application, leaving out the applicants from 2013 as our WoS data covers publications until the first quarter of 2020. This did not change the results.

Variable	Description
Grant awarded	Equal to 1 if the applicant has been awarded the grant (including applicants who did not accept the grant)
Rank	Rank of the applicant's committee score
Discipline	Discipline of the applicant (Alpha-Gamma, Beta or Life Sciences)
Gender	Equal to 1 if male, 0 if female
Stopped publishing	Equal to 1 if the most recent work of the applicant was published within five years after the year of application
Publications at application	The total number of articles, reviews, letters and proceedings papers the applicant has published until and including the year of application
Publications 5 years	The total number of articles, reviews, letters and proceedings papers the applicant has published in the five years after the application year
MNCS at application	The Mean Normalized Citation Score of all publications until and including the year of application
MNCS 5 years	The Mean Normalized Citation Score of all publications in the five years after the application year
MNJS at application	The Mean Normalized Journal Score of all publications until and including the year of application
MNJS 5 years	The Mean Normalized Journal Score of all publications in the five years after the application year
High impact share at application	The fraction of publications until and including the year of application that belong to the top ten percent most frequently cited publications in the research field
High impact share 5 years	The fraction of publications in the five years after the application year that belong to the top ten percent most frequently cited publications in the research field
Co-authors at application	The number of unique co-authors until and including the year of application
Co-authors 5 years	The number of new unique co-authors in the five years after the application year

Table 2: Variables description

3.3 Sample

In total, there are 2,292 applicants in the NWO dataset. We remove all five applicants that are in the round-discipline combination where all applicants were awarded a grant and use the resulting 2,287 applicants to construct the ranking as explained above. Next, we exclude from our analysis the 224 applicants that could not be identified in the WoS data. Of the remaining 2,063 applicants, 59 applicants did not accept the offered Rubicon grant. We also remove those applicants from our data, as their achievements after the application year are not due to the grant.[7] Finally, of the remaining 2,004 applicants, 523 applied for a stay in the Netherlands. In our analysis we focus on applicants

[7] Adding those applicants to the pool of non-awarded applicants does not solve the issue because the committee score and rank of those applicants is clearly better than the score and rank of the non-awarded applicants. The only way to make a fair comparison is to compare the awardees who did not accept the grant to similarly scoring awardees who accepted. However, the sample size of 59 applicants is too small for this exercise.

who apply for a stay outside the Netherlands, as this is a more homogenous group. However, when we do include applicants who want to stay in the Netherlands, our conclusions do not change.

In our main analysis we focus on the applicants with rank -4 till 3. The ranks we constructed run from -21 to 10, but as shown in Figure 1, the very low and high ranks have only few observations. Moreover, RDD is a local technique, which focuses on differences in outcomes between applicants that only differ in whether they 'just were awarded' or 'just were not awarded' the grant. The further away from the cutoff point, the more likely it is that applicants differ in more aspects than just the assignment of the grant. The range from -4 till 3 seems a reasonable choice that gives sufficient observations for analysis but stays fairly close to the cutoff. We also did the analysis using the ranges -3 till 2 and -5 till 4, but this did not change the results.[8] In the results section, we discuss the results of a robustness check using range -6 till 5.

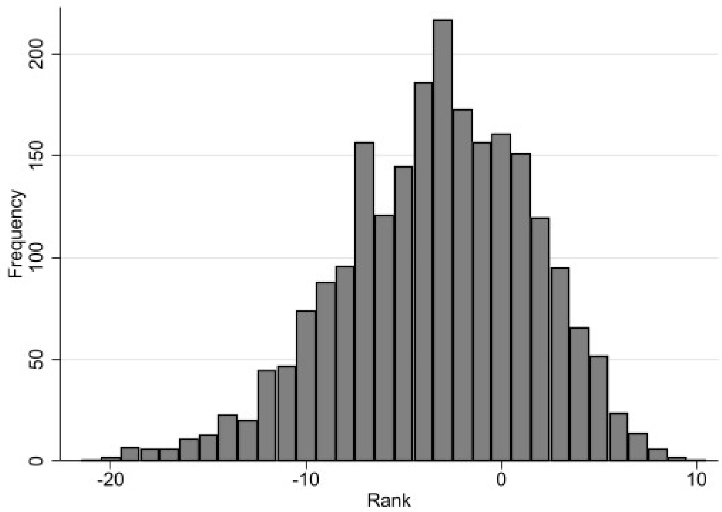

Figure 1: distribution of the rank

Table 3 gives the means and standard deviations of the variables used in the analysis for the applicants with rank -4 till 3, and for the awarded and non-awarded applicants in this sample. Life sciences is the largest discipline, containing 42 percent of the applicants, followed by Alpha-Gamma (33 percent) and Beta (25 percent). Slightly more than half of the applicants are male. The applicants in our sample on average are successful young researchers, with almost six publications at application and an above-average citation score and impact share. Five years after application, ten percent of the researchers in our sample have stopped publishing. The average publication count in the five years following application is ten publications, again with above-average citation score and impact share. The awarded applicants score somewhat higher on the outcome variables, both at application and five years after application. However, the standard deviation is high, and the differences are not statistically significant.

[8] The range -4 till 3 is also the MSE-optimal bandwidth using the method outlined in Calonico et al. (2014), but this method, and other methods to determine an optimal bandwidth, assumes a continuous running variable, while the ranking we use is discrete.

	Applicants rank -4 till 3			Applicants rank -4 till -1 (non-awarded)			Applicants rank 0 till 3 (awarded)		
	obs.	mean	s.d.	obs.	mean	s.d.	obs.	mean	s.d.
Alpha-Gamma	873	0.33	0.47	498	0.34	0.47	375	0.32	0.47
Beta	873	0.25	0.43	498	0.26	0.44	375	0.25	0.43
Life Sciences	873	0.42	0.49	498	0.41	0.49	375	0.43	0.50
Gender (1=male)	873	0.57	0.50	498	0.57	0.50	375	0.57	0.50
Publications at application	873	5.80	4.93	498	5.45	4.67	375	6.26	5.22
MNCS at application	796	1.78	3.73	450	1.59	1.87	346	2.02	5.24
MNJS at application	796	1.53	0.93	450	1.47	0.90	346	1.61	0.97
High impact share at application	796	0.20	0.22	450	0.19	0.21	346	0.20	0.23
Co-authors at application	805	15.99	15.04	457	14.96	13.28	348	17.34	16.99
Stopped publishing	873	0.10	0.30	498	0.14	0.34	375	0.06	0.23
Publications 5 years	873	10.25	11.84	498	9.52	13.19	375	11.22	9.69
MNCS 5 years	828	1.84	1.83	465	1.68	1.66	363	2.05	2.01
MNJS 5 years	828	1.67	0.95	465	1.59	0.88	363	1.78	1.02
High impact share 5 years	828	0.21	0.20	465	0.19	0.18	363	0.24	0.21
Co-authors 5 years	844	23.84	24.93	475	21.85	23.15	369	26.41	26.87

Table 3: descriptive statistics for sample used in main analysis

4. Empirical strategy

The institutional setting of the Rubicon grant allows us to use a sharp RDD design to estimate the causal effect of receiving the grant on scientific output. In general, awarded and non-awarded applicants cannot be compared because NWO strives to award the grant to the most promising researchers. However, as a scientific committee ranks the candidates and the grant is awarded to the best ranked applicants until the available budget is depleted, it is likely that applicants close to the cutoff are very similar and thus are essentially comparable.

Following Imbens and Lemieux (2008), we first graph the data by computing the average value of the outcome variables over the ranks -4 till 3. Next, we perform a t-test to determine whether there is a statistically significant difference between the average outcome at ranks -1 (just not awarded the grant) and 0 (just awarded the grant). Finally, we estimate the regression equation

$$Y_i = \alpha + \gamma I\{Rank_i \geq 0\} + \beta_1 Rank_i I\{Rank_i < 0\} + \beta_2 Rank_i I\{Rank_i \geq 0\} + \delta' Z_i + \varepsilon_i$$

where Y_i denotes the outcome of applicant *i*, $Rank_i$ is the rank of applicant *i* where a strictly negative rank denotes an applicant who was not awarded the grant and Z_i is a vector with additional explanatory variables. The parameter γ measures the treatment effect at the cutoff and is our main parameter of interest. As additional explanatory variables, we include dummies for discipline and gender and we include the number of publications, MNCS, and number of co-authors at application.[9]

[9] Although NWO provided the date of birth of the applicants, we do not include the applicant age in our main analysis as this variable has several missings. When we do include this variable, the results of our analysis do

The validity of the RDD analysis outlined above hinges on two assumptions: 1) the applicants around the cutoff differ only with respect to whether they were awarded the grant or not and 2) individual agents cannot manipulate the committee ranking or assignment of the grant. As for the first assumption, the descriptive statistics in Table 3 suggest that prior to the application the number of publications, MNCS, MNJS, and the number of co-authors are slightly higher for awarded applicants. However, in Appendix C we show that those outcomes increase gradually with the rank and are continuous around the cutoff. Moreover, there is no discernable discontinuity in gender around the cutoff. This lends credibility to the first assumption. As for the second assumption, we note that there is no fixed score that defines the cutoff. Instead, the cutoff score is determined by the available budget and the budget required by the best scoring applicants. The required budget depends among others on the destination and length of stay and is calculated after the committee decided on their scores. Hence, it seems impossible for an individual to manipulate the outcome. The distribution of ranks in Figure 1 shows no discontinuities around the cutoff and a density test (Cattaneo et al., 2020) is insignificant (p-value 0.2552), lending further credibility to assumption 2.

5. Results

5.1 Continuing in academia

The upper left panel of Figure 2 shows the means and corresponding 95% confidence intervals of the variable 'stopped publishing' by rank. At first sight, it seems there is a slight drop in the fraction of applicants that stop publishing at the cutoff. A t-test comparing ranks -1 and 0 has a p-value of 0.097 and hence is significant at a 10% level. However, the treatment effect at the cutoff is insignificant in the RDD regression, independent of whether additional explanatory variables are included or not (see Table 4, columns 1 and 2). Column (3) in Table 4 gives the regression results when we use an alternative proxy for continuing in academia, namely a dummy variable that indicates whether the applicant has published after 2017 (1=yes). Again, the treatment effect at the cutoff is insignificant. All in all, we conclude there is no statistically significant discontinuity at the cutoff.

We performed four additional robustness checks.[10] First, the explanatory variables number of publications, MNCS and number of co-authors at application all have a long tail to the right. The regression results are robust to removing possible outliers in these explanatory variables. Second, when we estimate the regressions separately for the different disciplines, none of them gives a significant treatment effect. Third, when we use a larger bandwidth, running from rank -6 till rank 5, the treatment effect does become significant for the outcome variable 'stopped publishing' (γ=-0.065, p=0.003 for the regression without additional explanatory variables and γ=-0.008, p= 0.052 for the regression with additional explanatory variables). However, the treatment effect stays insignificant (γ=0.028, p=0.543) for the outcome variable 'publications after 2017'. Finally, we estimated the regressions using a binwidth of two ranks instead of one rank, that is, instead of using the previously defined rank, we use a variable that takes value -2 for ranks -4 and -3, value -1 for ranks -2 and -1, value 0 for ranks 0 and 1 and value 1 for ranks 2 and 3. Again, this does not change

---

not change. We note that applicants tend to have a similar age as they all apply within a year of being awarded a PhD degree.

[10] To save space, the results of additional robustness checks are not reported, but are available on request.

the results.

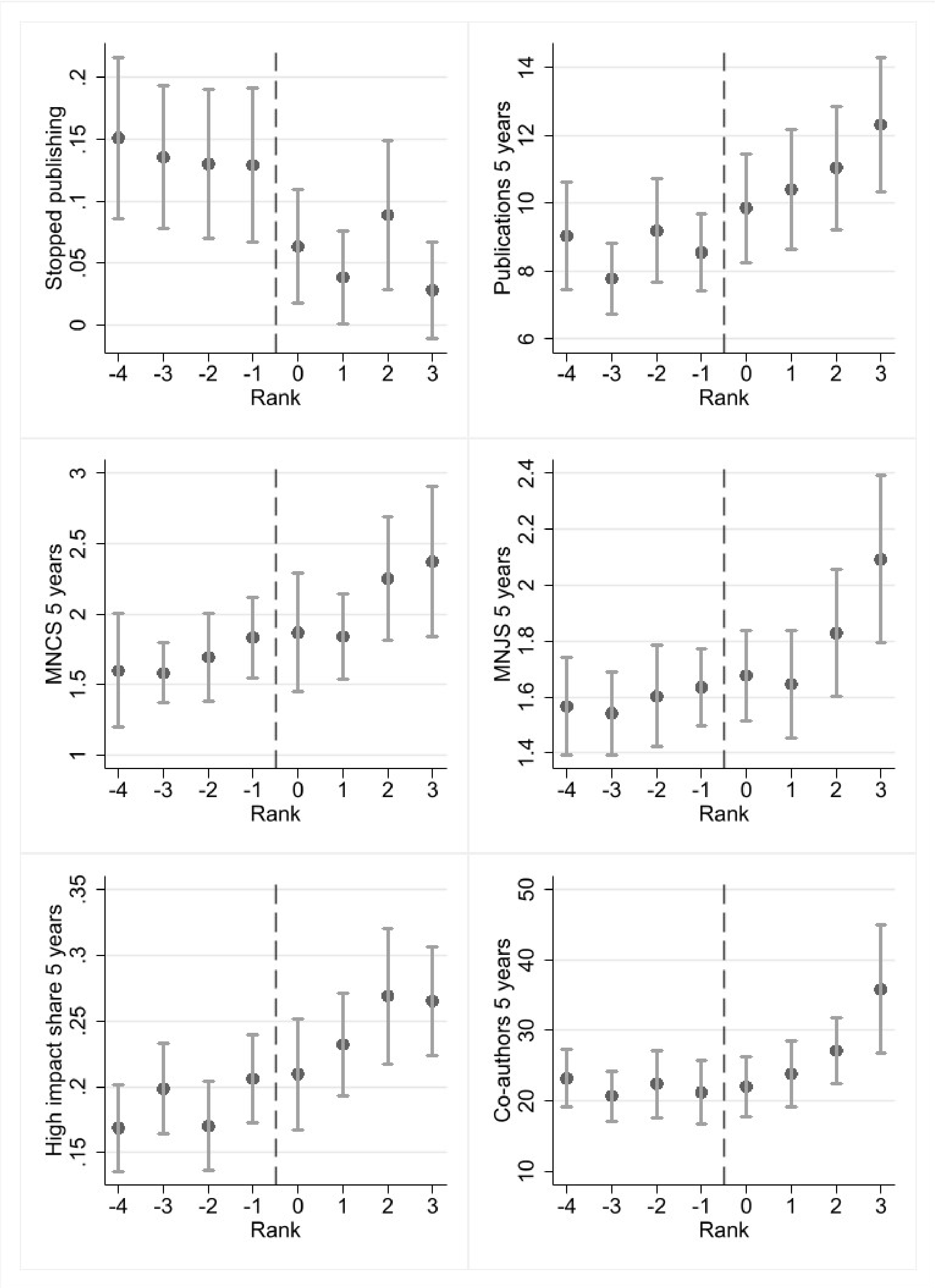

Figure 2: average outcome by rank

Table 4: regression results for continuing in academia

Dependent variable	(1) Stopped publishing	(2) Stopped publishing	(3) Publications after 2017
Grant awarded (i.e. rank ≥ 0)	-0.057	-0.008	-0.048
	(0.043)	(0.042)	(0.057)
Rank not-awarded applicant	-0.007	-0.017	0.035*
	(0.014)	(0.014)	(0.018)
Rank awarded applicant	-0.004	-0.009	0.005
	(0.010)	(0.010)	(0.019)
Gender (1=male)		-0.037*	0.103***
		(0.022)	(0.030)
Discipline = Beta		0.055*	-0.126***
		(0.031)	(0.041)
Discipline = Life sciences		-0.000	-0.020
		(0.026)	(0.037)
Publications at application		-0.001	0.004
		(0.003)	(0.004)
MNCS at application		-0.003*	0.005**
		(0.001)	(0.002)
Co-authors at application		-0.001	0.003*
		(0.001)	(0.001)
Constant	0.119***	0.113***	0.774***
	(0.038)	(0.041)	(0.054)
Observations	873	796	796
R-squared	0.018	0.032	0.053

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2 Scientific output

The upper right panel of Figure 2 shows the means and corresponding 95% confidence intervals of the variable 'Publications 5 years' by rank. This variable has a long tail to the right and in constructing the figure we removed nine observations with 50 or more publications. The upper right panel of Figure 2 shows no clear discontinuity between ranks -1 and 0, suggesting there is no treatment effect. A t-test comparing ranks -1 and 0 has a p-value of 0.184 and hence is not significant. When we include all observations or use a different cutoff value to determine outliers in the number of publications, the resulting graph also shows no discontinuity between ranks -1 and 0 and the t-test remains insignificant.

The RDD regression gives no significant treatment effect at the cutoff (see Table 5, columns 1 and 2). In these two regression equations, the nine observations with 50 or more publications are excluded, but including them gives similar results. As an alternative correction for the long tail, we estimated the RDD regression using the natural logarithm of one plus the number of publications in the five years after application, including all observations. Again, we find no significant treatment effect (see Table 5, column 3). Moreover, we constructed an alternative measure which divides the number of publications in the five years after application by the number of publications at application. As before, we find no significant treatment effect (see Table 5, column 4). Finally, in column (5) we report the results of a regression on the number of publications published in the first year after application. Again, we find no significant treatment effect.

Table 5: regression results for scientific output

Dependent variable	(1) Publications 5 years	(2) Publications 5 years	(3) Ln(1 + publica- tions 5 years)	(4) Relative publications	(5) Publication s 1 year
Grant awarded (i.e. rank ≥ 0)	1.094	1.021	0.004	-0.099	0.221
	(1.066)	(1.006)	(0.100)	(0.353)	(0.239)
Rank not-awarded applicant	0.012	0.150	0.056*	0.065	-0.046
	(0.311)	(0.308)	(0.032)	(0.120)	(0.073)
Rank awarded applicant	0.774*	0.091	0.024	0.051	0.106
	(0.401)	(0.367)	(0.032)	(0.085)	(0.086)
Gender (1=male)		0.552	0.050	0.332*	-0.115
		(0.545)	(0.054)	(0.182)	(0.131)
Discipline = Beta		0.075	0.188**	-0.087	0.318*
		(0.725)	(0.074)	(0.281)	(0.183)
Discipline = Life sciences		-1.221*	0.051	-0.607***	-0.119
		(0.701)	(0.068)	(0.234)	(0.171)
Publications at application		0.657***	0.052***	-0.167***	0.081***
		(0.135)	(0.011)	(0.030)	(0.028)
MNCS at application		0.257***	0.021**	0.071***	0.006
		(0.086)	(0.008)	(0.017)	(0.016)
Co-authors at application		0.017	0.002	0.010	0.010
		(0.040)	(0.003)	(0.008)	(0.008)
Constant	8.644***	5.331***	1.758***	3.253***	1.112***
	(0.806)	(0.956)	(0.097)	(0.372)	(0.231)
Observations	864	787	796	796	795
R-squared	0.022	0.207	0.181	0.109	0.103

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We performed six additional robustness checks. First, the regression results are robust to removing possible outliers in the explanatory variables. Second, when we estimate the equations separately for the different disciplines, none of them gives a significant treatment effect. Third, when we use a larger bandwidth, running from ranks -6 till 5, the treatment effect becomes significant at 10% level for the number of publication 5 years after application and for the natural logarithm of the publications (γ=1.465, p=0.072 and γ=0.148, p=0.071 respectively). The treatment effects for the relative number of publications and for the number of publications in the first year after application are not significant at 10% level. Fourth, when we estimate the equations using a binwidth of two ranks instead of one rank, none of them gives a significant treatment effect. Fifth, we estimated the equations using only the applicants who continue publishing, that is, whose most recent work was published more than five years after application. Again, we find no significant treatment effect. Finally, when we count all publications instead of only articles, reviews, letters, and proceedings papers, the treatment effect stays insignificant.

5.3 Scientific impact score

The middle row and the lower left panel of Figure 2 show the means and corresponding 95% confidence intervals of the MNCS, MNJS and high impact share in the five years after application by rank. None of those figures shows a discontinuity at the cutoff. The t-test comparing ranks -1 and 0 is insignificant for all three outcome variables (p=0.889 for MNCS, p=0.696 for MNJS and p=0.898 for high impact share). The RDD regressions in Table 6 also show no significant treatment effect.

Table 6: regression results for impact score

Dependent variable	(1) MNCS 5 years	(2) MNCS 5 years	(3) MNJS 5 years	(4) MNJS 5 years	(5) High impact share 5 years	(6) High impact share 5 years
Grant awarded (i.e. rank ≥ 0)	-0.084	-0.154	-0.049	-0.054	0.006	-0.004
	(0.258)	(0.250)	(0.120)	(0.119)	(0.027)	(0.026)
Rank not-awarded applicant	0.083	0.104	0.027	0.048	0.008	0.013*
	(0.077)	(0.074)	(0.036)	(0.035)	(0.008)	(0.007)
Rank awarded applicant	0.189*	0.124	0.135***	0.081	0.021**	0.012
	(0.105)	(0.093)	(0.051)	(0.051)	(0.010)	(0.010)
Gender (1=male)		0.268*		0.168**		0.010
		(0.139)		(0.067)		(0.014)
Discipline = Beta		-0.107		0.269***		0.013
		(0.171)		(0.071)		(0.017)
Discipline = Life sciences		0.157		0.479***		0.072***
		(0.223)		(0.080)		(0.018)
Publications at application		-0.041		-0.040***		-0.001
		(0.031)		(0.011)		(0.002)
MNCS at application		0.071*		0.013		0.009*
		(0.038)		(0.009)		(0.005)
Co-authors at application		0.037**		0.017***		0.001*
		(0.016)		(0.004)		(0.001)
Constant	1.883***	1.345***	1.654***	1.316***	0.207***	0.153***
	(0.193)	(0.219)	(0.095)	(0.105)	(0.021)	(0.024)
Observations	828	776	828	776	828	776
R-squared	0.017	0.109	0.022	0.130	0.026	0.101

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The distributions of MNCS and MNJS are slightly skewed to the right. As a robustness check, we also estimated the regressions in Table 6 leaving out some outliers, using the log of one plus MNCS or MNJS as dependent variable, and using the MNCS or MNJS relative to the MNCS or MNJS prior to application as dependent variable. In none of those regressions the treatment effect becomes significant.

We performed six additional robustness checks. First, we removed possible outliers in the explanatory variables. Second, we estimated the equations separately for the different disciplines. Third, we used a larger bandwidth, running from ranks -6 till 5. Fourth, we estimated the equations using a binwidth of two ranks instead of one rank. Fifth, we estimated the equations using only the applicants who continue publishing. And sixth, we estimated the equations using the outcomes in the first year after applications. All these robustness checks give similar outcomes as the results in Table 6, that is, the treatment effect is always nonsignificant at 10% level.

5.4 Coauthors

The lower right panel of Figure 2 shows the means and corresponding 95% confidence intervals of the variable 'Co-authors 5 years' by rank. There is no visible discontinuity at the cutoff. A t-test comparing ranks -1 and 0 is insignificant with p-value 0.789, and also the RDD regressions show no significant treatment effect (see Table 7, columns 1 and 2). The variable 'Co-authors 5 years' has a long tail to the right, but removing possible outliers has no effect on the figure, the t-test, and the RDD regressions. Column (3) in Table 7 shows the results of an RDD regression on the natural logarithm of one plus the number of new co-authors in the five years after application. Again, there is no significant treatment effect. We also used the number of new co-authors in the five years after application relative to the number of co-authors at application as dependent variable. Again, the treatment effect is nonsignificant (see Table 7, column 4). The treatment effect is also insignificant when using the number of new co-authors in the first year after application as outcome (see Table 7, column 5).

Table 7: regression results for co-authors

Dependent variable	(1) Co-authors 5 years	(2) Co-authors 5 years	(3) Ln(1 + co-authors 5 years)	(4) Relative co- authors	(5) Co-authors 1 year
Grant awarded (i.e. rank ≥ 0)	-0.107	-0.457	0.055	-0.343	0.369
	(3.383)	(3.189)	(0.126)	(0.354)	(0.713)
Rank not-awarded applicant	-0.413	0.388	0.032	0.139	-0.219
	(0.964)	(0.906)	(0.039)	(0.092)	(0.226)
Rank awarded applicant	4.275***	1.818	0.052	0.280*	0.045
	(1.459)	(1.322)	(0.040)	(0.148)	(0.242)
Gender (1=male)		0.332	-0.100	0.435**	0.064
		(1.750)	(0.067)	(0.174)	(0.397)
Discipline = Beta		2.650	0.496***	-0.347	0.661
		(1.900)	(0.095)	(0.261)	(0.490)
Discipline = Life sciences		4.688**	0.593***	-0.171	1.088**
		(1.906)	(0.096)	(0.277)	(0.533)
Publications at application		0.234	0.026**	-0.002	-0.086
		(0.358)	(0.012)	(0.025)	(0.074)
MNCS at application		0.347**	0.022**	0.030**	-0.001
		(0.168)	(0.010)	(0.012)	(0.038)
Co-authors at application		0.673***	0.017***	-0.050***	0.135***
		(0.127)	(0.004)	(0.012)	(0.026)
Constant	20.816***	9.053***	2.016***	3.122***	2.023***
	(2.761)	(2.850)	(0.125)	(0.345)	(0.686)
Observations	844	779	779	754	651
R-squared	0.024	0.245	0.277	0.123	0.160

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We performed five additional robustness checks. First, we removed possible outliers in the explanatory variables. Second, we estimated the equations separately for the different disciplines. Third, we used a larger bandwidth, running from ranks -6 till 5. Fourth, we estimated the equations using a binwidth of two ranks instead of one rank. And fifth, we estimated the equations using only the applicants who continue publishing. All these robustness checks give similar outcomes as the results in Table 7, that is, the treatment effect is always nonsignificant at 10% level.

6 Discussion

In the analysis above we find no measurable effects of the Dutch Rubicon grant on the probability of continuing in academia, the number of publications, the citation score, and the number of new co-authors. The RDD methodology of comparing those who ‘just were awarded’ with those who ‘just were not awarded’ in combination with the fact that the grant is aimed at a group of researchers in a similar career stage circumvents many causality issues that previous research on scientific mobility has. However, there also are some reasons to be cautious in the interpretation of our results.

First, RDD is a local technique, meaning that the effect of the grant is only estimated for a specific sample around the cut-off, and cannot be generalized to the full population of young researchers. On one hand, this is a strength, as it controls for selection effects that might occur when e.g. awardees would be compared to researchers who have no ambition to stay abroad or who have a lower scientific quality. On the other hand, the control group in our research consists of academically promising researchers, probably with an ambition to stay in academia and to acquire international experience. After all, all applicants in our data set are deemed suitable for funding and the only reason why the weakest applications are not awarded is a lack of budget. It is therefore likely that non-awardees find another academic position, in the Netherlands or abroad. Our result on staying in academia also points in this direction, although it uses a very rough proxy for academic position. Unfortunately, we do not know the job positions or geographical location of the applicants in our dataset in the years following the grant application, so we are not able to further test this hypothesis.

Second, the context of the grant we studied might also play a role in our findings. The Rubicon grant is a relatively short grant of maximum two years and, unless the host institute offers a position, the awardee will need to start looking for another job or grant within a few months of moving abroad. This might limit the benefits to be reaped from the grant. At the same time, non-awardees who secure a position as e.g. tenure track researcher might have a more carved-out career perspective in the short term than those who received the mobility grant. The context of the grant might also explain the difference between our findings and the findings of Baruffaldi et al. (2020). The Swiss grant that Baruffaldi et al. (2020) study has a maximum duration of three years and is aimed at a slightly later career stage, which might affect the benefits of a stay abroad (Guthrie et al., 2017a).

Third, our results are limited to quantifiable outcomes, which measure only part of the true outcomes of interest. For example, the citation score is only one element of the impact a researcher has, and valuable connections between researchers might not necessarily result in a joint publication. The measures we used are common in bibliometric research. Moreover, we find that most of our outcome measures increase slightly with the rank, both before and after the grant application. This suggests that the committee that ranks the candidates takes these measures into account, consciously or unconsciously, and that the committee ranking has predictive value on these measures. However, given the limitations in the measures, our findings do not imply that the grant does not have any effects at all.

Fourth, there are some data limitations. As mentioned before, we do not know the job positions or geographical location of the applicants in our dataset in the years following the grant application, which limits our options to study relevant career outcomes. Also, we do not exactly know what kind of work has been done during the funded stay abroad. As the grant funds a relatively short period and publication in a scientific journal might take time, it is very difficult to attribute publications to the period abroad. Related to this, it is difficult to correct for the publication culture in different fields. Not only are there differences in outlet, e.g. monographs or journals, but there also are differences in publication lags, number of co-authors, citation culture, etcetera. And although the data do contain a dummy for discipline, this is a classification in three very broad fields.

Our findings raise the question if public spending on mobility grants is effective to further the career of young researchers. Although there are limitations to our research, the grant we study does not seem to have an effect on a number of widely used measures of individual academic performance in the 5 years after the application. At the same time, the results in the literature are mixed, and more research is needed on the factors which determine the success of a grant and the mechanisms through which researchers might benefit from mobility. Another consideration is that funding agencies can have more general objectives that might justify public spending on mobility grants, even if they do not directly benefit the academic career at individual level. One of those objectives is the formation of ties between research communities in different countries; for instance, if the grant recipient returns to the Netherlands and in this way links the host institute with a Dutch research group. Also, the grant we studied is explicitly aimed at researchers at the very start of their career and might retain them for academia, especially if other funding options are limited and in fixed supply.

Bibliography

Ayoubi, C., Pezzoni, M., & 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.

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

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

Bloch, C., Graversen, E. K., & Pedersen, H. S. (2014). Competitive research grants and their impact on career performance. *Minerva*, *52*(1), 77-96.

Bol, T., de Vaan, M., & van de Rijt, A. (2018). The Matthew effect in science funding. *Proceedings of the National Academy of Sciences*, *115*(19), 4887-4890.

Bolli, T., & Schläpfer, J. (2015). Job mobility, peer effects, and research productivity in economics. *Scientometrics*, *104*(3), 629-650.

Calonico, S., Cattaneo, M.D., & Titiunik, R. (2014). Robust nonparametric confidence intervals for regression discontinuity designs. *Econometrica, 82*(6), 2295–326.

Caron, E., & Van Eck, N.J. (2014). Large scale author name disambiguation using rule-based scoring and clustering. In E. Noyons, editor, *Proceedings of the 19th International Conference on Science and Technology Indicators* (pp. 79-86).

Cattaneo, M.D., Jansson, M., & Ma, X. (2020). Simple local polynomial density estimators. *Journal of the American Statistical Association, 115(*531), 1449-1455.

De Filippo, D., Casado, E. S., & Gómez, I. (2009). Quantitative and qualitative approaches to the study of mobility and scientific performance: a case study of a Spanish university. *Research evaluation*, *18*(3), 191-200.

Gerritsen, S., Plug, E., & van der Wiel, K. (2013). Up or out? How individual research grants affect academic careers in the Netherlands. *CPB Netherlands Bureau for Economic Policy Analysis*.

Guthrie, S., Lichten, C., Corbett, J., & Wooding, S. (2017a). International mobility of researchers. A review of the literature. *RAND EUROPE*.

Guthrie, S., Lichten, C., Harte, E., Parks, S., & Wooding, S. (2017b). International mobility of researchers. A survey of researchers in the UK. *RAND EUROPE*.

Halevi, G., Moed, H. F., & Bar-Ilan, J. (2016). Does research mobility have an effect on productivity and impact?. *International higher education*, (86), 5-6.

Imbens, G. W., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of econometrics*, *142*(2), 615-635.

Jacob, B. A., & Lefgren, L. (2011a). The impact of NIH postdoctoral training grants on scientific productivity. *Research policy*, *40*(6), 864-874.

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

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

Li, F., & Tang, L. (2019). When international mobility meets local connections: Evidence from China. *Science and Public Policy*, *46*(4), 518-529.

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

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

Veugelers, R., & Van Bouwel, L. (2015). The effects of international mobility on European researchers: Comparing intra-EU and US mobility. *Research in Higher Education*, *56*(4), 360-377.

Waltman, L., van Eck, N. J., van Leeuwen, T. N., Visser, M. S., & van Raan, A. F. J. (2011). Towards a new crown indicator: Some theoretical considerations, *Journal of Informetrics*, *5*(1), 37-47

Waltman L., & Schreiber, M. (2013). On the calculation of percentile-based bibliometric indicators. *Journal of the American Society for Information Science and Technology*, *64*(2), 372-379.

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

Appendix A

Table A 1: number of applicants (awarded grants) by discipline and round

	Alpha-Gamma	Beta	Life Sciences	Total
2005	13 (8)	14 (10)	22 (14)	49 (32)
2006-1	33 (15)	17 (8)	31 (15)	81 (38)
2006-2	23 (7)	5 (5)	25 (13)	53 (25)
2006-3	28 (10)	12 (6)	25 (15)	65 (31)
2007-1	31 (13)	13 (6)	22 (15)	66 (34)
2007-2	15 (7)	14 (7)	22 (15)	51 (29)
2007-3	30 (10)	10 (6)	17 (15)	57 (31)
2008-1	32 (6)	19 (6)	31 (14)	82 (26)
2008-2	33 (10)	36 (9)	28 (11)	97 (30)
2008-3	35 (9)	19 (8)	30 (10)	84 (27)
2009-1	46 (11)	31 (12)	32 (11)	109 (34)
2009-2	22 (7)	27 (9)	47 (19)	96 (35)
2009-3	36 (9)	26 (10)	29 (14)	91 (33)
2010-1	38 (10)	43 (9)	32 (12)	113 (31)
2010-2	39 (11)	40 (9)	39 (11)	118 (31)
2010-3	42 (10)	32 (8)	48 (11)	122 (29)
2011-1	100 (10)	55 (6)	72 (12)	227 (28)
2011-2	58 (9)	39 (6)	59 (13)	156 (28)
2011-3	84 (13)	40 (7)	57 (9)	181 (29)
2012-1	22 (6)	17 (5)	16 (8)	55 (19)
2012-2	17 (3)	24 (6)	29 (11)	70 (20)
2012-3	26 (8)	7 (4)	39 (9)	72 (21)
2013-1	22 (5)	8 (3)	31 (9)	61 (17)
2013-2	19 (5)	10 (5)	33 (9)	62 (19)
2013-3	18 (5)	28 (8)	28 (7)	74 (20)
Total	862 (217)	586 (178)	844 (302)	2.292 (697)

Appendix B

Figure B1 shows the fractions and corresponding 95% confidence intervals of non-matched applicants by rank. There is no discernable discontinuity around the cutoff. A t-test comparing ranks -1 and 0 has p-value 0.363, and hence is not significant.[11] Also, RDD regressions on a dummy variable that is 1 for non-matched applicants show no significant discontinuity at the cutoff (Table B1).

[11] The t-test used the full dataset, including non-Dutch applicants. When we exclude the persons who apply for a stay in The Netherlands, the p-value is 0.563.

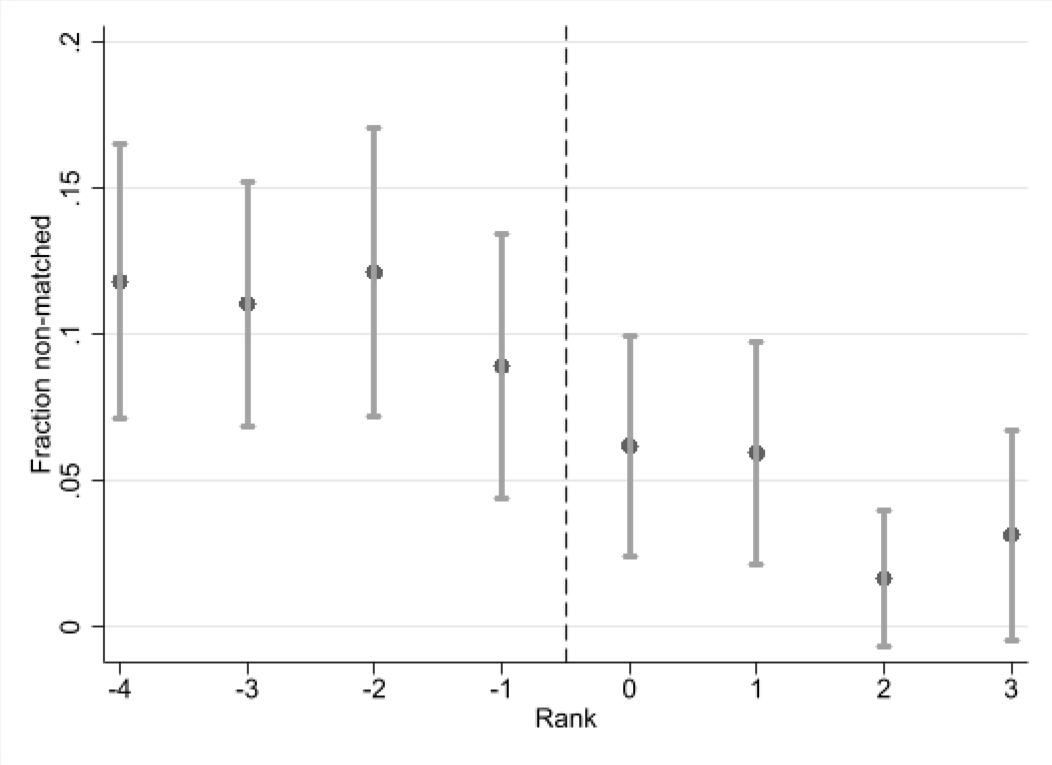

Figure B 1: Fraction non-matched applicants by rank

Table B 1: regression results for non-matched applicants

Dependent variable	(1) Non-matched applicant	(2) Non-matched applicant
Grant awarded (i.e. rank ≥ 0)	-0.028	-0.025
	(0.033)	(0.034)
Rank not awarded applicant	-0.007	-0.007
	(0.010)	(0.011)
Rank awarded applicant	-0.014*	-0.008
	(0.008)	(0.008)
Gender (1=male)		0.022
		(0.016)
Discipline = Beta		-0.061***
		(0.023)
Discipline = Life sciences		-0.079***
		(0.020)
Constant	0.092***	0.110***
	(0.029)	(0.034)
Observations	1,260	977
R-squared	0.015	0.032

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C

Figure C1 shows the means and corresponding 95% confidence intervals of several outcome variables at the moment of application by rank. The upper left panel shows the number of publications at application, the upper right panel and the middle panels show the MNCS, MNJS, and high impact share at application and the lower left panel shows the number of co-authors at application.[12] Finally, the lower right panel shows the fraction of males. In none of the figures is a discernable discontinuity around the cutoff. T-tests comparing ranks -1 and 0 confirm this, the p-values of the six different t-test are between 0.180 and 0.505. Also, RDD-regressions show no significant treatment effect for any of the variables (Table C1).

Table C 1: regression results for outcomes at the moment of application

Dependent variable (at application)	(1) Publications	(2) MNCS	(3) MNJS	(4) High impact share	(5) Co-authors	(6) Gender
Grant awarded (i.e. rank ≥ 0)	0.529	0.259	0.080	0.029	1.225	0.018
	(0.560)	(0.395)	(0.158)	(0.032)	(1.748)	(0.068)
Rank not awarded applicant	-0.151	0.013	0.033	-0.012	-0.252	-0.010
	(0.162)	(0.100)	(0.044)	(0.009)	(0.462)	(0.020)
Rank awarded applicant	0.462*	-0.085	-0.018	0.009	1.180	0.004
	(0.262)	(0.123)	(0.050)	(0.012)	(0.894)	(0.023)
Gender (1=male)	0.610**	0.105	0.034	0.011	-0.199	
	(0.303)	(0.139)	(0.076)	(0.017)	(0.991)	
Discipline = Beta	3.840***	0.325	0.183*	0.044**	7.557***	0.303***
	(0.389)	(0.200)	(0.104)	(0.021)	(0.992)	(0.041)
Discipline = Life sciences	3.444***	0.329**	0.320***	0.080***	15.389***	0.050
	(0.338)	(0.162)	(0.076)	(0.019)	(1.025)	(0.040)
Constant	2.346***	1.325***	1.339***	0.108***	5.605***	0.445***
	(0.448)	(0.322)	(0.138)	(0.028)	(1.329)	(0.059)
Observations	873	795	796	796	805	873
R-squared	0.148	0.009	0.026	0.028	0.199	0.060

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[12] The panel showing the MNCS leaves out one outlier with MNCS over 90 at rank 3, which has a disproportionate effect in the figure. Removing the outlier has no effect on the conclusions.

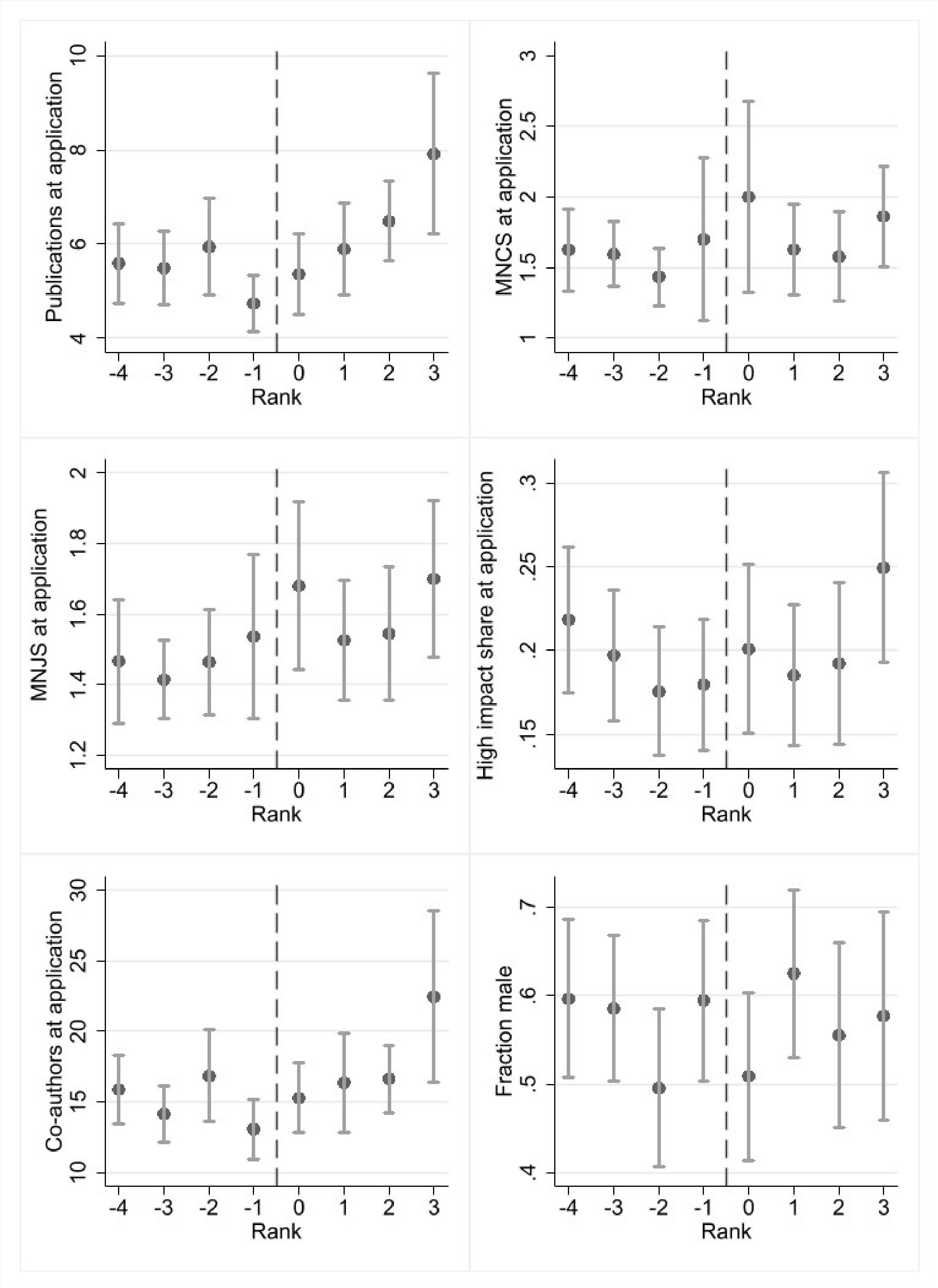

Figure C 1: average outcome at application by rank