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Do mission-oriented grant schemes shape the direction of science?

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Abstract

A growing literature has examined how applying for and winning competitive project grants affects the career trajectory of scientists in terms of productivity, quality, social networks and knowledge. However, the role of grant schemes in shaping the direction of scientific inquiry remains very poorly understood. In this study, we investigate how the research output of grant recipients, rejected applicants and a set of comparable non-applicants working in the same fields relates to a set of funding calls issued by the Swedish Foundation for Strategic Research. These calls are all of the 'request for applications' (RFA) type – i.e. targeting a certain type of research that the funder has identified and seeks to strengthen. We analyze topic similarity between applicants' research and the texts defining the RFA calls. Applying an optimal full matching followed by a difference-in-differences design, we find that – in line with expectations – applicants increase their topic similarity with the call more than non-applicants. However – contrary to expectations – the pace at which the research of the average grant winner shifts towards the topic of the call is not statistically different from that of non-winning applicants. These results can not be explained by differences in post-call productivity. Our findings have important implications for science policy, and for our understanding of how the formulation of RFA calls shape the direction of scientific inquiry.

Keywords: grant funding; mission-oriented research; RFA; topic choice; topic shift.

JEL classification: O31 (Innovation and Invention: Processes and Incentives); O38 (Government Policy); J16 (Economics of Gender).

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1. Introduction

Grant funding constitutes a core element of science funding (Azoulay and Li, 2020). The fundamental characteristics of competitive grant funding models are that they are operated by funding agencies (either public, like government bodies, or private, like foundations), and open to applications from scientists or scientific organizations. This procedure can thus be described as an allocation of funding in direct competition. In such funding schemes, all applications that satisfy the call's general terms and conditions are evaluated by the funding body, and decisions of funding outcomes are made on the basis of that evaluation (Westmore and Meadmore, 2020). Broadly speaking, competitive grant funding schemes can be sub-categorized in "open" grant schemes and "RFA" grant schemes. In open grant schemes[1], the funding agency sets a broad overall objective for the call and scientists submit their own proposals, suggesting their own research questions and their own methodology, and then compete for funding (Myers, 2020; Westmore and Meadmore, 2020). In contrast, in RFA grant schemes[2], funds from the funding agency are set aside for a single, one-time competition, related to a predefined area of science, on a predefined topic, with a predefined objective and methodology (Myers, 2020).

In many European countries, the balance between the competitive project funding model and block funding, whereby public funding is distributed by the government directly to universities (Hicks, 2012; Westmore and Meadmore, 2020), is a major topic of science policy debates (Wang et al., 2018). Broadly speaking, competitive grant funding models offer three types of advantages over block funding models that make them appealing to science policymakers.

First, they can be used to counter perceived problems of inefficiency in the university-based system for resource allocation. Competitive project funding models may be designed to systematically direct funding towards the most promising and most innovative projects, and towards

1 Also known as "investigator-initiated", "researcher-led" or "response mode" grant schemes.
2 The term "RFA" is a little ambiguous here, as some authors call these types of schemes "commissioned" grant schemes, while using the term "RFA" to denote the Research Funding Agency (Westmore and Meadmore, 2020).

the "best" scientists – all on the basis of peer review assessments (Li and Agha, 2015). For block funding models to achieve the same objectives, universities need to have effective allocation systems of their own in place (Geuna and Martin, 2003). By handing over funding directly to universities, policymakers also delegate responsibility for identifying the appropriate allocation of that funding between fields, groups and individuals to the university management. In well-functioning academic environments, competition in hiring and promotion as well as high-quality collegial support (i.e., collaboration and qualified exchange) will tend to make sure that the allocation of direct funding is effective. However, in the presence of extensive nepotism or intellectual inertia, academic environments may be accused of being ineffective (Hicks, 2012). Shifting funds from the block funding model to the competitive project funding model can in that context increase the quality (Park et al., 2015) and novelty (Wang et al., 2018) of the produced research.

A second rationale for organizing funding through competitive project funding schemes is that it allows policymakers to stimulate desirable patterns of collaboration in research (Westmore and Meadmore, 2020). For example, the European Commission's (EC) series of Framework programs[3] has traditionally sought to stimulate pan-European cooperation and university-industry interaction. This ambition has taken the form of calls that are only open to consortia of applicants, and in assessment criteria emphasizing the constellation of applicants in parallel to the relevance of the proposed projects when distributing funding.

Finally, a third type of rationale for competitive project funding schemes, in particular for the RFA subtypes, is that the allocation of funding involves targeting specific areas of research that have been identified by the funding body as particularly important in one way or another. We can refer to this type of grant scheme as being based on directional ambitions, in that the funder

3 https://ec.europa.eu/eurostat/cros/content/research-projects-under-framework-programmes-0_en (accessed 2023-01-01).

explicitly seeks to promote a particular type of research. Now, it may be argued that any type of funding scheme has elements of *directional* ambitions, in that a specific field or area is being targeted. For example, the US National Institutes of Health (NIH) funding body is made up of 27 institutes and centres[4] that each award grants for research within their specific domain of medical research. Decisions about the allocation of budget within NIH, and between the NIH and the National Science Foundation (NSF), are thus decisions about priorities between areas of enquiry. In what follows, however, we will refer to directional ambitions in science policy in relation to activities where a funding agency makes active and repeated decisions about what areas or questions to prioritize in calls within a broader range of potential areas or questions. Examples of grant schemes with embedded directed policy ambitions include calls opened under the so called 'second pillar' of the EC's Horizon Europe programme[5] and the RFA call scheme operated by the NIH in parallel to the main instrument of open "investigator-initiated" calls for funding proposals[6].

Directional, or strategic, practices of science funding are often heralded by representatives for industry, in that it represents an approach to policy making that is related in spirit to industrial R&D management. Furthermore, in many types of directional grant schemes industry preferences constitute an important basis for identification of what areas to target in a call (Broström, 2012). Directional approaches may also appeal to policymakers, in that they entail a shift of strategic agency from universities and individual scientists to the funding agency. Over the last few years, ambitions to direct scientific inquiry towards areas identified as particularly important has received renewed popularity in the form of 'RFA' funding schemes (Gans and Murray, 2011).

A number of concerns have been raised about the effects of shifting the public funding of science strongly towards reliance upon competitive project funding schemes. Most generally, grant

4 See https://www.nih.gov/institutes-nih (accessed 2023-01-01).
5 See https://ec.europa.eu/info/research-and-innovation/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-europe_en (accessed 2023-01-01).
6 For instance, "R01s can be investigator-initiated or can be solicited via a Request for Applications" (see https://grants.nih.gov/grants/funding/r01.htm, accessed 2023-01-01).

funding comes with a cost for managing calls, applications and assessments, and in an academic system strongly dependent on grants, efforts to acquire funding may crowd out actual scientific work for senior scholars (Gross and Bergstrom, 2019). Grant funding that requires industry participation has also been accused of shifting academic research into less productive and less novel avenues of inquiry (Banal-Estañol et al., 2015; Goduscheit, 2022), but the evidence is far from conclusive regarding this concern (Callaert et al., 2015). A more prevalent line of critique concerns how funding by grants leads to 'projectification' of science. In prominent work on this topic, Azoulay et al. (2011) and Boudreau et al. (2016) raised concerns about how the process of applying for and delivering on short-term projects induces scientists to skew their agenda away from more innovative but highly uncertain research endeavors in favor of projects more likely to generate immediate demonstrable results. Recent work by Veugelers et al. (2022) on ERC grants identified similar patterns, with the addition that grant recipients in early career stages are more likely to utilize their grants to conduct risky research. 'Projectification' of science has also been argued to risk the quality of doctoral education, in view of the risk that PhD students funded exclusively through grants acquired by the supervisor may be locked into overly well-defined projects during their training (Broström, 2019).

Our knowledge about the benefits and drawbacks of funding science by means of competitive project funding scheme has grown considerably over the last few years. However, extant work is strongly focused on fund recipients of open (non-directed) calls. These studies tend to either abstain from making comparison with other groups of scientists (Li and Agha, 2015), or to compare winners to non-winning applicants while examining outcomes such as research productivity (Arora and Gambardella, 2005), citations (Carayol and Lanoë, 2017), collaboration networks (Carayol and Lanoë, 2017), patenting (Azoulay et al., 2018; Li et al., 2017) and knowledge base diversity (Ayoubi et al., 2019).

This research stream provides for mixed result: from an insignificant or modest impact of the receipt of grant funding (Arora and Gambardella, 2005) to a quite significant impact even after controlling for various individual-level pre-funding characteristics (Li and Agha, 2015).

Only few previous studies focus on RFA schemes (i.e., on directed or 'targeted') calls (Carayol and Lanoë, 2017; Myers, 2020). No research at all has, to our knowledge, examined what happens to applicants and potential applicants in terms of *call topics,* that is, whether the various parties interested in the grant pursue, after the call, a research trajectory congruent with the topic of the call. In this paper, we address these questions in order to systematically investigate how directional grant funding ambitions shape scientific work.

Our analysis goes beyond extant literature also in that we explicitly study non-winning applicants. To our knowledge, only one paper follows applicants in general after the research process. Ayoubi et al. (2019) find that applicants to research grants increase their productivity, their collaboration network, and also draw on a broader body of scientific knowledge in their future research, even if they do not win.

We utilize a dataset provided to us by the Swedish Foundation for Strategic Research. The dataset contains information on 21 calls pursued between 2011 and 2018. The information provided includes all applicants, both winning and non-winning ones. We enlarge this dataset by finding a sample of potential applicants, i.e., we expand the set of applicants with corresponding scientists who could have applied to the call but did not do so. Similar to Furman and Teodoridis (2020), we employ topic modeling techniques from the machine learning domain to study scientific activities and their development over time. Specifically, we measure the semantic similarity between the call and the research published by the scientists in our dataset. After creating a comparable set of non-applicants on a call-by-call basis through full-optimal matching, we test (1) whether applicants increase their similarity to the call more than non-applicants, and (2) whether winners increase their similarity with respect to non-winning applicants. We further explore differences between groups of scientists, by seniority and gender.

We find partially surprising results. First, we establish that, as expected, the research published by applicants shifts more strongly towards similarity with the call text than does the research of non-applicants. However, we do not find significant differences between winning and non-winning applicants in this regard. The absence of a shift towards the call is particularly striking among male and junior grantees.

The paper proceeds as follows: Section 2 reviews the literature and sets forth our research hypotheses, Section 3 describes the data collection process, Section 4 defines the models we use to test for our hypotheses, Section 5 provides the results of our analysis, Section 6 discusses the results, and Section 7 concludes.

2. Literature Review and Research Hypotheses

The literature on grant funding and its effects focuses strongly on broad, non-directional calls, and on establishing differences between winning and non-winning applicants. For our research purpose, we note that while winning grants is important for the careers of scholars (in particular for junior researchers), the estimated effects in terms of publication output and scientific impact are relatively limited in magnitude, with diverging evidence. For example, while Lawson et al. (2021) do not find evidence for increased productivity of grant recipients in Turin (Italy), an analysis of university professors in Luxembourg by Hussinger and Carvalho (2022) find an association between winning a grant and publishing one more paper. There is also somewhat divergent views whether positive effects of grants are to be sought only among winners, or also among non-winning applicants. Benavente et al. (2012) find a positive impact of two additional papers published within a six year period for the average Chilean grant winner, as compared to non-winning applicants. However, Ayoubi et al. (2019) find that grant applicants increase the quantity and quality of their research more than a comparable set of potential applicants who did not apply, with no statistical differences between winning and non-winning applicants. Similar discrepancies exist for analyses of grant writing and collaboration networks (Davies et al., 2022).

2.1. Related work

Two previous studies examined directional grant calls and their effects using contra-factual analysis.

Myers (2020) builds a dataset of potential applicants to the Requests for Applications (RFA) operated by the NIH in order to analyse scientists' willingness to apply for funding in such calls. He finds that the scientists who apply to an RFA are those who already have done research in the topics targeted by the RFA, suggesting that significant costs are associated with a change of research direction for scientists. He argues that such costs also explain the "RFA premium", i.e., that RFAs allocate bigger grants than non-directed open call competitions. RFAs lead to more publications than the open grants, but this difference seems driven by differences in the type of science and scientists that are being targeted by the RFAs, and not by the structure of the funding scheme itself. Carayol & Lanoë (2017) study a new institution for project-based funding created in France in 2005, which funds natural, hard, and social sciences through both directional ("thematic") and non-directional calls. Identifying potential applicants through propensity score matching methodology, they find that research funded through non-thematic calls have a larger impact (citation frequency) than research funded through thematic program calls. They also find, however, that scientists funded through the latter type of call broaden their co-author networks more than their peers who are funded through grants awarded through broader (non-thematic) calls.

2.2. Do directed calls affect scientists' research agendas?

Directed calls can in principle have two types of effects. First, scientists funded by a call are expected to pursue research in line with the focus of the call. This is the fundamental logic behind directed calls, and implies that, all else being equal, the research conducted by funded scientists should be expected to shift towards the topic of the call. We refer to this as the *funding effect* of a directed call. The mechanisms behind the funding effect consist of 1) the new obligations towards the funder, as detailed in the approved application and grant contract, and 2) the enhanced resources available to grant recipients, allowing them to engage in the project. Since both of these effects do not accrue to non-winning applicants or to non-applicants, the empirical manifestation of this effect is that winners increase their similarity to the call more than the other two groups. We are only aware of one study reporting evidence with bearing on this conjecture. Myers (2020) find that recipients of NIH grants from targeted RFA calls initially publish articles with high similarity (measured by means of MeSH terms) to the research objectives of the RFA. However, this similarity decreases again a few years after obtaining the funds.

Beyond these first-order effects accruing to grant recipients, recent research on non-directional call funding has suggested that grant proposal writing in itself may affect future research (Wang et al., 2018). Ayoubi et al. (2019) exploit a dataset of 775 grant applicants to SINERGIA, a Swiss funding program sponsoring interdisciplinary collaboration, finding that applicants, regardless of whether they win or not, increase their number of publications with respect to potential applicants (a comparable set that did not apply for funding). This result is well in line with previous studies on (non-directional) call funding finding relatively limited differences between winning and non-winning applicants in terms of research output (Arora and Gambardella, 2005; Gush et al., 2018; Jacob and Lefgren, 2011). Ayoubi et al. (2019) also find that applicants publish in journals with higher impact factors than potential applicants, and expand their collaboration network by co-authoring with their co-applicants. Similar findings are reported by Carayol & Lanoë (2017) and by Davies et al. (2022). Our conjecture is that directed calls also affect the future research of an applicant by means of an *application effect*, whereby the research of an average applicant – whether (s)he obtains the grant or not – shifts towards the topic of the call. The mechanisms behind this effect consist of the generation of 1) new ideas and 2) new networks during the application process. While preparing an application, scientists are likely to build up a greater interest in and knowledge about the topics of the call. The work invested in preparing an application may also strengthen social ties between applicants, as well as generate shared understanding and new ideas about how to leverage each others expertise in work related to the topic of the call.

While any joint effort can be expected to generate new linkages or strengthen existing linkages between scientists, we see a directed call as particularly likely to generate application effects. In many cases, in order to meet the criteria set up for a directed call, scientists will have to develop proposals beyond their established ideas, and establish new contacts (Carayol and Lanoë, 2017). Having engaged with the line(s) of research targeted by a directed call, those who do not win the grant may decide to pursue their research anyway, either by finding alternative sources of finance (Jacob and Lefgren, 2011), or by pursuing a (dumped down) version of their research even in the absence of such financing (Chubin et al., 1990, p. 63).

We summarize our expectations regarding funding and application effects in the following set of hypotheses:

H1 (application effect, funding effect): *Applicants, whether they win or not, increase the similarity between their research and the call more than non-applicants.*

H2 (application effect): *Non-winning applicants increase the similarity between their research and the call more than non-applicants.*

H3 (funding effect): *Winning applicants increase the similarity between their research and the call more than non-winning applicants.*

Our first hypothesis follows the logic that if at least one of the two effects discussed here exists, we should observe the average applicant, whether (s)he wins or not, moving more strongly towards the call than the average non-applicant. We may find evidence supporting H1 also if no application effect exists, if winners are subject to a significant funding effect and winners and non-winners are treated as one group. The second and third hypotheses are logical consequences of application and funding effects, respectively, in isolation. We note, however, that the pattern predicted in H3 could potentially arise from application effects, if 1) there are (unobserved) differences in application-writing effort, with the magnitude of efforts determining the level of application effects, and 2) winners on average exert higher effort than non-winning applicants. Should we find evidence supporting H3, we may thus want to explore opportunities to reduce the unobserved difference in effort exerted between the winning applications and the control group.

3. Data Collection

3.1. The Swedish Foundation for Strategic Research

In order to test our hypotheses, we built a new and original database. Our data comes from the Swedish Foundation for Strategic Research (SSF)[7]. The SSF "is an independent non-profit research foundation" whose purposes are to "support research within natural science, engineering, and medicine" and to "promote the development of strong research environments [...] for the development of Sweden's long-term competitiveness" (SSF, 2021). Set up in 1994, by the start of 2021 it had spent nearly SEK 16 billion (€1.55 billion or $1.68 billion) on research grants (SSF, 2021), at a rate of approximately SEK 600 million (€58.08 million or $62.74 million) per year[8]. Grants recipients are "active within Swedish universities [...], research institutes, regional hospitals or companies" (SSF, 2021).

SSF funds research that is neither entirely curiosity-driven nor strictly applied in nature[9]. A core element of the foundation's work is its mission-oriented funding approach, where about 2–3

7 https://strategiska.se/en/, accessed 2021-05-31.
8 https://strategiska.se/en/call-for-proposals/, accessed 2021-05-31.
9 The SSF "creates bridges between basic research and needs-motivated research where results will be utilized" (https://strategiska.se/en/about-ssf/, accessed 2021-05-31).

'framework programme' calls for proposals (just "calls" henceforth) are published each year. These calls are directed at addressing challenges in new and emergent domains of hard sciences and technology, often with an interdisciplinary or multidisciplinary focus[10]. The focal challenges vary each year. For each call, the SSF sets up a panel which reviews the proposals submitted for a particular call. Proposals not deemed in line with the call after initial screening are rejected, while all remaining proposals are sent out to external reviewers[11] who are asked to assess the application using a given set of evaluation criteria that remains the same for all calls. The reviews then come back, and the panel makes a final decision.

3.2. Applications and potential applicants

The SSF gave us access to information about all 21 'framework programme' competitions for research grants held between 2011 and 2018, including call for proposals and all the applications (both successful and unsuccessful) submitted for such calls. Each application contain information about the proposed research project, the budget needed to pursue it, and detailed information about the applicant (also called "Principal Investigator", or "PI" henceforth) and his team of co-applicants. Information about the PI include name, surname, gender, affiliation, birth date, year of PhD, and list of relevant publications. In this period, there were a total of 1,234 applications submitted by 931 unique applicants; of these applications, 611 (49.51%) were sent out for review and 152 (12.32%) won the grant.

Using the name, surname and affiliation of the applicant as provided in the application, we paired applicants to their respective Scopus IDs, checking the results manually and manually

10 See SSF (2021) for the difference between interdisciplinary and multidisciplinary.
11 The entire proposal is sent out to external reviewers, including information (CV, publications, etc.) about applicants and their co-applicants. The reviewers then express an opinion on the research proposal and assess the ability of the applicant team to carry out the proposed research. It is then a single-blinded review process.

resolving not found applicants, and downloaded their publication record from Scopus using pybliometrics (Rose and Kitchin, 2019)[12].

For each call in our sample, we reconstructed a fictitious pool of *potential applicants*, i.e. a pool of scientists that could have potentially applied to the call (and may or may not have done so), based on three criteria: (1) having a Swedish affiliation (eligibility criteria for the foundation), (2) being active in research in the *focal years* of the call, and (3) being active in the *subject categories* of the call. In building this pool, we adopted a conservative approach aimed at including all scientists who could have applied. As SSF focuses only on hard sciences and technology, and applying criteria 1 and 2, we retrieved all Sweden-based scholars from Scopus who were research active (i.e. had at least one publication) in the Scopus subject categories of the hard sciences (i.e., "Health Sciences", "Life Sciences" and "Physical Sciences", thus excluding the "Social Sciences" categories[13]) in the *focal years* of the call, defined as the year of the call, the year prior to it and the year after it[14]. Next, applying criterion 3, for each call we restricted the group of potential applicants to the ones that were actively publishing research in the *focal subject categories* of the call. These categories were not identified directly by the funder, so we chose to reconstruct a list of categories by investigating the profile of the scientists who submitted applications that the foundation chose to submit to external review.[15] Specifically, we matched the journals in which the applicants had published against the Scimago Journal Ranking[16] database, retrieving the subject categories of those

12 We could not match 2 PIs to their Scopus ID neither on the basis of their joint name, surname, and affiliation, nor on the basis of the publications listed in their applications, since those applicants listed no publications in their application. For this latter reason we conclude they do not have a Scopus profile and remove them from the set of applicants.
13 The categories classified under “Social Sciences” include "Arts and Humanities", "Business, Management and Accounting", "Decision Sciences", "Economics, Econometrics and Finance", "Psychology" and "Social Sciences" (see https://www.scopus.com/search/form.uri?display=advanced).
14 The inclusion of the year after the call lets us account for printing lags and does not cause endogeneity, because the award process of the SSF lasts several months, making it unlikely that publications in the year after the call reflect the research financed by the grants eventually assigned in the call.
15 The first screening by the panel is used to weed out applications that are considered less promising, or out-of-topic for the call. By focusing on scientists whose applications passed this first screening, we expect to identify subject categories most directly related to the focus of the call.
16 https://www.scimagojr.com/journalrank.php.

journals. For each call, we then counted the publications of the applicants who passed the first screening in each subject category and considered as focal subject categories of the call those subject categories that accounted for no less than 25% of the total publications of the applicants who passed the first screening. 395 potential applicants had no publications in a journal in the 5 years before or after the call (391 non-applicants and 4 applicants: 2 non-reviewed, and 2 reviewed non-winners), and were dropped from the analysis in view of uncertainty regarding their scientific profile.

The results were checked and confirmed manually. For example, the subject categories for the call RIT10, named "Software Intensive Systems", are: "Computer Science", "Electrical and Electronic Engineering", and "Software". Table 1 reports the focal subject categories identified under this procedure for each call. In the end, for each call we obtained a group of authors that had published at least one paper (1) with a Swedish affiliation (2) in the focal years of the call and (3) in the focal subject categories of the call. We then merged the group of authors so obtained with the set of applicants (PIs). We call this merged set the set of *potential applicants*, and include both scientists that effectively applied to the call (applicants or PIs) and scientists who could have applied to the call but did not do so (non-applicants). We then retrieved the publications of all potential applicants from Scopus using pybliometrics (Rose and Kitchin, 2019).

[TABLE 1 HERE]

3.3. Semantic similarity

Our main variable of interest is semantic similarity between a potential applicant and a call. Intuitively, this is a measure of how much the topic of the call meets the research interests of the potential applicant.

To compute semantic similarity, we coded a Latent Semantic Analysis (LSA) algorithm (Deerwester et al., 1990; Řehůřek, 2011) using the Gensim 4 library[17] (Rehurek and Sojka, 2010)

17 https://radimrehurek.com/gensim/, accessed 2023-01-01.

and trained it on the titles and abstracts of potential applicants' publications. This algorithm works as follows. First, a matrix with a column for each document and a row for each token (roughly, a word) is constructed. In the cells one can simply put the raw count of that token in that document, but more commonly a measure that takes into account the importance of each token is used, like TF-IDF which assigns more weight to tokens that rarely appear in the entire corpus. Then, an SVD decomposition is applied to that matrix, the eigenvalues are ordered in decreasing magnitude, and the first larger eigenvalues are retained, while the rests are dropped. The eigenvectors corresponding to those eigenvalues would be the result of a linear combination of the different token vectors, and thus corresponds to topics[18] (Deerwester et al., 1990).

The detailed process we followed to construct our measure of semantic similarity is as follows. First, the tiles and abstracts of each publication in our dataset were concatenated, and the result was preprocessed by removing stop words, words shorter than 2 characters or longer than 15 characters, numbers, punctuation marks, and by stemming for word inflections. Second, a dictionary was built from the entire corpus, and from this dictionary we removed words that appeared only once because they are not very informative for our analysis.[19] Third, the text was converted into a bag-of-words model (using the dictionary trained previously), then into a Term Frequency - Inverse Document Frequency (TF-IDF) model (trained on the corpus itself), and then into an LSA model (again, trained on the corpus itself) with 200 topics (Bradford, 2008). Fourth, we used the LSA model so obtained to compute the semantic similarity between the call and each publication in our database.

Then, for each potential applicant and for each year from 5 years before the call until 5 years after the call, we calculated the topic similarity between the focal potential applicant and his

18 See also the Wikipedia page for a good introduction: https://en.wikipedia.org/wiki/Latent_semantic_analysis (retrieved 2023-01-01).

19 This may be a particular molecule that appear only once in our corpus, or a misspelling of a word. Certainly these words don't bound topics, and the LSA algorithm could not do much with them. This decision also saves on computational power.

corresponding call as the simple average between the topic similarity of the publications of the potential applicant in the focal year and the (text of the) call. Finally, we applied to topic similarity a within-potential applicant 3-year moving average, weighted by number of publications in the 3-year time window, to obtain the final measure of topic similarity for each potential applicant in each year. Moreover, as our similarity measure does not have a standard unit of measurement, we compute the z-score of the similarity and use that for all our following analyses.

Figure 1 reports the time series of topic similarity in a timespan that ranges from 5 years before the call until 5 years after it, by type of potential applicant.

[FIGURE 1 HERE]

3.4. Other variables

We collected information on the gender of the applicants from self-reported data in their applications. The gender of non-applicants was identified from their first name using Genni 2.0 (Smith et al., 2013), while their ethnicity was identified using Ethnea (Torvik and Agarwal, 2016)[20]. We dropped 21,352 non-applicants for which the algorithm was unable to determine a gender. Undetermined gender is not correlated to calls nor to fields, so this exclusion of records should not bias the results. We encode gender in a dummy variable *DFemale*, equal to 1 if the potential applicant is a female, and ethnicity in a dummy variable *DNordic,* equal to 1 if the potential applicant is of Nordic ethnicity. Furthermore, we compute the variable *Sen* (Seniority) as the difference between the year of the call and the year in which the first publication of the scientist was published. We dropped observations with seniority greater than 55, which are either Scopus errors[21] or denote a potential applicant which would be too senior to apply for a call that lasts several years[22]. This drops 237 potential applicants, of which 235 are non-applicants and 2 are applicants.

20 See http://abel.lis.illinois.edu/cgi-bin/ethnea/search.py (accessed 2023-01-01) for both Genni 2.0 and Ethnea.

21 By checking some of them manually, we found that Scopus in fact assigned to those people publications which belong to other scientists (with similar names, for instance).

22 Assuming that on average a scientist begin at about 25 years, this would be equivalent to dropping from the pool of potential applicants scientists older than 80 years old.

We then converted *Sen* into a binary variable *DSenH*, which equals 1 if *Sen* is greater than the median seniority, and 0 otherwise.

Beyond gender and seniority, we construct a set of variables meant to capture the career status of scientists. We encode the variable *Disc* (Discontinuity), which equals the total number of years with zero publications, in a timespan that ranges from the year of first publication to the year of the call, and the dummy variable *DUniversity*, which equals to 1 if the potential applicant is affiliated with a university in the focal years of the call. We also compiled information about the scientific productivity of potential applicants, in terms of both quantity and quality. In particular, for each potential applicant we counted the number of papers published in each bin of the Scimago Best Journal Ranking, ranked by quartile.[23] Finally, we compute *PAC* (Prior Application Counter) as the number of previous applications the potential applicant has submitted to the SSF before the focal one.

After the clean-up described in this section, we end up with a database of 156,512 unique pairs of potential applicants-calls (a median of 6,123 potential applicants per call[24]). Table 2 reports the count of identified potential applicants by call.

[TABLE 2 HERE]

3.5. Descriptive statistics

Table 3 reports the variables used in our analysis, together with their description and their descriptive statistics, while Table 4 reports the correlation among variables.

[TABLE 3 HERE]

[TABLE 4 HERE]

23 Journal Rankings downloaded from https://www.scimagojr.com/journalrank.php (accessed 2023-01-01). If a journal belongs to more than one Subject Categories, we take the Best Quartile among all the Journal Categories the journal belongs to.

24 By comparison, the headcount of researchers in Sweden was 101,820 in 2013; 108,761 in 2015; 107,042 in 2017; and 111,179 in 2019 (source OECD: https://data.oecd.org/rd/researchers.htm, accessed 2023-01-01).

4. Methodology

To test our hypotheses, we use a difference in differences (diff-in-diff) framework. A diff-in-diff methodology allows estimating the Average Treatment Effect on the Treated (ATET) from a natural experiment (rather than a laboratory one) by comparing the outcome of interest between two groups: a control group and a treatment group, both of them observed before and after treatment. By differentiating the mean outcome within groups, the diff-in-diff model can account for time-invariant unobserved group-specific confounders, and by differentiating the mean outcome across groups, the model can account for time-varying unobserved confounders that affect both groups in the same way.

4.1. Model specification

We specify the following generalized diff-in-diff model (Angrist and Pischke, 2008; Wing et al., 2018):

$$\mathrm{Y}_{gt} = a_g + b_t + \delta \cdot D_{gt} + \epsilon_{gt} \tag{1a}$$

In this model, a_g are group fixed-effects, b_t are time fixed-effects, and D_{gt} is the "treatment variable" (Wing et al., 2018), i.e. a dummy variable equal to 1 for the observations actually treated (i.e., the observations in the treatment group after treatment), and 0 otherwise. For our four hypotheses, the relevant treatment is the event "applying to the call". We estimate our models using the *didregress* command of STATA 17, and we also perform and report the parallel trends and the Granger causality post-estimation tests. The parallel trends test perform a test of whether the linear trends in the outcome variable are parallel between control and treatment groups in the pretreatment period, and the null hypothesis is that trends are parallel. Finding no evidence against the null hypothesis of parallel trends in the pretreatment period leads credibility to the assumption that trends would have been parallel in the post-treatment period had no treatment occurred. The Granger causality test tests whether treatment effect can be observed in anticipation of treatment, and its null hypothesis is of no treatment effect before treatment period (i.e., no anticipation of treatment by study participants). Finding no evidence against the null hypothesis of no treatment effect before treatment period improve our confidence that the effect we find is really due to treatment. See the STATA manual[25] and Huntington-Klein (2021)[26] for further information on those tests.

4.2. Matching and normalization

By construction, our control groups are populated by scientists who (1) have a Swedish affiliation (2) have published at least one article in the time frame that spans from the year before the call to the year after it, and (3) are research active in the same Scimago Journal Subject Categories as the applicants of the call. However, our control groups may still not be comparable to our treatment groups due to imbalance in pretreatment covariates. For example, a scientist with a higher seniority or more publications may be more likely to apply (i.e., get treated), while also more likely to shift the direction of his research at the same time (whether he applies or not). There is also a risk that the control group may contain scientists for whom the call is much less relevant than it is for applicants, due to the inherent ambiguity of journal categorization (Wang and Waltman, 2016).

In order to balance the pretreatment distribution of covariates between the two groups we resort to matching. Optimal full matching was performed using the "MatchIt" package (version 4.3.4) (Ho et al., 2011) in R, which calls functions from the "optmatch" package (version 0.10.0) (Hansen and Klopfer, 2006).

We perform a new matching for each hypothesis, that is, every hypothesis has its own matched group. For hypotheses H1 and H2, matching was performed on a call-by-call basis, for two reasons: (1) to match a scientist in the treatment group with the counterfactual scientist in the control group who could have applied to the *same* call (and not to a different call), and (2) to spare RAM which is insufficient to match on the entire database (Hansen et al., 2022). For H3, matching

25 https://www.stata.com/manuals/tedidregresspostestimation.pdf (accessed 2023-01-01).
26 See chapter 18.1.4 for parallel trends test, and chapter 18.2.3 for the Granger causality test, which is called "Placebo test" in the book.

was instead performed across all calls, due to the low number of observations in the subset of the dataset used to test these hypotheses and a consequently unsatisfactory matching if performed on a call-by-call-basis.

We match on all the individual level covariates that we previously described, plus semantic similarity (i.e., the outcome) in each of the 5 years prior to the call. Because the algorithm demands no missing values in pretreatment covariates, and because some scientists have missing similarity in some years,[27] we impute missing similarity in a year by carrying over the similarity in previous or following years, whichever is nearer. In total we imputed 245,878/1,721,632 (14.28%) observations.

5. Results

The set of main difference in differences results are summarized in Table 5. The corresponding parallel trends plots are presented in Figure 2. Throughout all models, the p-trends test is not significant ($p>0.1$), suggesting there is no evidence to reject the null hypothesis that pretreatment trends are not parallel across the two groups. The Granger causality tests are also non-significant in all models, suggesting there is no evidence to reject the null hypothesis of absence of a treatment effect before the treatment occurs (*i.e.*, the call is issued).

[TABLE 5 HERE]

[FIGURE 2 HERE]

In column 1 of Table 5, the coefficient on the treatment effect equals 0.123, and it is positive and statistically significant ($p<0.01$), which is in line with Hypothesis 1. In the five years after the call, applicants on average increase their similarity by 12.3% of similarity's standard deviation more than non-applicants.

27 That corresponds to scientists who have not published nor in the focal year, neither in the year prior to it and after it, given that we have performed a 3-years moving average on semantic similarity, as described previously.

Column 2 reports the result of the model that tests for Hypothesis 2. The coefficient on the treatment effect is estimated at 0.116 and is significant at conventional levels ($p<0.01$). This means that, after applying for funding, non-winning applicants increase the similarity of their research with the call by 11.6% of similarity's standard deviation more than non-applicants.

The third column tests hypothesis H3. The estimated coefficient equals -0.016 but is not statistically significant ($p>0.1$). This means that winners do not increase their similarity with the call more than non-winning applicants.

5.1. Robustness to alternative choice of potential applicants set

Before we proceed, we investigate the robustness of our results on H1 and H2 to changes in our method of identifying potential applicants. We repeat the analysis of Table 5, but instead of defining the comparable set of potential applicants on the basis of journal subject categories, we define the comparable set on the basis of journals directly. That is, we take as non-applicants scientists who, in the time frame from the year before the call to the year after it, were (1) research active (published at least one paper), (2) had a Swedish affiliation, and (3) published in the journals in which the applicants sent to review had published. Results from this additional analysis are available in the Appendix. Results are consistent with those obtained in the main analysis.

5.2. Contingency factors

Our main analysis concerns average effects across the full population of scientists. In further analysis, we explore group differences along the three hypothesis that were tested above. We re-run the difference in differences model while interacting the treatment dummy with the set of variables described in section 3.4. These include measures capturing experience in terms of seniority (DSenH), previous application experience (PAC) and discontinuity in publishing activity (Disc). Furthermore, our contingency variables include logarithmically transformed measures of publication activity by outlet prestige (PubsQ1, PubsQ2, PubsQ3, PubsQ4, PubsNC, PubsNF).

Finally, we investigate potential differences by gender, and difference between scientists whose name indicates an ethnic background in the Nordic countries. Table 6 displays the results.

[TABLE 6 HERE]

Results for H1 and H2 only reveal weakly significant contingencies, with the most pertinent result being that applicants who publish more papers in lowly ranked journals (PubsQ4 and PubsNF) are publishing research that is less similar to the call than other applicants. The results for H3, however, reveal interesting contingency patterns, with a weakly significant average treatment effect (β=-27.9%, $p<0.1$) and significant contingencies on seniority (β=22%, $p<0.05$) and female gender (β=11.3%, $p<0.05$). This means that there is a tendency among young winners and, in particular, among male young winners of actually decreasing their similarity with the call compared to non-winning applicants. A t-test shows that the linear combination of the treatment effect and seniority is non-significantly different from 0 ($p<0.1$). The same is true for the combination of the treatment effect and *DFemale*. Finally, we find significant contingency effects for the number of Q4 publications (β=8.9%, $p<0.05$) and NC publications (β=-20.4%, $p<0.01$).

5.3. Effect on productivity

Reflecting on our results so far, the non-significant results regarding H3 may be interpreted as contradicting the existence of funding effects. An alternative interpretation, however, is that the addition of resources to funded researchers allow them to expand their work and publish more papers (e.g. together with PhD students and postdocs hired with the use of grant money) than their non-funded colleagues. That is, it is possible that the funded scientists (and males, juniors in particular) do indeed publish some papers with higher similarity to the call than their unfunded peers, but that the average similarity that we have analyzed is dragged down by them increasing their total number of papers (with some of these papers only weakly related to the call) in the post-call period. In order to investigate this possibility, we re-run the analyses presented in Table 5, but this time with the total number of published papers as the dependent variable. Table 7 reports the results.

[TABLE 7 HERE]

We find that our main effects of increased similarity as per hypotheses H1 and H2 take place in parallel to an increase in scientific output. In particular, applicants increase their productivity with respect to non-applicants (β=1.697, p<0.01), non-winning applicants increase their productivity with respect to non-applicants (β=1.625, p<0.01), while there are no statistically significant differences in productivity between winning and non-winning applicants (β=0.880, p>0.1). These results, suggesting that both unsuccessful and successful application work is associated with productivity increases, are in line with previous studies (Ayoubi et al., 2019).

In order to study the contingency effects of productivity, we also re-run the analysis presented in Table 6, but this time with the total number of published papers as the dependent variable. Table 8 reports the results.

[TABLE 8 HERE]

We can see how, for H1, after controlling for contingency factors, the treatment effect is non-significant (β=1.836, p>0.1), the interaction with *DFemale* is non-significant as well (β=1.454, p>0.1), while the coefficient for *DSenH* is negative and significant (β=-7.175, p<0.01). This means that, while junior applicants do not change their productivity with respect to non-applicants, applying to the call actually decreases the productivity of senior scientists with respect to non-applicants. Results for H2 basically replicates this pattern. H3 results have non-significant coefficients for the treatment effect, and non-significant coefficients for seniority and gender.

Since applying to the call does not have an effect on the productivity of winners with respect to the productivity of non-winning applicants, we conclude that we may not explain the non-results regarding this comparison in our main analysis by a dilution driven by productivity gains from winning. Together, these results do not easily lend themselves to an interpretation in support of the existence of funding effects.

In a final set of analysis, we investigate whether our main results on H2 and H3 may be affected by unobserved differences in the effort exerted among non-winning applications. In order to achieve this, we exploit the fact that the SSF conducts pre-screening of applications. This pre-assessment process sorts applications into a fully evaluated group (among which some applications eventually are funded) and a group of applications that are not sent out for external review. Under the assumption that the outcome of this pre-assessment is positively related to the quality of proposal, and to the effort exerted to create them, application effects should be stronger for the group of applicants whose applications are sent to review. Table 9 reports the results.

[TABLE 9 HERE]

While there are indications that application effects are indeed somewhat stronger for the group of applications selected for external review – suggesting a slight difference in quality/effort – the overall pattern is consistent with our main results.

6. Discussion

Together, our results seem to support the existence of an *application effect*, with the support for hypothesis 2 constituting the most appealing evidence. Even when failing to secure funding, applicants still shift their research to become more similar to the call. While it is possible that this pattern is partially driven by scientists proposing research that is already underway (Li, 2017), we expect such opportunities to be relatively limited for the type of RFA grant schemes that we study (as compared to "open" grant schemes, where scientists are free to fit their applications to a pre-existing line of work). We interpret our empirical results as being driven by mechanisms where the work undertaken to set together a high-quality application leads scientists to develop certain ideas further, and to strengthen and broader their networks, so that the appeal of research ideas in line with the call is considerably strengthened. We expect that scientists are able to compensate for the lack of funding from this particular call through other sources of funding, including open grant calls (Jacob and Lefgren, 2011).

We find no differences regarding gender or seniority regarding this result. Male and female scientists may not differ in their ability to generate new ideas and networks during an application process, in their ability to access substitutionary funding (ERC, 2021, 2019; NIH, 2021; NSF, 2020) or in their confidence in their research proposals. This latter interpretation would be consistent with previous results on self-confidence and gender (Chusmir et al., 1992; Lenney et al., 1980), but notably not with arguments of under-confidence among female scientists ("Editorial: Science and gender," 2010).

We find no evidence of a *funding effect*. Contrary to hypothesis 3, we find that winning applicants do not publish papers more similar to the call, nor do they publish more papers, compared to non-winning applicants (both sent and not sent to review).

This lack of support does not actively disprove the existence of funding effects. It could be that our results are sensitive to delays, in the sense that winners' publication of research along the lines of the call to a significant extent happens outside our window of observation. To test for this, we build the Granger plots for our models, which we report in Figure 3.

[FIGURE 3 HERE]

For both H1 and H2, the treatment effect seems to flatten out from year 3 onward. Thus, our data does not support such an interpretation, because there are no visible signs of an increase in similarity towards the end of our observed period.

A possible interpretation of the absence of differences between winners and non-winning applicants is that the selection is geared towards something else than relevance to the call. This can be driven by external reviewers being more loyal to disciplinary logic than to the call per se. Then again, decisions about funding are taken by the panel, who also participates in designing the call, and call appropriateness is a criteria, so this interpretation does not seem entirely plausible. It is more likely that our results reflect weak principal-agent relationships (contracts and evaluation forms are not forcing winners to stick to the call) and interest (the research priorities of grant-winners shift away from those ingrained in the call text). It is also possible that selection is geared towards projects already underway, which may lead winners (junior, male winners in particular) to shift their attention to the "next thing" some time after receiving the grant rather than pursuing research closely related to the call. Our empirical approach allows us to control for any published research, but it is possible that there are differences between groups in the amount of unpublished work in line with the call that is underway when the call is announced.

7. Conclusion

A key component of mission-oriented research policy, RFA grant schemes seek to foster research in a particular topic or area. In this study we have compared the published research of grant recipients, rejected applicants and a group of non-applicants to call texts. We find indications that researchers receiving a grant from a RFA call indeed shift their research towards the topics of the call. However, we also find that the same type of shift takes place among non-winning applicants. Our research thus suggests that by issuing a RFA call, the funding agency is achieving its basic ambition of boosting research in an identified area. However, it is not primarily doing so in the expected way, e.g. by financing researchers who then shift their agenda towards the areas stipulated by the call. Instead, it is the mere issuing of the RFA that stimulates scientists to develop partly novel ideas and networks. This is how the funder seems to bring about change in science.

7.1. Contributions

Our study contributes to the emerging "science of science funding" literature (Azoulay and Li, 2022; Franzoni and Stephan, 2021). Previous studies has mostly investigated the impact of winning a grant on various individual-level outcomes, like number of publications, citations, collaboration networks, and knowledge base. No study so far, to our knowledge, has studied the effect of grant funding on the similarity of future research with the topic financed by the RFA.

An important reference point for our work is the study by Ayoubi et al. (2019). This study found that applicants to research funds, whether they win or not, increase their productivity in terms of number of publications, increase the quality of their publication as measured by the impact factor of the journals in which they publish, and also expand their collaboration networks by co-authoring with their co-applicants. However, applicants also decrease the average number of citations they receive per paper, as they enter new fields which require the acquisition of new knowledge and where their reputation has to be established. We expand on these results by showing how applicants, regardless of the result of the application, also move towards the topic sponsored by the call, with respect to a comparable set of non-applicants, chosen to work in the same journal subject categories as applicants, active in the years around the call, and with a Swedish affiliation, matched on pre-treatment observable covariates as well as pre-treatment outcome. Our results notably contrasts with Myers (2020), who found that winners of RFA calls for some time do shift their topics in the direction of the RFA more strongly than non-winning applicants, but that this effect fades out after five years time. It is possible that these differences in results can be attributed to Myers (2020) studying a particular setting (NIH), a particular field (biotechnology and medicine), and that Myers use a particular way to measure similarity which is only relevant for life sciences (MeSH terms).

Our study throws new light on RFA grant schemes as an instrument of science policy. The received view suggests that RFA grant schemes is an instrument with fundamentally different logic and effect than that of awarding prizes, in that funding is forward-looking and enables future activity, while prizes are backward-looking and reward scientific achievements ex-post. However, our research would seem to suggest that from the perspective of grant recipients, this distinction is not entirely valid. RFA funding has a rather similar function as a prize: it rewards winners for being relatively well positioned in relation to a type of research that the funder wants to promote (and thus more likely to apply for and win grant funding) – but that is also all. At the same time, RFA funding also shapes the agenda of non-winning applicants, similar to how prizes may stimulate and incentivize also those researchers that to not end up winning that prize (Jin et al., 2021).

Our research certainly also has implications for science funders. On a general note, our study informs funders and policy makers who consider what mix of different type of science funding that is likely to generate the desirable results. Funders operating RFA funding schemes can also build on our results to develop their practices. If funders embrace the view that their main impact happens through their formulation and marketing of a call rather than through the research conducted by funded scientists, they may chose to relax efforts to control and follow up on granted research. Funders may also develop significant tolerance regarding how well grantees stick to the original research plan.

7.2. Limitations and further research

Our study exploits data from a specific funder and from applicants active in one country (Sweden). Hence, we must tread with caution when generalizing from our findings to a broader set of directed calls. We also acknowledge that there are aspects of our analysis where further research would be called upon to investigate the internal validity of our results. Our analysis draws on a novel methodological approach whereby call texts and published papers are compared through text similarity analysis. Further research is called upon to validate and develop this type of measure. In particular, it would be valuable to test our measure in a setting where it can be compared to alternative measures of similarity based on MeSH terms (which is not possible in our case, since only two of the calls fall within the domain of Medicine). We also note that group-specific time-varying confounders could bias the results of the main models.

Our results also point at the need for further research investigating what we refer to as application effects. Is idea generation the most important mechanism through which the process affects the scientific efforts of applicants, or are social network effects more important? To what extent are scientists perceiving RFA calls as providing meaningful information about what types of research that is most important and relevant, or most likely to get funded for doing? Research using surveys could be useful here.

On the other hand, our results also call for further work on what we refer to as funding effects, in particular as regards barriers and limitations to such effects. Do winning applicants tend to be particularly sensitive to what may constitute 'the next thing', and hence to shift their research efforts towards other, yet emerging topics and trends? Our results also point to the need to investigate gender and career-stage differences in this respect, with our results identifying interesting patterns where male and junior scientists are particularly unlikely to shift their research towards the call when winning a grant.

Finally, this study focuses on the research trajectories of PIs. Further research should also investigate application effects and funding effects within the broader group of (e.g. more junior) co-applicants.

8. Tables

Table 1: Journal subject categories per call.

Call	Title	Categories
AM13	Applied mathematics	Applied Mathematics Computational Mathematics Electrical and Electronic Engineering Software
BD15	Big Data and Computational Science	Biochemistry Computer Science Applications Computer Vision and Pattern Recognition Genetics Molecular Biology Software
EM11	Energy-Related Materials	Condensed Matter Physics Materials Science Physics and Astronomy
EM16	Materials for Energy Applications	Chemistry Condensed Matter Physics Electronic, Optical and Magnetic Materials Materials Science
GMT14	Generic Methods and Tools for Future Production	Condensed Matter Physics Control and Systems Engineering Electrical and Electronic Engineering Industrial and Manufacturing Engineering Mechanical Engineering
IIS11	Information Intensive Systems: Making good use of everincreasing data volumes	Applied Microbiology and Biotechnology Biotechnology Computer Science Software Theoretical Computer Science

IRT11	Innovative Technologies for the Extraction of Metals from Raw Materials	Chemistry Condensed Matter Physics Materials Chemistry Physical and Theoretical Chemistry
KF10	Clinical research – use of National Quality Registers	Cancer Research Medicine Oncology
RB13	Novel biomarkers of clinical relevance	Genetics Immunology Medicine Oncology
RBP14	Biological Production Systems	Applied Microbiology and Biotechnology Biotechnology Medicine
RE10	Electronics and Photonics systems	Condensed Matter Physics Electrical and Electronic Engineering
RIT10	Software-Intensive Systems	Computer Science Electrical and Electronic Engineering Software
RIT15	Smart Systems	Control and Systems Engineering Electrical and Electronic Engineering Software
RIT17	Cybersecurity and Information Security	Computer Science Theoretical Computer Science
RMA11	Materials Science research	Condensed Matter Physics Materials Chemistry Materials Science Surfaces, Coatings and Films
RMA15	Materials Science and Engineering – New methods	Chemistry

	for synthesis and processing	Condensed Matter Physics Materials Chemistry Materials Science
RMX18	MED-X; Medicine meets IT, electronics, and materials research	Biochemistry Biomedical Engineering Cell Biology Medicine Molecular Biology Multidisciplinary Neurology
SB12	Infection biology: Molecular mechanisms in the interplay between microorganisms/parasites and their hosts (man, domestic animals, plants and forest trees) in relation to disease	Immunology Immunology and Allergy Microbiology
SB16	Systems Biology	Biochemistry Biotechnology Genetics Medicine Molecular Biology
SBE13	Molecular Imaging Tissue Engineering and Regenerative Medicine Implanted sensors, Wearable sensors and Lab-on-a-chip New Biomaterials	Biochemistry Biomedical Engineering Cell Biology Electrical and Electronic Engineering Medicine Molecular Biology Neurology
SE13	“Post CMOS” and “More than Moore” electronics, and techniques for high data-rate communications.	Condensed Matter Physics Electrical and Electronic Engineering

Table 2: Potential Applicants count: per call, per field, and total.

	Non-Applicants	Applicants			Total
		Not Sent To Review	Reviewed Non-Winners	Winners	
Call					
AM13	5,363	34	24	6	5,427
BD15	7,934	46	14	7	8,001
EM11	3,302	3	15	5	3,325
EM16	7,440	34	20	9	7,503
GMT14	8,713	32	18	8	8,771
IIS11	3,260	17	24	4	3,305
IRT11	3,784	0	15	1	3,800
KF10	7,761	29	11	5	7,806
RB13	12,271	103	21	9	12,404
RBP14	12,098	18	14	8	12,138
RE10	3,250	16	40	6	3,312
RIT10	3,650	14	28	8	3,700
RIT15	6,042	52	19	10	6,123
RIT17	1,796	15	6	10	1,827
RMA11	3,831	16	38	6	3,891
RMA15	7,334	31	43	10	7,418
RMX18	18,804	41	18	6	18,869
SB12	4,011	29	19	9	4,068
SB16	15,980	36	16	9	16,041
SBE13	13,834	42	33	8	13,917
SE13	4,828	9	21	8	4,866
Field					
ICT	30,716	158	114	43	31,031
ENG	80,282	309	266	88	80,945
PHYS	71,091	222	217	60	71,590
CHEM	91,212	349	218	65	91,844
MED	72,661	280	118	46	73,105
BIO	64,941	250	100	38	65,329
Total	155,286	617	457	152	156,512

Table 3: Descriptive statistics.

Name	Description	Mean	Std. Dev.	Min	Max
DAppl	Dummy variable equal to 1 if the potential applicant applied to the call.	0.78%	0.09	0.00%	100.00%
DFemale	Dummy variable equal to 1 if the potential applicant is female.	37.70%	0.48	0.00%	100.00%
Disc	(Discontinuity) Number of years with 0 publications, from the first publication until the year of the call.	2.85	3.81	0.00	49.00
DNordic	Dummy variable equal to 1 if the potential applicant is of nordic ethnicity.	58.82%	0.49	0.00%	100.00%
DNWA	Dummy variable equal to 1 if the potential applicant did not win the grant.	0.69%	0.08	0.00%	100.00%
DReviewed	Dummy variable equal to 1 if the potential applicant was sent for review.	0.39%	0.06	0.00%	100.00%
DSenH	Dummy variable equal to 1 if Sen is greater than the median seniority, and 0 otherwise.	48.72%	0.50	0.00%	100.00%
DUniversity	Dummy variable equal to 1 if the potential applicant is affiliated with a university at any time from the year before the call until the year after the call.	53.39%	0.50	0.00%	100.00%
DWinner	Dummy variable equal to 1 if the potential applicant won the call.	0.10%	0.03	0.00%	100.00%
PAC	(Prior Application Counter) Number of prior applications submitted by the potential applicant.	0.03	0.20	0.00	7.00
$Pubs_y$	Total number of publications in year y. Used as a dependent variable.	9.78	17.22	0.00	693.00

PubsQ1	Cumulated number of SJR Q1 publications.	27.92	51.55	0.00	1,000.00
PubsQ2	Cumulated number of SJR Q2 publications.	8.81	19.60	0.00	465.00
PubsQ3	Cumulated number of SJR Q3 publications.	1.99	5.85	0.00	342.00
PubsQ4	Cumulated number of SJR Q4 publications.	1.14	4.85	0.00	558.00
PubsNC	Cumulated number of publications in journals without a SJR classification.	0.02	0.23	0.00	10.00
PubsNF	Cumulated number of publications in journals not tracked by the SJR.	4.66	14.39	0.00	399.00
Sen	(Seniority) Difference between year of the call and year of first publication.	13.11	11.34	0.00	55.00
Sim_y	Yearly semantic similarity (z-score) between potential applicant's publications and the call. Used as a dependent variable.	0.01	1.04	-2.56	8.21

Table 4: Correlation among variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1)	1.00																		
(2)	-0.03	1.00																	
(3)	-0.01	0.01	1.00																
(4)	0.01	0.02	0.15	1.00															
(5)	0.94	-0.03	-0.00	0.01	1.00														
(6)	0.70	-0.03	-0.01	0.01	0.56	1.00													
(7)	0.07	-0.17	0.44	0.21	0.07	0.05	1.00												
(8)	0.04	-0.08	-0.06	0.01	0.04	0.03	0.04	1.00											
(9)	0.35	-0.01	-0.01	0.01	-0.00	0.50	0.03	0.02	1.00										
(10)	0.13	-0.05	-0.03	0.04	0.11	0.09	0.14	0.06	0.06	1.00									
(11)	0.07	-0.15	-0.09	0.02	0.06	0.06	0.29	0.07	0.04	0.18	1.00								
(12)	0.04	-0.18	-0.06	0.12	0.03	0.03	0.43	0.03	0.02	0.16	0.64	1.00							
(13)	0.05	-0.17	-0.04	0.10	0.05	0.05	0.37	0.06	0.03	0.19	0.49	0.65	1.00						
(14)	0.04	-0.14	-0.03	0.05	0.03	0.03	0.28	0.04	0.01	0.12	0.32	0.46	0.59	1.00					
(15)	0.01	-0.09	-0.01	0.06	0.01	0.00	0.20	-0.01	-0.00	0.05	0.26	0.40	0.37	0.37	1.00				
(16)	0.05	-0.05	-0.01	0.02	0.05	0.05	0.09	0.03	0.02	0.10	0.10	0.11	0.14	0.10	0.04	1.00			
(17)	0.02	-0.16	-0.02	0.09	0.02	0.02	0.30	0.04	0.01	0.10	0.38	0.64	0.71	0.50	0.38	0.09	1.00		
(18)	0.06	-0.22	0.48	0.23	0.05	0.04	0.80	0.05	0.02	0.14	0.31	0.60	0.54	0.41	0.31	0.12	0.52	1.00	
(19)	0.08	-0.05	0.05	-0.01	0.08	0.06	-0.03	0.05	0.03	0.01	-0.06	-0.12	-0.08	-0.04	-0.05	0.01	-0.09	-0.06	1.00

Legend: (1) DAppl (2) DFemale (3) Disc (4) DNordic (5) DNWA (6) DReviewed (7) DSenH (8) DUniversity (9) DWinner (10) PAC (11) $Pubs_y$ (12) PubsQ1 (13) PubsQ2 (14) PubsQ3 (15) PubsQ4 (16) PubsNC (17) PubsNF (18) Sen (19) Sim_y.

All coefficients are significant at $p<0.01$.

Table 5: Main results.

	H1	H2	H3
Treated Group	Applicants	Non-Winning Applicants	Winning Applicants
Non-Treated Group	Non-Applicants	Non-Applicants	Non-Winning Applicants
D_{gt}	0.123 ***	0.116 ***	-0.016
	(0.02)	(0.02)	(0.03)
Year FE	YES	YES	YES
Group FE	YES	YES	YES
Intercept	0.673 ***	0.677 ***	0.914 ***
	(0.01)	(0.01)	(0.02)
N	1,721,632	1,719,960	13,486

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

Table 6: Contingency analysis.

	H1	**H2**	**H3**
Treated Group	Applicants	Non-Winning Applicants	Winning Applicants
Non-Treated Group	Non-Applicants	Non-Applicants	Non-Winning Applicants
D_{gt}	0.184 **	0.196 **	-0.279 *
	(0.09)	(0.10)	(0.15)
DSenH # D_{gt}	0.034	0.020	0.220 **
	(0.06)	(0.07)	(0.10)
Disc # D_{gt}	-0.010	-0.011 *	0.003
	(0.01)	(0.01)	(0.01)
PAC # D_{gt}	-0.019	-0.017	-0.029
	(0.02)	(0.02)	(0.04)
ln(PubsQ1) # D_{gt}	-0.015	-0.014	-0.012
	(0.02)	(0.02)	(0.04)
ln(PubsQ2) # D_{gt}	-0.024	-0.027	-0.002
	(0.02)	(0.02)	(0.03)
ln(PubsQ3) # D_{gt}	0.014	0.017	-0.006
	(0.02)	(0.02)	(0.04)
ln(PubsQ4) # D_{gt}	-0.030 *	-0.044 **	0.089 **
	(0.02)	(0.02)	(0.04)
ln(PubsNC) # D_{gt}	-0.056	-0.044	-0.204 ***
	(0.04)	(0.05)	(0.05)
ln(PubsNF) # D_{gt}	0.027 *	0.028	0.019
	(0.02)	(0.02)	(0.03)
DUniversity # D_{gt}	-0.002	0.000	0.041
	(0.03)	(0.04)	(0.06)
DNordic # D_{gt}	0.018	0.019	0.008
	(0.03)	(0.03)	(0.06)
DFemale # D_{gt}	0.020	0.007	0.113 **
	(0.03)	(0.04)	(0.05)
Intercept	0.673 ***	0.677 ***	0.914 ***
	(0.01)	(0.01)	(0.02)
Year FE	YES	YES	YES
Group FE	YES	YES	YES
N	1,721,632	1,719,960	13,486
F statistic	10.21	11.46	5.57
R^2	0.00	0.00	0.04
Adj. R^2	0.00	0.00	0.04

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

Table 7: Outcome=Number of Papers, for H1, H2, and H3.

	H1	H2	H3
Treated Group	Applicants	Non-Winning Applicants	Winners
Non-Treated Group	Non-Applicants	Non-Applicants	Non-Winning Applicants
D_{gt}	1.697 ***	1.625 ***	0.880
	(0.61)	(0.54)	(1.47)
Year FE	YES	YES	YES
Group FE	YES	YES	YES
Intercept	18.174 ***	16.984 ***	23.720 ***
	(0.51)	(0.34)	(0.76)
N	1,721,632	1,719,960	13,486

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

Table 8: Outcome=Number of Papers, contingency factors, for H1, H2, and H3.

	H1	**H2**	**H3**
Treated Group	Applicants	Non-Winning Applicants	Winning Applicants
Non-Treated Group	Non-Applicants	Non-Applicants	Non-Winning Applicants
D_{gt}	1.836	2.792 *	-6.806
	(1.68)	(1.69)	(6.40)
DSenH # D_{gt}	-7.175 ***	-7.670 ***	-0.863
	(2.09)	(2.27)	(4.58)
Disc # D_{gt}	-0.024	-0.045	0.247
	(0.10)	(0.09)	(0.37)
PAC # D_{gt}	-1.165 *	-0.975	-3.254 *
	(0.70)	(0.77)	(1.75)
ln(PubsQ1) # D_{gt}	2.051 ***	1.960 ***	2.350 *
	(0.54)	(0.61)	(1.26)
ln(PubsQ2) # D_{gt}	0.061	-0.077	0.828
	(0.46)	(0.47)	(1.63)
ln(PubsQ3) # D_{gt}	-1.493 ***	-1.415 ***	-2.397
	(0.49)	(0.53)	(1.51)
ln(PubsQ4) # D_{gt}	2.190 ***	2.199 ***	2.264
	(0.76)	(0.82)	(1.73)
ln(PubsNC) # D_{gt}	3.015	2.510	7.502
	(2.04)	(2.21)	(4.91)
ln(PubsNF) # D_{gt}	-1.324 ***	-1.146 ***	-2.294 *
	(0.42)	(0.43)	(1.33)
DUniversity # D_{gt}	1.201	0.953	2.343
	(0.86)	(0.92)	(2.53)
DNordic # D_{gt}	1.210	1.018	2.369
	(0.77)	(0.81)	(2.55)
DFemale # D_{gt}	1.454	1.626	-0.449
	(0.95)	(1.00)	(2.94)
Intercept	18.174 ***	16.984 ***	23.720 ***
	(0.51)	(0.34)	(0.76)
Year FE	YES	YES	YES
Group FE	YES	YES	YES
N	1.721.632	1,719,960	13,486
F statistic	19.36	17.65	5.70
R^2	0.02	0.02	0.07
Adj. R^2	0.02	0.02	0.07

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

Table 9: Additional analysis dividing non-winning applicants by review status.

	H2(a)	H2(b)	H3(a)	H3(b)
Treated Group	Applicants Not Sent To Review	Non-Winning Applicants Sent To Review	Winners	Winners
Non-Treated Group	Non-Applicants	Non-Applicants	Applicants Not Sent To Review	Non-Winning Applicants Sent To Review
D_{gt}	0.118 ***	0.141 ***	-0.023	-0.036
	(0.03)	(0.03)	(0.04)	(0.04)
Year FE	YES	YES	YES	YES
Group FE	YES	YES	YES	YES
Intercept	0.693 ***	0.688 ***	0.863 ***	0.836 ***
	(0.01)	(0.02)	(0.02)	(0.02)
N	1,673,309	1,713,173	8,459	6,699

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

9. Figures

Figure 1: Time series of semantic similarity, per potential applicant type.

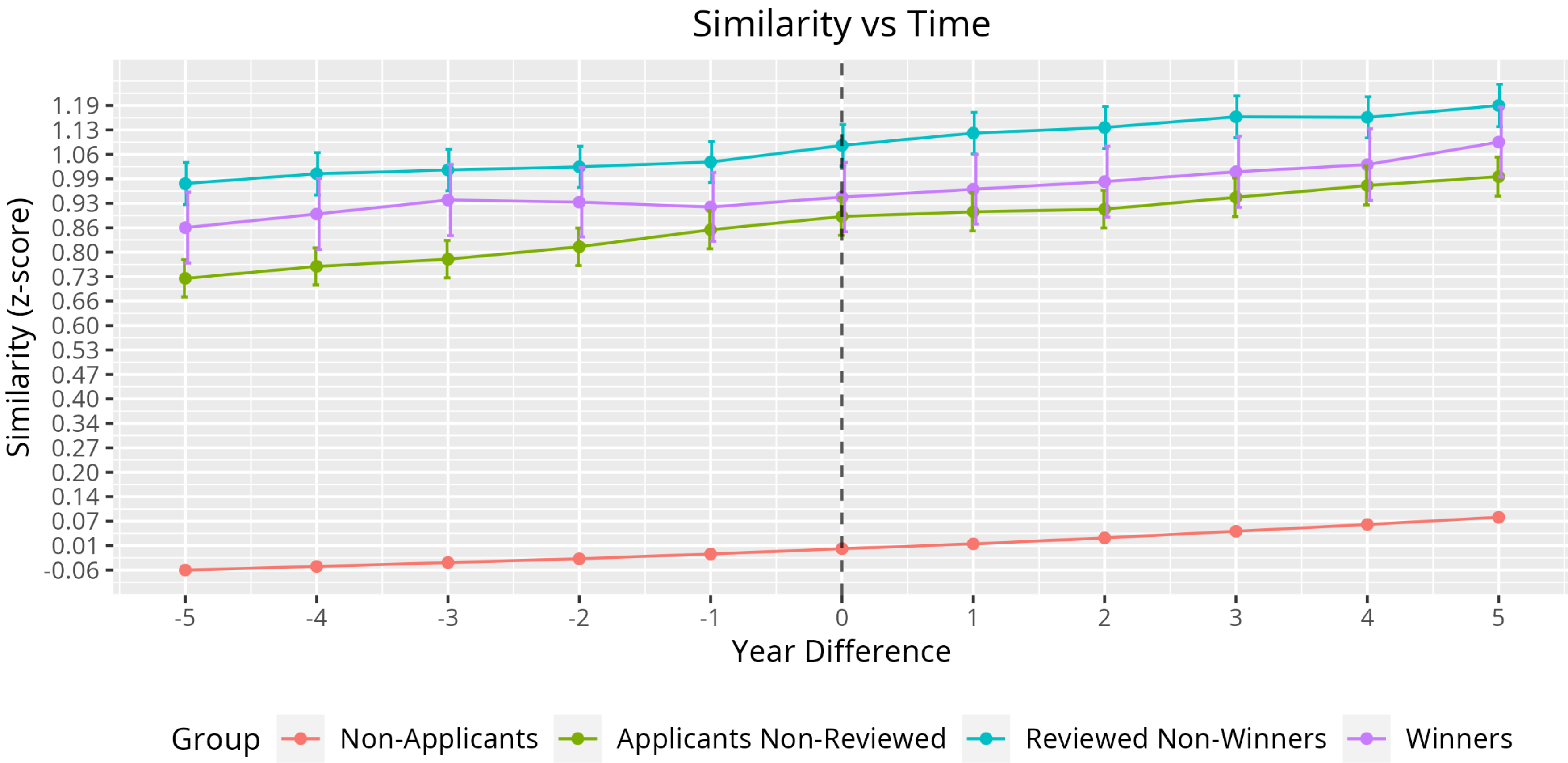


Figure 2: Parallel trends for DID, for all hypotheses.

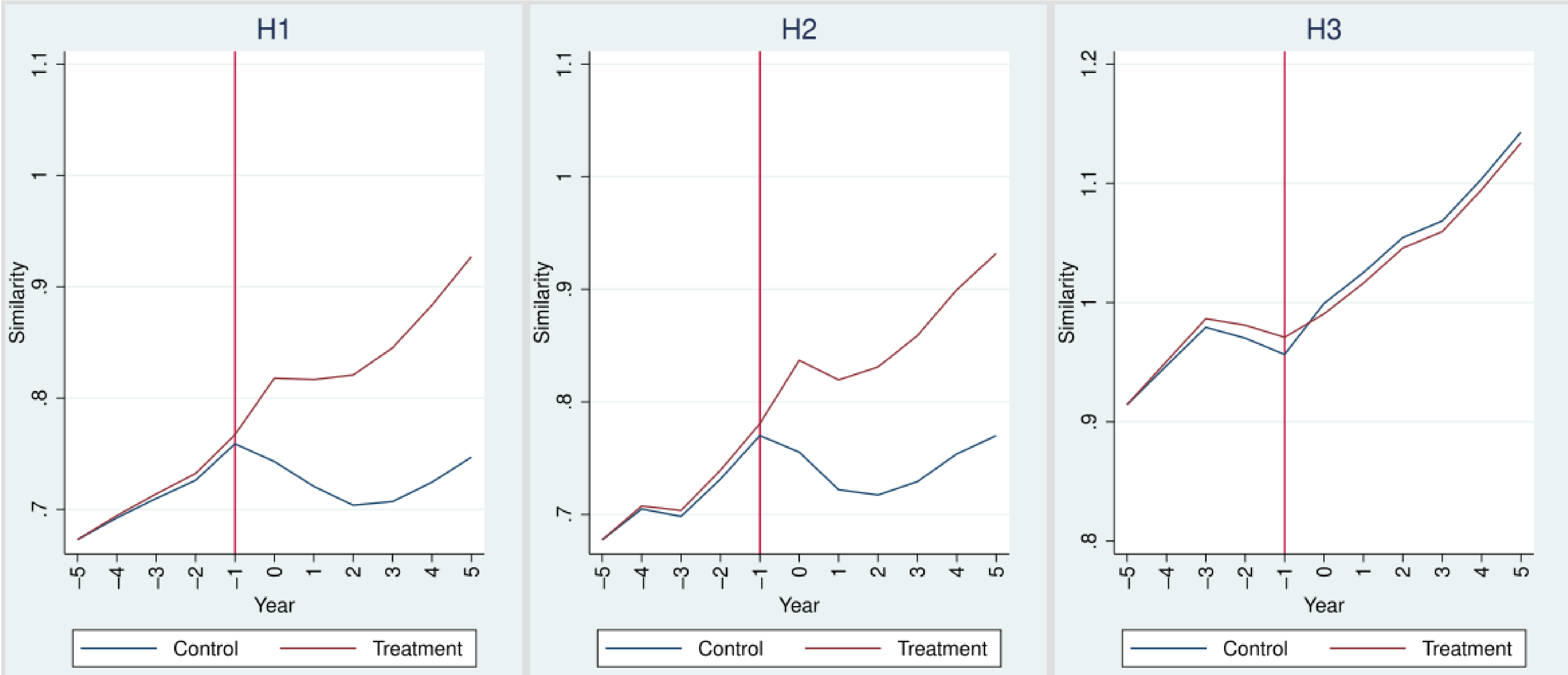
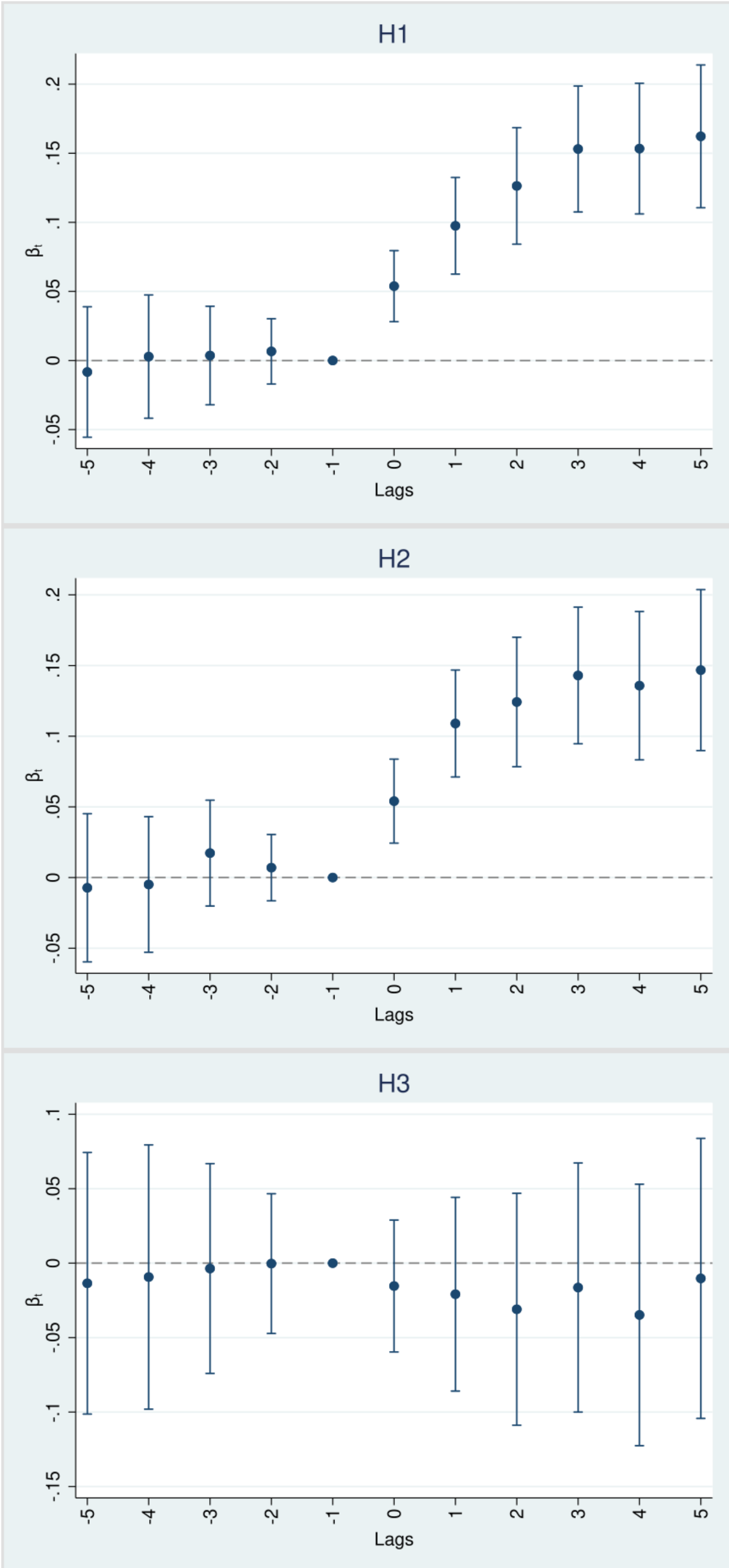


Figure 3: Granger plot for all hypotheses.



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1. Potential Applicants identified by journals

In what follows we repeat the analyses of the main paper, but with a new set of potential applicants, found using the journals in which the applicants sent to review publish, rather than journals' subject categories.

We report the tables and the figures computed using this new set of potential applicants.

Results are consistent to what we find in the main paper.

Table 10: Main results.

	H1	H2	H3
Treated Group	Applicants	Non-Winning Applicants	Winners
Non-Treated Group	Non-Applicants	Non-Applicants	Non-Winning Applicants
D_{gt}	0.164 ***	0.152 ***	0.023
	(0.03)	(0.04)	(0.04)
Year FE	YES	YES	YES
Group FE	YES	YES	YES
Intercept	0.742 ***	0.748 ***	0.859 ***
	(0.03)	(0.03)	(0.02)
N	134,420	132,748	13,486

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

Table 11: Contingency analysis.

	H1	H2	H3
Treated Group	Applicants	Non-Winning Applicants	Winning Applicants
Non-Treated Group	Non-Applicants	Non-Applicants	Non-Winning Applicants
D_{gt}	0.233 ***	0.236 **	-0.098
	(0.09)	(0.09)	(0.14)
SenB # D_{gt}	0.049	0.046	0.060
	(0.05)	(0.05)	(0.08)
Disc # D_{gt}	-0.011 *	-0.013 *	0.004
	(0.01)	(0.01)	(0.01)
PAC # D_{gt}	-0.020	-0.018	-0.031
	(0.02)	(0.02)	(0.04)
lnPubsQ1 # D_{gt}	-0.017	-0.017	-0.009
	(0.02)	(0.02)	(0.04)
lnPubsQ2 # D_{gt}	-0.026	-0.028	0.001
	(0.02)	(0.02)	(0.03)
lnPubsQ3 # D_{gt}	0.013	0.016	-0.010
	(0.02)	(0.02)	(0.04)
lnPubsQ4 # D_{gt}	-0.030	-0.044 **	0.095 **
	(0.02)	(0.02)	(0.05)
lnPubsNC # D_{gt}	-0.058	-0.046	-0.210 ***
	(0.04)	(0.05)	(0.05)
lnPubsNF # D_{gt}	0.025	0.026	0.022
	(0.02)	(0.02)	(0.03)
DUniversity # D_{gt}	-0.001	0.001	0.046
	(0.04)	(0.04)	(0.07)
DNordic # D_{gt}	0.016	0.018	-0.003
	(0.03)	(0.03)	(0.06)
DFemale # D_{gt}	0.022	0.009	0.111 **
	(0.04)	(0.04)	(0.06)
Intercept	0.673 ***	0.748 ***	0.859 ***
	(0.01)	(0.03)	(0.02)
Year FE	YES	YES	YES
Group FE	YES	YES	YES
N	134,420	132,748	13,486
F statistic	7.67	6.87	4.14
R^2	0.01	0.00	0.02
Adj. R^2	0.01	0.00	0.02

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

Table 12: Outcome=Number of Papers, for H1, H2, and H3.

	H1	**H2**	**H3**
Treated Group	Applicants	Non-Winning Applicants	Winners
Non-Treated Group	Non-Applicants	Non-Applicants	Non-Winning Applicants
D_{gt}	4.478 ***	3.895 **	2.045
	(1.51)	(1.57)	(1.42)
Year FE	YES	YES	YES
Group FE	YES	YES	YES
Intercept	20.420 ***	19.251 ***	23.340 ***
	(0.64)	(0.69)	(0.68)
N	134,420	132,748	13,486

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

Table 13 Outcome=Number of Papers, contingency factors, for H1, H2 and H3.

	H1	**H2**	**H3**
Treated Group	Applicants	Non-Winning Applicants	Winners
Non-Treated Group	Non-Applicants	Non-Applicants	Non-Winning Applicants
D_{gt}	2.195	2.559	-4.538
	(2.13)	(2.24)	(5.26)
SenB # D_{gt}	-5.511 ***	-5.618 ***	-4.259
	(1.38)	(1.51)	(3.52)
Disc # D_{gt}	0.044	0.007	0.414
	(0.10)	(0.10)	(0.36)
PAC # D_{gt}	-1.125	-0.973	-3.025 *
	(0.71)	(0.77)	(1.76)
lnPubsQ1 # D_{gt}	1.976 ***	1.860 ***	2.232 *
	(0.53)	(0.60)	(1.25)
lnPubsQ2 # D_{gt}	0.098	-0.073	1.238
	(0.46)	(0.47)	(1.56)
lnPubsQ3 # D_{gt}	-1.396 ***	-1.332 **	-2.225
	(0.49)	(0.53)	(1.54)
lnPubsQ4 # D_{gt}	2.207 ***	2.219 ***	2.373
	(0.76)	(0.82)	(1.71)
lnPubsNC # D_{gt}	2.949	2.369	7.532
	(2.04)	(2.21)	(4.88)
lnPubsNF # D_{gt}	-1.121 ***	-0.934 **	-2.119
	(0.43)	(0.44)	(1.32)
DUniversity # D_{gt}	0.947	0.693	1.986
	(0.83)	(0.89)	(2.50)
DNordic # D_{gt}	1.429 *	1.198	2.764
	(0.78)	(0.82)	(2.53)
DFemale # D_{gt}	1.279	1.428	-0.478
	(0.96)	(1.01)	(2.98)
Intercept	20.420 ***	19.251 ***	23.340 ***
	(0.64)	(0.69)	(0.68)
Year FE	YES	YES	YES
Group FE	YES	YES	YES
N	134,420	132,748	13,486
F statistic	12.44	10.85	6.18
R^2	0.05	0.05	0.06
Adj. R^2	0.05	0.05	0.06

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

Table 14: Additional analysis dividing non-winning applicants by review status.

	H2(a)	H2(b)	H3(a)	H3(b)
Treated Group	Applicants Not Sent To Review	Non-Winning Applicants Sent To Review	Winners	Winners
Non-Treated Group	Non-Applicants	Non-Applicants	Applicants Not Sent To Review	Non-Winning Applicants Sent To Review
D_{gt}	0.188 ***	0.092 **	-0.010	-0.017
	(0.04)	(0.04)	(0.04)	(0.04)
Year FE	YES	YES	YES	YES
Group FE	YES	YES	YES	YES
Intercept	0.739 ***	0.521 ***	0.779 ***	0.829 ***
	(0.03)	(0.03)	(0.02)	(0.02)
N	125,543	125,961	8,459	6,699

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

2. Descriptive statistics for similarity

In complement to our main analysis, we here present univariate statistics on our similarity measure *Sim.* Table Error: Reference source not found reports the mean of *Sim* at the year of the call by call, by field, and in total, along with t-tests for the difference in mean similarity across groups, for the set of potential applicants found using subject categories (main paper).

In the overall dataset, the difference in mean similarity between Applicants and Non-Applicants equals 0.97, and is significant at conventional levels ($p<0.01$); while the difference in mean similarity between Winners and Non-Winning Applicants equals -0.03, and is not significant ($p>0.1$).

The results for the comparison between Applicants and Non-Applicants hold across all fields with statistical significance ($p<0.01$), while the negative difference in average mean between Winners and Non-Winning Applicants is statistically significant for call in Physics ($p<0.05$) and Chemistry ($p<0.1$), while is not statistically significant in all other fields.

The difference between Applicants and Non-Applicants is positive in 19 out of 21 calls, achieving statistical significance in all the 19 calls for which it is positive. The difference is instead negative in 2 out of 21 calls (RMX18 and RB13), but without statistical significance. The difference between Winners and Non-Winning Applicants is negative in 13 out of 21 calls, with statistical significance in only 1 of it (EM16, $p<0.1$), positive in 7 out of 21 calls, never with statistical significance. One call (IRT11) has only 1 winner and thus cannot be tested for difference in means.

Table 15: Similarity (z-score) in the year of the call, per call, per field, and total, for non-applicants, applicants, non-winning applicants, and winners, with t-tests.

	Applicants vs Non-Applicants					Non-Winning Applicants vs Winners				
	Non-Applicants	Applicants	Δ	σ		Non-Winning Applicants	Winners	Δ	σ	
Call										
AM13	-0.08	0.82	0.90	0.12	***	0.86	0.48	-0.38	0.27	
BD15	-0.05	1.48	1.52	0.12	***	1.49	1.38	-0.11	0.59	
EM11	-0.24	0.18	0.43	0.19	**	0.16	0.26	0.10	0.31	
EM16	0.07	0.58	0.51	0.13	***	0.64	0.25	-0.38	0.21	*
GMT14	-0.07	1.13	1.20	0.15	***	1.24	0.43	-0.82	0.61	
IIS11	-0.24	1.95	2.19	0.11	***	1.90	2.42	0.52	0.63	
IRT11	-0.42	1.80	2.21	0.20	***	1.90	0.24	.	.	
KF10	-0.37	-0.09	0.28	0.13	**	-0.08	-0.16	-0.08	0.41	
RB13	0.04	-0.07	-0.12	0.08		-0.07	-0.12	-0.05	0.22	
RBP14	0.04	0.99	0.96	0.17	***	0.97	1.07	0.10	0.25	
RE10	-0.32	1.12	1.44	0.11	***	1.11	1.31	0.20	0.42	
RIT10	-0.32	2.04	2.36	0.12	***	2.05	1.98	-0.07	0.45	
RIT15	0.01	2.36	2.34	0.12	**	2.42	1.93	-0.49	0.42	
RIT17	0.00	3.00	3.00	0.19	***	2.94	3.14	0.20	0.52	
RMA11	-0.23	1.43	1.67	0.11	***	1.50	0.88	-0.62	0.43	
RMA15	-0.05	1.06	1.11	0.11	**	1.11	0.74	-0.37	0.27	
MX18	0.02	-0.12	-0.14	0.14		-0.11	-0.23	-0.12	0.34	
SB12	0.15	0.44	0.29	0.12	**	0.40	0.62	0.21	0.20	
SB16	0.26	0.49	0.23	0.13	*	0.52	0.35	-0.17	0.26	
SBE13	0.31	0.87	0.55	0.09	***	0.90	0.56	-0.34	0.26	
SE13	-0.06	1.03	1.09	0.16	***	1.02	1.10	0.08	0.30	
Field										
ICT	-0.11	1.59	1.70	0.06	***	1.57	1.69	0.12	0.23	
ENG	0.00	1.22	1.21	0.04	***	1.22	1.20	-0.02	0.15	
PHYS	0.01	0.90	0.88	0.05	***	0.93	0.63	-0.30	0.14	**
CHEM	0.07	0.67	0.60	0.04	***	0.69	0.46	-0.23	0.14	*
MED	0.10	0.24	0.14	0.05	***	0.24	0.21	-0.03	0.12	

BIO	0.08	0.50	0.42	0.05	***	0.49	0.53	0.04	0.18
Total	0.00	0.97	0.97	0.03	***	0.97	0.94	-0.03	0.11

* p<0.10, ** p<0.05, *** p<0.01