Topic Choice, Gendered Language, and the Under-Funding of Female Scholars in Mission-Oriented Research

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Abstract

We investigate the participation of male and female applicants to a competition for research funding, using an original dataset with detailed information on both successful and unsuccessful applicants to 21 calls by a mission-oriented funding agency. We use this information to construct a fictitious pool of 277,464 potential applicants and to model their probability to submit an application. We find that, even after controlling for productivity, quality of research, seniority, years of career discontinuity, ethnicity, and number of prior applications, women were still less likely to apply than men. The lower likelihood of females to apply was not explained by the use of masculine language in the text of the calls. Instead, women's research interests were more distant from the topics of the calls than men's. Topic proximity fully mediated female penalization in the likelihood to apply for research funding. These results are an important heads-up, in view of the increasing focus of governments in mission-oriented programs.

Keywords: female penalty, grant funding, masculine language, topic mismatch, mission-oriented research.

JEL classification: J16, O31, O38.

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1. Introduction

Every year, female scholars receive only a minor portion of the budgets allocated by research funding agencies across countries and research fields. This disparity remains large despite the efforts made by funding agencies and governments to promote gender diversity in science. By way of example, only 35% of the National Institutes of Health (NIH) grant recipients in 2020 and 29% of the National Science Foundation (NSF) grant recipients in 2019 were women (NIH, 2021; NSF, 2019). Likewise, in 2019, women accounted for only 32% of ERC awardees (ERC, 2021).

The literature on gender disparity in the distribution of research funding points toward two possible reasons that jointly cause this imbalance: a disparity of treatment by gender in the evaluation of research proposals and the lower number of women who participate in competitions for grants (Bornmann et al., 2007; Ginther, 2022). The former reason has been more widely investigated than the latter. This is why we wish to focus specifically on the latter in this paper.

The starting point for understanding the lower participation of women in grant competitions is the fact, well documented in prior studies, that females constitute a minority of graduates in the STEM fields and in the academic ranks (Ceci et al., 2014; Ceci & Williams, 2010). This inevitably translates into fewer females who are potentially available to apply for funding. However, we want to investigate if other reasons beyond the small proportion of females in academia may contribute to exacerbating the imbalance. We are particularly interested in subtle factors, such as certain sets of choices made by granting agencies that are apparently neutral to gender but that may involuntarily play a role in discouraging the already small group of female scholars from applying. Learning more about such factors is arguably one of the most important challenges that granting agencies and governments are currently facing. Specifically, we investigate two possible factors: i) the possible use of *masculine* language in the calls for funding and ii) the *research topics* of the calls, when these are predetermined, such as in mission-oriented research. Unfortunately, we lack research in this area, particularly of an empirical nature, because of the known difficulty of obtaining information both on actual (successful and unsuccessful) applicants and on potential applicants (scientists that could have applied but may or may not have done so).

This paper sets out to address this lacuna. We acquired data from the Swedish Foundation for Strategic Research (SSF),[1] a funding agency in Sweden. SSF is a mission-oriented funding agency with an endowment from the Swedish government. SSF releases calls for funding research that addresses specific issues, deemed of special strategic relevance for Sweden. We use detailed information on the (successful and unsuccessful) *applicants* to each call and reconstruct the corresponding (fictitious) pools of *potential applicants*, namely scholars that could have taken part in the same calls, based on their eligibility and research field. The data confirm that women were less likely to participate in grant competitions, *i.e.*, they applied for funding at a lower rate than men, above and beyond the imbalance in male and female scholars active in the focal fields and after controlling for a number of factors, including seniority, productivity, quality of their research, career discontinuities, ethnicity, and prior application. We then show that the probability of women applying did not correlate to the use of masculine language, but it did correlate to the topics that the funding agency targeted in its challenges. In particular, we measured the semantic proximity between the topics of the research challenges and the scholars' research interests using Latent Semantic Analysis. We found that, on average, women were less proximate than men to the topics of the calls. Moreover, topic proximity mediated the relationship between female gender and the probability of applying, conditional on all our other covariates. In other words, when we considered topic proximity and all our other covariates, we found no evidence that

[1] Swedish: Stiftelsen för Strategisk Forskning, https://strategiska.se/en/call-for-proposals/. Accessed 8th June 2021.

women applied at a lower rate than men. We found instead that proportionally more women than men found the topics of the calls distant from their research interests. Our results indicate that the choice of prioritizing certain topics over others is not gender-neutral and can indeed be one of the reasons for sustained gender disparity in research funding. To reduce the gender gap, we should not only have equality of treatment in selection, but also ensure that the competition is not pre-arranged in ways that implicitly disfavor women.

The findings also invite broader reflection on the inherently political nature of the formation of research agendas. This is especially important in light of the many ongoing reforms, which are expanding mission-oriented programs in which proposals are solicited on predetermined topics, as opposed to investigator-initiated programs, where scientists are free to propose topics of their liking (Tollefson, 2021). With the increase in mission-oriented programs, proportionally more funding is going to be directed towards certain topics or areas of research. Our results are a warning that the choices of research agendas are not necessarily neutral to gender and may potentially exacerbate the already strong gender disparity in access to research funds. Moving forward, a discussion about how and by whom research priorities should be identified seems imperative.

The paper proceeds as follows. Section 2 reviews the literature and formulates the research hypotheses. Section 3 describes the data collection process, the data processing algorithms, and the variables used to test the research hypotheses. Section 4 illustrates the econometric models and their results. Section 5 concludes.

2. State of the art and research hypotheses

2.1. Female penalty in the acquisition of research funding: empirical evidence

Every year, women receive a minor part of the funding for research. In 2020, only 35% of the NIH

Research Project Grants (RPG) were awarded to women,[2] an improvement compared to the 28% of 2010 (NIH, 2021).[3] In other funding agencies, the share of female grant recipients is even lower. For example, at the NSF, the proportion of awards to women in 2019 was 32%, up from 24% in 2009 (NSF, 2019, p. 15).[4] At the ERC, the most prestigious European funding agency female awardees accounted for only 32% of the total in 2019 (ERC, 2021, p. 13),[5] up from 22% of the 2007-2016 period (ERC, 2019, p. 2). Despite the proportion of female grant recipients increasing over time, the balance is still far from equal.

Searching for the underlying reasons of gender disparity, a strand of research has investigated the fairness of the selection process, questioning whether women are subjected to explicit or implicit gender discrimination (Ginther et al., 2016; Kolev et al., 2019; Ley & Hamilton, 2008; Pohlhaus et al., 2011; Rissler et al., 2020). While the attention to fairness in selection has certainly improved in the last two decades, evidence of an undue disparity is still present in several countries. In Europe, for example, the success rate of female scholars who compete for funding at public granting agencies was on average 3% lower than that of men (European Commission, 2019, p. 173). Specifically, out of the 27 examined countries, in 18 countries the success rate of men exceeded that of women by more than 1%, in 6 countries the success rate of women exceeded that of men by more than 1%, while in 3 countries men and women had nearly equal success rates (European Commission, 2019, p. 173). At the ERC, the success rate of females was on average 3% lower than the success rate of males during 2007-2013 (ERC, 2021, p. 7), although after 2013 the success rates of men and women were comparable (ERC, 2021, p. 7). Studies of single EU countries and/or

[2] Authors' calculations based on https://report.nih.gov/nihdatabook/report/132: of 11,332 awards, 3,911 were to women.
[3] Authors' calculations based on https://report.nih.gov/nihdatabook/report/132: of 9,455 awards, 2,673 were to women.
[4] Authors' computation based on NSF (2019, p. 15).
[5] Ranging from 23% in Physical Sciences and Engineering, 34% in Life Sciences, and 44% in Social Sciences and Humanities.

programs are more nuanced and often find small or no evidence of gender disparity (Beck & Halloin, 2017; Mutz et al., 2012). In the US, the studies conducted on the federal granting agencies suggest that, at least in recent decades, men and women had comparable success rates, in nearly all grant types and career stages of the applicants (Ginther, 2022; Ginther et al., 2016; Ley & Hamilton, 2008; Pohlhaus et al., 2011; Rissler et al., 2020). However, some differences remain in relation to the amount of money received by women (Hosek et al., 2005), particularly in investment-intensive research fields (Duch et al., 2012). The studies conducted in recent years in Australia, Canada, and the UK report comparable success rates for men and women (Boyle et al., 2015; Marsh et al., 2008; Research Council of Canada, 2010; Zhou et al., 2018).

Some scholars nonetheless argue that the equality in success rates of males and females may be illusive, as it is often due to amendments done by the granting agencies out of gender concerns, rather than to an equal treatment in peer review (Belz et al., 2022; Bol et al., 2022). For example, Beck and Halloin (2017) find that, in some cases, reviewers had a tendency to rate male applicants higher than female applicants. A study conducted using data about the grants issued by the Canadian Institutes of Health Research in 2014 finds that female Principal Investigators (hereinafter: PIs) receive less favorable assessments than their male colleagues, irrespective of the quality of their proposed research (Witteman et al., 2019). A study conducted on one US university finds that evaluations of women contained more comments on competencies and abilities, along with more words of appraisal, than the reports of their male colleagues (Kaatz et al., 2015). A work by Kolev et al., using data from the Melinda and Bill Gates Foundation, found that females receive systematically lower scores from reviewers, despite the use of gender-blind applications (Kolev et al., 2019). By way of contrast, a study conducted using data from the Australian Research Council finds no differences in the average grades of reviewers by gender (Marsh et al., 2011).

Regardless of the choices of the reviewers and agencies, females remain a minority of the total scientists who seek funding. Many studies have documented that in all countries and agencies, female PIs account for 35% or less of the applicants for scientific grants (European Commission, 2019; Ginther et al., 2016; Marsh et al., 2008; NSF, 2019). The imbalance appears to be wider among senior applicants (Blake & La Valle, 2000). For example, at the ERC, which has different grant types for three career stages (*i.e.,* starting, consolidator and advanced), the proportions of female applicants in 2019 were 38%, 31%, and 17% respectively (ERC, 2021, p. 12). Similarly, Pohlhaus and colleagues (2011) found that the NIH programs for early career scholars saw a balanced participation of male and female applicants, but the programs for intermediate and senior scholars saw significantly more men than women. Ley and Hamilton (2008) found that many qualified female scientists stopped applying for NIH grants in the late postdoctoral stage or early faculty stage of their careers.

While counting the share of males and females applying to research grants is straightforward, it is more complicated to assess the *application rates* of men and women, *i.e.,* the percentage of men and women that effectively applied, out of the total number of men and women that could have potentially done so. This estimation poses the methodological problem of gauging the total pool of *potential* applicants, split by gender. A study by Rissler and colleagues (2020) uses the aggregate estimates of men and women employed full time in academia (split by field and academic rank) in the US from 2001 to 2015 as reported in the Survey of Doctorate Recipients (SDR). The authors compared the general proportions of male and female scientists to those of the NSF applicant pool and found that men submit in the same proportion as they are represented in the population of US scholars resulting from SDR, whereas women submit at a lower proportion. This holds true in all fields except engineering. A less recent study from Blake and La Valle (2000) surveyed 3,090 academic staff from 44 Higher Education Institutions in the UK, finding that 50% of women applied, compared to 59% of men. Martinez et al. (2007) surveyed postdoctoral fellows working intramural at the NIH and found that female postdocs were less likely than male postdocs to apply for grants in PI positions.

To sum up, some evidence suggests that female scholars, besides being less numerous than men, are also less likely to participate in competitions for funding. However, this evidence is far from being conclusive: all the three works cited above fall short in assessing the phenomenon. The study by Rissler and colleagues (2020) is based only on aggregate data; both Blake and La Valle (2000) and Martinez et al. (2007) have individual-level data, but these sets of data are collected through surveys, thus being vulnerable to the well-known biases of the survey methodology.

2.2. Reasons for the low participation of female scientists in competitions for scientific grants

The literature has also identified many different reasons explaining why women participate less than men in competitions for research funding. We summarize the main reasons in this section.

Under-representation in science. Women are generally underrepresented in scientific professions (Ceci et al., 2014; Ceci & Williams, 2011; Kahn & Ginther, 2017). A study by the OECD documented that in 2017 only 6 countries (Spain, Estonia, Portugal, Iceland, Lithuania, and Latvia) had a national scientific workforce composed of at least 40% of women, and only one country (Latvia) had an approximately-equal balance (OECD, 2019). There are several reasons for the low proportion of women in science (Ceci et al., 2014; Ceci & Williams, 2011), including the known stereotypes that depict women as less-talented in math and sciences and more apt for arts and humanities (Beilock et al., 2010; Eagly, 1987; Eagly & Karau, 2002). This breeds a divide in educational choices from a young age. For example, a study by Ceci et al. (2014) documents the fact that female US college graduates are under-represented vis-à-vis their male counterparts in GEEMP (Geoscience, Engineering, Economics, Mathematics, and Physics) fields, whereas they are over-represented among college graduates in the LPS (Life Science, Psychology, and Social

Science) fields. Even after college, men with majors in math-intensive subjects are more likely than women to pursue PhDs in related fields (Ceci et al., 2014, p. 78). Zawistowska & Sadowski (2019) found that women drift-away from math-intensive fields early in life, as they do not take the tests required to enroll in most technical and engineering colleges. This effect also holds for individuals in the upper tail of the distribution of math proficiency and after controlling for skills and school effects. At the same time, women with high verbal skills tend to choose math-intensive subjects less than men with comparable abilities.

Lower ranks in scientific careers. In comparison to their male colleagues, female scholars typically hold positions in lower-ranks of the academic ladder (European Commission, 2019, p. 118; Fox, 2020; Rotbart et al., 2012; Wright et al., 2003). Their careers are more discontinuous (Blake & La Valle, 2000), and precarious (European Commission, 2019, p. 97), as they face more difficulties in balancing their family and professional life (Martinez et al., 2007; Stack, 2004; Walters et al., 2022). Women are often appointed to positions with more teaching and administrative burden and less research (Rissler et al., 2020; Waisbren et al., 2008; Walters et al., 2022). Furthermore, even accounting for productivity differentials, they are less likely than men to be invited to take up prestigious appointments (Husu, 2000; van den Brink et al., 2010), get tenure (Ginther & Kahn, 2004), be promoted (Fox & Gaughan, 2021; Lissoni et al., 2011), and become PIs (Lerchenmueller & Sorenson, 2018). Lower career positions may reduce the propensity to apply for grants both directly and indirectly. Directly, because eligibility criteria may explicitly require that the PI has a certain seniority or academic rank, or that the PI has some level of scientific independence (Waisbren et al., 2008). Indirectly, because lower-ranked positions involve less work flexibility and limited freedom in the choices of what to research (Franzoni & Rossi-Lamastra, 2017) and because lower-ranked positions have a lower level of organizational support (Blake & La Valle, 2000; Fuchs et al., 2001).[6] Without organizational support, the burden of grant-writing (and of grant-management in case of success) may discourage females from participating in competitions.

Lower scientific performances. Female scholars also have lower scientific performance than their male colleagues on average, and this result is rather stable across all disciplines and countries (Larivière et al., 2013). The performance gap is especially large if measured among top-scientists (Abramo et al., 2009; Bordons et al., 2003), who, in turn, are mostly men (Abramo et al., 2009). Part of the performance gap of females disappears when controlling for seniority and rank, as women tend to be younger and employed at lower ranks of the academic ladder (Fox & Nikivincze, 2021; Larivière et al., 2013). However, there are other reasons that contribute to the imbalance. For instance, women are less credited with authorship (Ross et al., 2022) and less likely to receive credit when their work is coauthored with men (Sarsons, 2017). They are also less likely to appear in the prominent (first and last) author positions (West et al., 2013) and, when they do, they receive fewer citations than men in the same positions (Chatterjee & Werner, 2021; Larivière et al., 2013). Lower scientific performance results in less competitive profiles of female PIs, thus potentially contributing to lower application rates.

Lower re-application rates. Some scholars have also investigated whether females resubmit grants less often than men when they are rejected. The evidence is mixed. One study finds no gender differentials (Waisbren et al., 2008), while another study does (Martinez et al., 2007). Hosek et al. (2005) studied re-application after success and rejection in three US federal agencies (NSF, NIH, and the Department of Agriculture), during the period 2000-2003. They found that women who apply for the first time are less likely to apply again at NIH and NSF, for both successful and unsuccessful first applications. The difference is much larger at the NIH than at the

[6] The fact that women receive limited organizational support is consistent with the finding that women publish significantly fewer papers in scientific fields that require access to research facilities, such as high-energy physics (Duch et al., 2012).

NSF (20% and 5% respectively).

To conclude, extant research has evidenced disparities in the acquisition of research grants by male and female scholars, which seem to also depend on constraints in the supply of female applicants. Accordingly, we expect our data to confirm that female scholars, in addition to being less numerous in science, also exhibit a lower propensity to apply for grants than male scholars. Our starting assumption, to be checked in the data, will therefore be that women have a lower propensity than men to participate in scientific grant competitions (baseline assumption; H0). Prior works have discussed the funding gap as depending on too few women in academia, discrimination in evaluation, poorer careers, lower performance, and lower re-application rates. These reasons are critically important, but also have deep roots in the educational, cultural, and social conditions of the environment, which can only change slowly and in ways that are largely beyond the reach of funding agencies. In the following, we focus, instead, on two additional factors that can be directly addressed to promote gender equality, as they pertain to the sphere of direct influence of the funding agencies: the use of gendered (masculine) language in the calls for applications and the choice of topics of the calls in mission-oriented programs.

2.3. Masculine language

A first issue worthy of investigation relates to the possibility that women and men respond differently to the gendered cues used in the language within calls for applications. Language studies have largely documented that male and female speakers use different language styles, and likewise react to language styles differently. For example, men use more assertive speech, and more words denoting action, leadership, individualism, and competition, while women, instead, use more affiliative speech and more words denoting cooperation, feelings, and trust (see Leaper & Ayres, 2007 for a review). These differences are attenuated in children (Leaper & Smith, 2004). Speakers of both genders also modulate their choice of language depending on the subject of the discussion, *i.e.,* they use more masculine words when the discussion involves a man and vice versa (Madera et al., 2009, 2019; Schmader et al., 2007).

Language cues in the text of the calls may affect the readers' perception of fit when they appraise the congruity between themselves and the call. This phenomenon has been documented since the 1970s in seminal studies conducted on job advertisements, showing that women were more likely to respond to job postings when these were gender-neutral or counter-stereotypical, as opposed to conforming to gender-stereotypes (Bem & Bem, 1973). Today, job ads explicitly targeted at only one gender would probably be unlawful, but some studies find that traditional gender stereotypes reflected in language have not changed much over time (Eagly et al., 2020; Haines et al., 2016). Moreover, a message may induce a gendered response even by means of subtle and unconscious cues of gender that operate through language in an indirect way. For example, Gaucher et al. (2011) showed that, even with gender-neutral job ads, participants anticipated more male applicants in traditionally male-dominated fields and more female applicants in traditionally female-dominated fields. Furthermore, they showed, in a series of experimental studies, that job ads manipulated by adding more masculine words were less appealing to women and raised expectations of having more male applicants. Finally, gendered language, induced implicitly via the use of more masculine words in job postings, altered the perceptions of congruity to the role advertised (but not to the skills required to be in such a role), raising concerns of misfit among women and making them less interested in applying.

By analogy, we expect similar mechanisms to be in place in calls for applications for research grants. The use of gendered-language in the calls may influence considerations of role-congruence by male and female scholars, inducing a difference in the willingness to apply. If the call contains masculine words, women may find the call less appealing or see it as less fitting to them, reducing their willingness to apply. The presence of gendered language has been documented in internal communications of granting agencies to panelists, reviewers, and applicants (Van Der Lee & Ellemers, 2015), but, to the best of our knowledge, the implications on the willingness to apply has never been tested. Thus, we postulate our first research hypothesis:

H1: *The presence of masculine words in the text of a call reduces the probability that women apply to the call.*

2.4. Topic proximity

As discussed in the previous section, women are a minority in the scientific workforce and the percentage of female scholars varies considerably across the fields of science (Ceci et al., 2009, 2014). Female scholars are especially under-represented in Mathematics (10%), Philosophy (12%), and Economics (13%), while they are relatively more abundant in Sociology (41%), Demography (42%), and Education (46%) (West et al., 2013).

Moreover, a recent strand of research has pointed out that large differences in the distribution of men and women also exist at the level of sub-fields and research interests, suggesting that women may be inclined to study different topics than men. This pattern has been documented in several fields. Brisbin and Whitcher (2017) report large disparities in the percentage of female scholars in sub-fields of Mathematics, with the percentage of females varying from a low of 16% to a high of 61%. In Medical Studies, females were found to do more research in diseases that are gendered or sex-related (Nielsen et al., 2017). They are also more likely to specialize in Pediatrics and Gynecology and less likely to specialize in Orthopedics and Surgery (Alers et al., 2014). Similar patterns indicating gendered preferences for sub-fields and research interests have been reported in Management (Nielsen & Börjeson, 2019), Economics (Chari & Goldsmith-Pinkham, 2017), and Political Sciences (Key & Sumner, 2019). Relatedly, patents filed by all-female inventor teams are more likely than the ones filed by all-male teams to focus on women's health (Koning et al., 2021). Some authors have suggested that gendered preferences reflect different cognitive inclinations of men and women (Leahey, 2007; Luoto, 2020; Thelwall, Bailey, Makita, et al., 2019; Thelwall, Bailey, Tobin, et al., 2019), with men preferring to work with things and women preferring to work with people (Su et al., 2009). Other authors stress that gendered preferences are rooted in the desire to express self-conception and identity in working environments (Cech, 2013).

Male and female authors were also found to differ at a deeper level. Kim and colleagues (2022) analyze a vast repository of PhD dissertations from US universities and find gendered differences in the use constructs, methods, and frames of research. Other authors highlight differences in research methods, with women more likely to use qualitative and exploratory methods and men more likely to use quantitative methods (Grant et al., 1987; Thelwall, Bailey, Tobin, et al., 2019). Women were also found to be less specialized (Leahey, 2007) and more likely to engage in interdisciplinary research compared to men (Rhoten & Pfirman, 2007).

To the extent that gender differences are present at both the level of scientific fields and at sub-fields and topics, it is possible that applications by female scholars are constrained by the topics of the calls that are issued in mission-oriented programs. In other words, it is possible that, even accounting for the unequal share of men and women in fields, the topics of the call were chosen in areas that were especially male-dominated. Assuming that the propensity of a scholar to apply directly relates to the proximity between the scholar's core research interests and the topics of the call and that, overall, women's research interests are different from those of men, we put forth the following research hypotheses:

H2a: *Women's research interests, all else being equal, are less proximate to the calls than those of men.*

H2b: *Topic proximity mediates the relationship between gender and the propensity of applying to a call; namely, women are disproportionately distributed in less proximate topics and this lower topic proximity accounts for the lower application propensity among women (mediation effect).*

It is also possible that men and women differ in their propensity to respond to topic proximity. For instance, men could be more confident or optimistic, or less afraid of failing compared to women and, thus, they might be more likely than females to apply, at any given level of topic proximity. Furthermore, men generally have broader research interests than women (Baram-Tsabari et al., 2006; Leahey, 2007) so their proximity might be less sensitive to the choice of topics. The following hypothesis follows:

H2c: *Topic proximity has a different effect on men and women. Specifically, an increase (decrease) in topic proximity leads to a lower increase (decrease) in the probability of females applying than that of males (moderation effect).*

3. Data collection and coding

3.1. The Swedish Foundation for Strategic Research

In order to test our research hypotheses, we built a new and original dataset. The main source of the data is the Swedish Foundation for Strategic Research (SSF).[7] SSF is an independent granting agency that had an endowment of approximately 10 billion Swedish krona (approximately 1 billion euros or 1.1 billion dollars) (SSF, 2016) at the outset of 2016. The Foundation was created by the Swedish government to support research in science, engineering, and medicine conducted in Sweden. The funding distributed amounts to 600 million Swedish krona per year,[8] which is equivalent to 59 million euros or 69 million dollars.

SSF operates with a mission-oriented approach. It publishes about 2-3 calls per year; each call is directed to address a challenge in new and emergent domains of hard sciences and technology, often with a multidisciplinary approach. The challenges addressed vary every year. Only applicants with Swedish affiliations are eligible to apply. For each call, the SSF nominates a panel of scientists

[7] https://strategiska.se. Accessed June 30th, 2022.
[8] Source: https://strategiska.se/en/call-for-proposals/. Accessed June 30th, 2022.

in charge of reviewing proposals and selecting the winning ones. The panel initially performs a first screening that filters-out the applications deemed unsuitable for addressing the challenge posed by the call. All remaining applications are sent out to external reviewers. Then, the final decisions are taken by the panel in a consensus meeting.

3.2. Applications and potential applicants

The SSF gave us access to information concerning all 21 competitions for research grants conducted from 2011 to 2018, including detailed information about all successful and unsuccessful applications and their respective applicants. In this period of observation, there were a total of 1,234 applications submitted by 932 unique applicants; of these applications, 586 (47.49%) were sent-out for review and 152 (12.32%) were awarded a grant.

We browsed applicants' CVs, enclosed in the applications, and compiled information on name, gender, affiliation, and year of PhD award. Using given name, surname, and affiliation, we paired applicants to their respective Scopus IDs and downloaded all publications from the Scopus database, using the pybliometrics package (Rose & Kitchin, 2019).[9] 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, but may or may not have done so. This would be the set *at risk* of applying. The set *at risk* should not be defined too narrowly or too broadly, in order to allow sufficient room for the observation, but also to avoid including individuals whose differences are not captured in the covariates (Lerchenmueller & Sorenson, 2018).

Our set of potential applicants *at risk* are defined by three criteria. First, potential applicants need to be eligible to apply for the call. In all calls, only scientists with a Swedish affiliation are eligible to apply. Therefore, our first criterion includes all scientists with a Swedish affiliation in the *focal years* of the call, defined as the year of the call, the year before it, and the year after it.

[9] https://pybliometrics.readthedocs.io/en/stable/. Accessed July 15th, 2022.

Second, potential applicants need to be active in research areas that are fit to the call, implying that, for example, a philosopher is not at risk of applying to a call about medicine. Accordingly, our second criterion is that the potential applicants should be active in the *focal subject categories* of the call. The application of this criterion is not straightforward in our case, as SSF calls are oriented to interdisciplinary missions, and the subject categories are not identified upfront by the SSF. We thus adopted a procedure to extrapolate the appropriate focal subject categories of each call directly from the data. Assuming that the applications which passed the first screening of the review were deemed relevant to the call, we started by considering all publications by applicants that had passed the first screening, on a call-by-call basis. We retrieved the journals in which these papers were published, mapped those journals in their respective subject categories based on the journal classification of Scimago Journal Ranking, and for each subject category we computed the number of papers published by the applicants that passed the first screening. We sorted those subject categories in descending order, and, starting from the first (i.e. more frequent) one, we considered as *focal subject categories* the minimum set of more frequently appearing subject categories that, taken together, covered not less than 25% of the total corpus of publications. The resulting list of calls and subject categories was checked and confirmed by human reading. For example, the focal subject categories of the call "Novel biomarkers of clinical relevance" (RB13) are: "Biochemistry", "Cancer Research", "Genetics", "Cardiology and Cardiovascular Medicine" and "Immunology". Table 1 reports the focal subject categories identified for each call. We applied the criteria to our set of potential applicants, by restricting it to the Swedish scientists who had at least one publication in the focal subject categories. As a robustness check, we constructed a set of potential applicants using focal journals rather than focal subject categories, and reran the analyses on it, finding similar results (see Section 4.3 of this paper and Section 1 of the Appendix).

Third, a scientist must be scientifically active in the years of the call to be considered at risk. For example, out of 1,234 applications, only 2 (0.16%) were from practitioners who listed no publications in their application, and neither passed the first screening. At the same time, it would make little sense to consider a scientist whose last publication in the subject categories is dated many years before the call at risk of applying. Consequently, our third criterion states that, to be considered at risk, a scientist must have published at least one paper in the focal years of the call.[10] Indeed, in our dataset, out of 1,234 applications, only 46 (3.73%) were submitted by scientists with no publications in the focal years of the call; and, of the 648 applications sent out to review, only 16 (2.47%) were submitted by scientists with no publications in the focal years of the call.

After applying the above criteria call-by-call, we obtained for each call the set of authors who had published at least one paper with a Swedish affiliation in the focal years and in the focal subject categories of the call. We merged the sets of authors so obtained with the set of applicants (*i.e.,* PIs): out of a total of 1,234 call-applicant pairs, 1,126 call-applicant pairs were already present in the group of authors so obtained, meaning 91.25% of overlap. This strengthens our confidence in this methodology. With this merge we obtained our final set of *potential applicants*, defined as all scientists who could have applied to the call. Within this set, we have two-subgroups: those who effectively applied to the call (*i.e.,* applicants or PIs), and those who could have applied, but did not (*i.e.,* non-applicants). We completed the publication records by retrieving from Scopus all the publications of the non-applicants.

[TABLE 1 ABOUT HERE]

3.3. Variables of interest

Our research hypotheses revolve around the lower propensity to apply of female potential

[10] The inclusion of the year *after* the call in the definition of "focal years" of the call lets us account for printing lags, as it takes some time to publish research (Powell, 2016). This 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.

applicants (H0), the gendered-language of the calls (H1), and the proximity between scientists' research interests and the topics of the call (H2a-H2c). To investigate our hypotheses, we coded the dummy variable *Female* as assuming value 1 for females and 0 for males. The gender of applicants was self-reported in the applications. For the non-applicants, we used the software Genni 2.0 (Smith et al., 2013; Torvik & Agarwal, 2016),[11] which determines gender probabilistically, by taking both the first and last name of the potential applicants into account. Genni could assess the gender with reasonable certainty for all but 12.88% of potential applicants, which were consequently dropped.[12] Missing gender is not correlated with calls or focal subject categories, suggesting that dropping of records should not bias the results.

We assessed the masculinity of the language of the call using the dictionary of *masculine words* contained in Gaucher et al. (2011)13 on the English text of each call. Specifically, we computed the variable *Masculine Words* using the software "DICTION",[14] which computes word frequency in the entire (unsegmented) texts and normalizes the frequency count by text length.

To measure topic proximity, we computed the semantic similarity between the words used in the text of each call and those used in the publications of each potential applicant. To do so, we applied a Latent Semantic Analysis (LSA) algorithm (Deerwester et al., 1990; Dumais, 2004) using Gensim 4 (Rehurek & Sojka, 2010)[15] on the title and abstract of all potential applicants' publications. The detailed process is as follows. First, each text (*i.e.,* title and abstract) was pre-processed by removing stop-words, words longer than 15 characters, numbers, punctuation marks, and by stemming word inflections. Second, from the entire corpus composed of all

[11] http://abel.lis.illinois.edu/cgi-bin/ethnea/search.py. Accessed July 15th, 2022.
[12] The proportion of uncategorized gender is comparable to those found in prior studies (Lerchenmueller & Sorenson, 2018, p. 1010). Note that no applicants were dropped due to missing gender.
[13] The dictionary is available in Gaucher et al. (2011) in Appendix A at page 17. Its construct validity was proved in that same paper.
[14] https://dictionsoftware.com/downloads/. Accessed July 21st, 2022.
[15] https://radimrehurek.com/gensim/. Accessed June 30th, 2022.

stemmed words in titles and abstracts, we dropped those words that appeared only once, as they do not contribute to topic identification, had a high incidence of misspellings, and in order to save on computational power. Third, the corpus was converted into a bag-of-words vector space, then into a Term Frequency - Inverse Document Frequency (TF-IDF) vector space, and finally into a LSA vector space, with the LSA model trained with 200 topics (Bradford, 2008). Fourth, we indexed the resulting LSA and computed the semantic similarity between the call and each publication in our database. We then calculated the average semantic similarity for each potential applicant to the focal call, as the arithmetic mean of the similarities of the potential applicant's publications in the year of the call and up to 5 years before it. Finally, we transformed the semantic similarities into z-scores, to improve interpretability. The resulting variable, called *Proximity*, is a normalized measure of the semantic similarity between the potential applicants' past research and the topic of the focal call.

We also computed additional variables to be used as controls in econometric models. From publication records, we computed the S*eniority* of all potential applicants as the difference between the year of the call and the year of their first publication. We dropped 536 scientists with a seniority greater than 55 years because they were presumably too senior to apply for grants that last several years.[16] We further took the affiliations of scholars at the time of the call from their publications in the focal years. We coded these affiliations into a dummy variable *University* that takes the value of 1 if the scientist is affiliated with a university, and 0 if he/she is affiliated with a non-university institution. We coded into a dummy variable *Nordic* the Nordic/non-Nordic ethnicity of the potential applicants based on their last name using Ethnea (Torvik & Agarwal, 2016).[17] We compiled information on the scientific productivity (in terms of quantity and quality)

[16] Of these, 534 were non-applicants, while 2 were applicants, none of who passed the first screening. Assuming that on average a scientist begins publishing at about 25 years, this would be equivalent to dropping from the sample the potential applicants older than 80 years old.
[17] http://abel.lis.illinois.edu/cgi-bin/ethnea/search.py. Accessed July 15th, 2022.

of potential applicants based on their Scopus publication records. The quality of publications was attributed by looking at the position of the respective journal in the four quartiles of the Scimago Journal Ranking.[18] In the variable *N. of prior applications*, we counted repeated applications by the same applicant to the calls of SSF. Finally, in the variable *Seniority* we estimated periods of leave or discontinuities experienced in the scientific career by counting the number of years in which a potential applicant had zero publications, starting from the year of first publication and ending at the year of the call.

The final dataset consists of 277,464 unique potential applicants-calls (a median of 9,064 potential applicants per call),[19] of which 1,232 were applicants, 586 passed the first screening and 152 were winners. Table 2 reports the descriptive statistics of all the variables used in the regression models, along with a short explanation about their construction.

[TABLE 2 ABOUT HERE]

4. Results

4.1. Descriptive evidence about gender disparities in the stages of grant acquisition

Figure 1 reports the percentage of women and men in the four funneling steps towards grant acquisition: i) potential applicants, ii) applicants, iii) reviewed applicants (*i.e.*, those who passed the first screening) and iv) winners (*i.e.*, the awardees of the grant). An interesting pattern emerges. At the initial stage (before the application), 88,113 (31.76%) of the 277,464 potential applicants are women. The percentage of women shrinks considerably in the application stage, where only 237 of the 1,232 scientists that did apply (19.24%) were women. After this stage, the percentage of women in the process remains relatively stable: they account for 16.89% of the

[18] If a journal belongs to more than one subject category, we consider the best quartile among all the subject categories the journal belongs to.

[19] By way of comparison, the headcount of researchers in Sweden was 101,820 in 2013, 108,761 in 2015, and 107,042 in 2017 (source OECD: https://data.oecd.org/rd/researchers.htm). Accessed July 15th, 2022.

reviewed applicants (i.e., 99 out of 586) and 18.42% of the winners (i.e., 28 out of 152). This suggests that as much as 12.52% women dropped out of the pipeline before the application stage, while only less than 1% leaked-out in the next stages. The first step in the funneling -between the potential applicants and the applicants- is also the only one where the proportion of females is statistically different from the prior stage (χ^2=89.50, p<0.01).

[FIGURE 1 ABOUT HERE]

Table 3 further reports the percentage of women in the categories of potential applicants (column 1), applicants (column 2), reviewed-applicants (column 3), and winners (column 4), in the total sample, for each field, and for each call, separately. It also shows the differences in the proportion of women observed between applicants and potential applicants (column 5), between applicants sent to review and applicants (column 6), and between winners and applicants sent to review (column 7). Columns 5, 6 and 7 of Table 3 also show the statistical significance of the Pearson's Chi-squared tests.

When we group the observations by field of the call, we observe that the proportion of potential female applicants goes from a maximum of 41.25% in Medicine to a minimum of 21.59% in ICT. The proportion of women among the potential applicants is higher than the proportion of women among the applicants in all the fields, and all these differences are statistically significant at conventional levels. However, irrespective of the field, the proportion of female applicants sent to review is not statistically different from the proportion of female applicants, and the proportion of female winners is not statistically different from the proportion of female applicants sent to review.

Looking at the breakdown by calls, we notice that the proportion of female applicants is lower than the proportion of female potential applicants in 19 of the 21 calls, although the difference is statistically significant only for 9 of them. No call has a proportion of female applicants sent to review statistically different from the proportion of female applicants, and no call has a proportion of female winners statistically different from the proportion of female applicants sent to review. In conclusion, the univariate analyses show that there are fewer women than men at all stages of the funding process of grant acquisition. However, although women account for nearly one third of potential applicants, they comprise less than one-fifth of actual applicants. This evidence suggests that there are proportionally more women in science (in the subject categories of the calls) than women that step forward to apply for a grant. Once women apply, their likelihood of passing the review stage and winning the competition does not differ from those of men. Thus, it seems that the imbalance between male and female winners is arguably not attributable to unequal success rates during the evaluation process, but instead depends on the supply of applications. This corroborates the importance of investigating the low propensity of women to apply for grants and the reasons behind it in greater depth, which we do in the rest of this paper.

[TABLE 3 ABOUT HERE]

4.2. Econometric models for the testing of research hypotheses

Before running the econometric models, we notice that *Female*, *Masculine Words*, and *Proximity* do not exhibit a high level of correlation with any of the other variables included in our econometric models (see Pearson's correlation coefficients in Table 4).

[TABLE 4 ABOUT HERE]

To test our research hypotheses, we run a set of econometric models. In all of them, we control for the number of papers that the scientist has published at and before the year of the call (split by quartiles of journal quality), seniority (both linear and squared), affiliation type, ethnicity, years of career discontinuity, and number of applications submitted to prior calls of the same foundation. We use robust standard errors to handle heteroskedasticity (see Section 4.3 for alternative treatments of standard errors).

We begin by testing our first expectation that female potential applicants are less likely to apply than male ones. We run a logistic regression as follows:

$$Logit(P(Apply=1)) = \alpha + \beta * Female + \Omega * Controls + \varepsilon \qquad [Model\ 0]$$

where *Apply* is a binary variable equal to 1 if the potential applicant has effectively applied to the call, while *Female* is a binary variable equal to 1 if the applicant is female.

[TABLE 5 ABOUT HERE]

Table 5 reports the results of the estimates. We start to estimate a model with only the gender variable (column 1), then add the control variables, one group at a time, in columns 2-7: publication quantity and quality (column 2), seniority (column 3), discontinuity (column 4), prior applications (column 5), affiliation with a university (column 6) and nordic ethnicity (column 7). As expected, the odds ratios of *Female* are always well below one ($e^{\beta} <1$) and statistically significant ($p<0.01$), suggesting that women are generally less likely than men to apply. In column 8, we add call fixed effects, with the aim of capturing all possible call-specific source of variability (e.g., year, subject, budget amount, etc.). The pseudo-R^2 of the model is equal to 15.34% and the odds ratio of *Female* remains below one ($p<0.05$), indicating that the odds of female scientists applying, all else being equal, are roughly 0.844 times the odds of male scientists applying.20

In this model, the average predicted probability of applying of males (*i.e.,* after restricting the dataset to males, we predict the probability to apply for each observation, and average the results) equals 0.55%, while that of females equals 0.27%. The difference of 0.28% is significant at conventional levels ($p<0.01$) and equals 51.62% of the average predicted probability of applying of males. If all applicants in the dataset were male, the average predicted probability of applying would be 0.48% ($p<0.01$), while if all were females, the average predicted probability of applying would be 0.40% ($p<0.01$). The difference of 0.08% is statistically significant ($p<0.05$). This means

[20] Interestingly, this odds ratio is similar to the one found for women to become faculty advisors (Kim et al., 2022), and receive the first NIH grant (Lerchenmueller & Sorenson, 2018).

that 72.01% of the lower probability of females applying is explained by differences in the pattern of the covariates (*e.g.,* lower productivity of females, or lower seniority of females), while the remaining 27.99% of the difference is explained by gender alone. The analysis thus corroborates our initial expectation that women are less likely to apply to calls than men, net of all control factors and call fixed effects.

Next we move to our first hypothesis, which investigates whether the use of gendered language affects the probability of men and women applying to the call. In particular, we hypothesized that the use of masculine words in the text of a call (*Masculine Words*) would be associated with a decrease in the probability of female scholars applying to it. To test H1, we add to Model 0 the variable that captures masculine language, plus its interaction term with the variable *Female*, as follows:

$$\mathit{Logit(P(Apply=1))} = \alpha + \beta * \mathit{Female} + \gamma * \mathit{Masculine\ Words}$$
$$+ \delta * \mathit{Female} * \mathit{Masculine\ Words} + \Omega * \mathit{Controls} + \varepsilon \qquad \mathit{[Model\ 1]}$$

The estimate would support H1 if the odds ratio of the interaction term is lower than one ($e^{\text{™}}<1$). Importantly, *Masculine Words* is a fixed attribute of each call. Thus, estimating Model 1 requires dropping calls fixed effects. As a replacement for them, we added a set of controls for call characteristics and availability of funding: the field of the call (*i.e.,* ICT, Engineering, Physics, Chemical, Medical, and Biology), the length of the calls' textual description (*Total Words Analyzed*), the total budget allocated by the SSF to the call (*Budget*), and the total level of R&D funding in Sweden in the year of the call (*Sweden R&D Expenditure*). We also include a set of controls (*Text Controls*) to capture subtle nuances in the semantic style of the text of the calls, which could potentially affect the willingness of male and female scholars to apply, beyond the use of masculine language. Specifically, we control for the following lexicon variables computed by the DICTION 7.1.3 software: (i) *Exclusion*, *i.e.,* the use of words describing the sources and effects of social isolation; (ii) *Aggression*, *i.e.,* the use of words describing human competition and forceful action; (iii) *Leveling Terms*, *i.e.,* the use of words denoting the degree by which the text embraces egalitarianism; (iv) *Ambivalence*, *i.e*., the use of words expressing hesitation or uncertainty; and (v) *Human Interest*, *i.e.,* the use of words capturing whether the language emphasizes people and their activities.[21] Prior to adding these variables, we check and rule out multicollinearity problems, by ensuring that the Pearson correlation coefficient between each of these variables and *Masculine Words* was low.

Table 6 reports the results of the estimate of Model 1.

[TABLE 6 ABOUT HERE]

As before, we add control variables one group at a time. Column 5 reports the estimate of the baseline model where fixed effects are replaced with the aforementioned set of call characteristics. Note that, in this model, the odds ratio of *Female* equals 0.832 ($p<0.05$), in line with the 0.844 obtained in column 8 of Table 5. In Column 6, we add the variable *Masculine Words* to the baseline model. The odds ratio of *Female* is roughly the same, with a similar significance level. The variable *Masculine Words* is not statistically significant, and its inclusion does not improve the pseudo-R^2, indicating that *Masculine Words* does not explain more variance in the data.

Finally, column 7 reports the estimates for the full Model 1, including the interaction term between *Masculine Words* and *Female*. The interaction term is not statistically significant ($p>0.1$) and the pseudo-R^2 does not improve substantially. Overall, the result does not provide support for

[21] The choice of this set of variables was instructed by our own reading of prior findings of the related literature. In particular, *Exclusion* was chosen because women are usually described as "concerned about others" (Heilman, 2001). *Aggression* was chosen because men are usually described as having aggressive and competitive behaviour (Heilman, 2001). *Leveling Terms* was chosen as women are described as more egalitarian than men (Araújo et al., 2017). *Ambivalence* was chosen as women are reported as more risk averse than men (Eckel & Grossman, 2008). *Human Interest* was chosen as men are reported to prefer working with things, while women are reported to prefer working with people (Su et al., 2009).

H1, suggesting that the presence of masculine language in the call does not explain the probability of women and men applying.

Next, we study whether *Proximity*, *i.e.,* the semantic similarity between the research of the potential applicants and the topics of the calls, explains the decision to apply. Before testing H2, we check in Table 7 how *Proximity* varies between applicants and potential applicants, and then between males and females.

[TABLE 7 ABOUT HERE]

The average *Proximity* of the applicants to the call is 0.58 standard deviations greater than that of the potential applicants (t=0.03, p<0.01). This corroborates our confidence in the measure, as it is reasonable, and consistent with prior findings, that researching topics closer to those of the call should generally induce more interest in applying (Myers, 2020).

Importantly, we notice that the average proximity of men is 0.07 standard deviations from the mean, while that of women is -0.15 standard deviations from the mean. The difference (-0.22) is statistically significant (t=0.00, p<0.01), suggesting that, on average, the research of female potential applicants is more semantically distant from the topics of the calls than the research of male potential applicants. This is the case in each and all of the fields. At the call level, we see that female potential applicants are less proximate than male potential applicants in 14 out of 21 calls, with statistical significance at conventional levels for 10 of them, and are more proximate in 7 out of 21 calls, with statistical significance at conventional levels for 3 of them.

Our H2a posits that women's research interests are less proximate to the calls than men's ones. To test H2a, we estimate the following linear regression model for *Proximity*, as a function of *Female* and the control variables:

$$Proximity = \alpha + \beta_M * Female + \Omega * Controls + \varepsilon_M \qquad [Model\ 2a]$$

The results are reported in Table 8.

[TABLE 8 HERE]

As in Model 0, we included all groups of controls, one by one, and finally added calls fixed effects. The estimate of the full model is in column 8 and has an R^2 of 17.57%; the coefficient of *Female* is negative and significant (p<0.01), even after taking into account all the control variables. In terms of magnitude, the penalty in average proximity associated to *Female* is -16.6% of one standard deviation of *Proximity*.[22] These results corroborate H2a that the research conducted by female scholars is on average less proximate to the topics of the calls than the research conducted by male scholars. Note that, because of call fixed effects, the penalty is not attributable to the smaller proportion of female scholars in the fields of some calls, and instead comes on top of it. In other words, even considering that calls are in male-dominated fields, the calls fall in topics of these fields in which the dominance of men is even greater than in the overall field.

H2b posits that *Proximity* mediates the relationship between gender and the probability of applying. We then establish GLM models for the probability of applying as a function of Proximity (the mediator), Female (the treatment) and the other control variables. The models are specified as follows:

$$g(P(Apply=1)) = \alpha + \beta_O * Female + \gamma_O * Proximity + \Omega * Controls + \varepsilon_O \qquad [Model\ 2b]$$

Where *g* is the link function. Columns 1, 2, and 4 of Table 9 report the estimates for Model 2b.

[TABLE 9 HERE]

In Columns 1 and 2 we use the Logit function as our link function, for easier interpretation of the coefficients, and report exponentiated coefficients, which corresponds to odds ratios. In Column 4 we use the Probit function as the link function, to be able to carry the sensitivity analysis for the

[22] The VIF reveals no major problems of multicollinearity within the set of observation variables used (which implies no major problems of correlation for Model 1 too, as the latter uses a strict subset of the variables of this model). In fact, by estimating an OLS without the square of Seniority, the VIF equals 1.12 for Female and 1.17 for Proximity. The maximum VIF is the one of *Seniority* which equals 9.74 (which is below the conventional threshold of 10 (O'brien, 2007), and which is an expected result as *Seniority* is highly correlated with productivity), while the mean VIF is 5.71 (below the conventional threshold of 6).

mediation model that will follow (and also as a robustness check)23.

In Column 1 of Table 9 we re-estimate the model of Column 8 of Table 5, but restricted to the observations for which we have *Proximity*, showing that the results are unchanged.

In Column 2 we add *Proximity* to the model. The Pseudo-R^2 increases from 15.51% (column 1) to 19.64% (column 2), suggesting that *Proximity* is an important variable to explain the variance in the application rate. The odds ratio of *Proximity* equals 2.104 ($p<0.01$) indicating that, all else being equal, an increase of *Proximity* of 1 standard deviation multiplies the odds of applying by 2.104. The marginal effect of *Proximity* on the probability to apply, keeping all the other variables at their observed values, equals 0.32% ($p<0.01$). Given that, in this model, the average predicted probability to apply equals 0.46%, one standard deviation increase in *Proximity* equates to an increase of +69.56% over the average predicted probability to apply. This is a remarkable increase. The odds ratio of *Female* increases from 0.827 in column 1 to 0.939 in column 2, and it is no longer statistically significant ($p>0.1$), indicating that, when we include *Proximity* in the model, we cannot reject the null hypothesis that *Females* have the same probability of applying than men. This suggests that, conditionally on all the other covariates in the model, *Proximity* fully mediates the correlation of gender to the probability of applying (Baron & Kenny, 1986).

As Model 2b of the outcome variable *Apply* is non-linear, the product $\beta_{M^*} \gamma_O$ does not provide a consistent estimate of the Average Causal Mediated Effect (ACME) and thus we further perform the mediation analysis with the R "mediation" package *(Imai et al., 2011; Tingley et al., 2014)*. Our treatment variable is *Female*; our outcome is *Apply*, and our mediator is *Proximity*. As the mediator model, we use Model 2a, while as the outcome model, we use Model 2b with a Probit link function (that is, the model in Column 4 of Table 9). We calculate Quasi-Bayesian Confidence Intervals through 530 simulations. Results are reported in Column 1 of Table 10.

[23] The "mediation" R package does not allow carrying the sensitivity analysis if the outcome model is specified as a logistic regression.

[TABLE 10 HERE]

The Total Effect of *Female* on the probability to apply equals -0.078%, and is statistically significant ($p<0.01$). This means that, with these models for outcome and mediator and keeping the covariates at their observed values, females have a 0.078% lower probability to apply than males. This effect can be decomposed into a direct effect, due to gender alone, and an indirect effect mediated by *Proximity*. The indirect effect mediated by *Proximity* on the female scientists in our sample (i.e., ACME (treated)) equals -0.051%, and the proportion of the effect mediated by *Proximity*, on the female group (i.e., Prop. Mediated (treated)), equals 65.24%. Both of them are statistically significant at conventional levels ($p<0.01$). On the other hand, the Average Direct Effect of *Female* on the female group (i.e., ADE (treated)) equals -0.025%, but is not statistically significant ($p>0.1$). In fact, the 95% confidence intervals for the ADE include 0%, while the 95% confidence intervals for the proportion of the effect that is mediated include 100%. This means that, at 95% confidence level, and after controlling for all the other covariates in our model, we cannot reject the null hypothesis that the direct effect of *Female* on *Apply* is 0 (i.e., we do not reject full mediation). This corroborates H2b that *Proximity* mediates the relationship between *Female* and *Apply*. Moreover, the results are consistent with full mediation, i.e. that the female gender has no residual effect on the probability to apply, once *Proximity* and all other covariates are taken into account.

To study hypothesis 2c, we establish the following Model:

$$g(P(Apply=1)) = \alpha + \beta_O * Female + \gamma_O * Proximity + \delta * Female * Proximity + \Omega * Controls + \varepsilon_O \qquad [Model\ 2c]$$

We report the result of the analysis in Column 3 and 5 of Table 9. We use a Logit link function in Column 3, and a Probit link function in Column 5. We use the model in Column 5 to carry the mediation analysis, and results are reported in Column 2 of Table 10.

We can see that the ACME is different between females and males.24 The ACME of males equal -0.056% (p<0.01), while the ACME for females equal -0.042% (p<0.01). The difference of 0.014% is significant at conventional levels (p<0.01). This corroborates H2c, suggesting that females are less responsive than males to variations in *Proximity.* In other words, when *Proximity* increases (decreases), females would respond by increasing their propensity to apply less (more) than males.

4.3. Robustness checks

We conducted several robustness checks of our results.

First, in all our estimates, including the mediation model, we use robust standard errors, to control for heteroskedasticity. Following the advice of an anonymous reviewer, we consider that applicants could submit applications to multiple calls over the years, and repeat all our analysis using cluster-robust standard errors at the individual level, with results consistent with prior findings.

Second, we also test that our results are robust to changing the criteria for inclusion in the set of potential applicants. Following the advice of an anonymous reviewer, we use an alternative method to reconstruct the sample of potential reviewers. Specifically, we impose as the second criteria for inclusion that the potential applicants publish in the same journals, instead of the same journal subject categories, as the applicants who passed the first screening. Results are consistent with the main models. See Section 1 of the Appendix for details.

Third, we also re-estimate H2a-b-c using the median Proximity, instead of the average one, and the mean and median proximity computed on all publications prior to applications (not just the 5-years prior). Results are consistent with the main estimates. They are omitted for brevity, but available upon request to the authors.

[24] Notice that the ACME on the two groups were different also in the model of Column 1, but that was due to the non-linear nature of the outcome model.

Fourth, we re-estimate H0 and H1 using the probit model, obtaining similar results.

Fifth, we re-estimate H0, H1 and H2b-c using a linear probability model. Results are qualitatively similar and are available upon request. The only exception is that the OLS estimate of H1 captures a small negative effect of the interaction term of *Masculine Words* and *Female* ($p<0.5$), which is not confirmed in logit and probit models of H1. We do not deem this evidence sufficiently robust to support H1, but the result calls for future explorations with alternative datasets and/or dictionaries.

Sixth, results are robust to using the algorithm Genderize.io, instead of Genni, to estimate the gender of the potential applicants.

Seventh, the results for H2b-c presupposes the sequential ignorability assumption (Imai et al., 2011), which implies that the error term for the outcome model is uncorrelated with the error term of the mediator model, that is, that $Corr(\varepsilon_O, \varepsilon_M)=0$. Starting from the probit model for H2b, we carried out a sensitivity analysis to test the robustness of our results to this assumption. The result is plotted in Figure 2.

[FIGURE 2 ABOUT HERE]

The left panel reports, on the y-axis, the true Average Causal Mediation Effect on the treated, and, on the x-axis, the correlation ρ between the error term for the outcome model and the error term for the mediator model. We can see that the ACME is negative as long as $\rho \leq 0.2$. This means that our results are robust up to a 20% correlation between the two error terms. The uncorrelatedness of the two error terms implies that there are no unobserved confounders between the mediator and the outcome. The shaded region represents 95% confidence intervals for the ACME. The upper bound of the confidence interval for the ACME is negative as long as $\rho \leq 0.1$.

The right panel of Figure 2 reports the contour plots of the true ACME as a function of the proportion of the total variance in the mediator model (x-axis) and in the outcome model (y-axis) explained by the unobserved confounder, in the case where the unobserved confounder affects the mediator and the outcome in the same direction.25 The true ACME would change sign if the product of these two proportions exceeds 0.0237. To provide more intuition on this result, if the unobserved confounder explains the same amount of variance in the two models, the true ACME changes sign if this explained variance accounts for 15.39% ($\approx \sqrt{0.0237}$) or more of the total variance in the mediator and in the outcome model.

5. Conclusions, limitations, and future research agenda

The literature on gender in science has highlighted that the penalty that females suffer in research funding may depend on many concurring factors that include potential discrimination of women in the evaluation process of research proposals, as well as factors that constrain the propensity of female scholars to apply for grants. The latter explanation has rarely been investigated empirically because of methodological difficulties in accounting for scholars who could have applied but did not. In this paper, we conducted one of the first large-scale studies that models the probability of female scholars applying for grants by developing an empirical strategy that allows us to identify a pool of potential applicants. Our estimates indicate that the odds of a female scientist applying for funding are 0.844 times, or 15.6% less, than the odds of a male scientist, after accounting for a wide number of factors that may explain the gender gap, including lower scientific performance, lower seniority, more career discontinuities, lower propensity to re-apply, international mobility, affiliation, and any call-specific fixed effects, like field and year.

Our dataset looks at how scientists respond to mission-oriented calls, *i.e.*, at programs where the research topics are solicited by a granting agency. Taking advantage of this circumstance, we investigated two mechanisms that may cause lower application rates by women and are call-

[25] If the unobserved confounder affects the mediator and the outcome in opposite direction, the indirect effect would be even more negative, as stated previously (we would be in the case where $\rho < 0$).

related, thus pertaining to the sphere of influence of the granting agency. First, we tested if any alleged use of masculine language in the text of the calls could play a role in discouraging female scholars from applying. We found no robust evidence in our data for claiming that this might be the case. Second, we focused on the similarity (proximity) between the research topics of calls and the research interests of potential applicants, as visible from the publications of scientists in the 5 years preceding the calls. We found that women were on average more distant (less proximate) than men to the topics of the calls. In other words, there were more male than female potential applicants in the subfields of the calls. Importantly, this smaller proportion of females in the subfields comes on top of the already smaller proportion of females in the broader respective fields. Naturally, scientists whose research interests are more distant to the topics of the calls are less inclined to apply. We find that topic proximity mediates the relationship between gender and probability to apply. Moreover, when we take into account differences in topic proximity, we cannot reject the null hypothesis that the propensity to apply of women and men is the same (i.e., that the direct effect of gender is zero), suggesting that, after controlling for all the other covariates in our model, topic proximity, not gender *per se,* explains the lower probability of females to apply. We also found that male scientists are more responsive to increases and decreases in topic proximity than female scientists, although the difference is small.

Our paper has limitations that call for future research. First, our study is based on the data from one funding agency in Sweden. Although there are no immediate reasons to believe that Swedish scientists differ substantially from scientists in other countries, it would be important to replicate the analyses in other samples and countries to gauge the generalizability of our results.

Second, our estimate of the baseline model (Table 5) and our testing of H1 (masculine language) might suffer from endogeneity issues. The identification problem may descend especially from the potential unobserved heterogeneity (omitted variables), whereas reverse causality is not a concern (gender could not be determined by the decision to apply). A potentially omitted variable is the career rank of the scientist in the year of the call (*e.g.,* Post-doc, Assistant Professor, Associate Professor or Full Professor). Although we controlled for (linear and squared) seniority, quantity/quality of publications, affiliation type, and nationality, we acknowledge that not controlling for the rank of the scientist is a remarkable limitation that we hope future studies can overcome. Gender could also be related to other unobserved variables. For example, funding agencies normally organize outreach activities to encourage applications from scholars. It is possible that women had less time than men to take part in the outreach activities, for example because of greater family or administrative workload. Likewise, it is possible that personal traits, such as lower self-confidence, greater risk-aversion, and less tolerance for failure, may be more salient among women, and therefore contribute to explaining the relationship between women and the probability of applying or being affected by masculine language. We thus invite scholars to avoid making causal inference from our tests of H1.

Concerning H2a-b-c there might be endogeneity problems if: (i) there are unobserved confounders between gender and the probability of applying, as this may bias the estimate of the direct effect of gender on probability to apply in the outcome model (Cinelli et al., 2020), (ii) there are unobserved confounders between gender and proximity, as this may bias the estimate of the effect of gender on proximity in the mediator model, which is part of the indirect effect (Cinelli et al., 2020; Imai et al., 2011), and (iii) there are unobserved confounders between proximity and the probability to apply, as this may bias the estimate of the effect of proximity on the probability to apply in the outcome model, which is part of the indirect effect (Imai et al., 2011). We believe the first two possible confounders do not constitute a problem for our case, as no social variable can cause gender, which is determined by nature. For the third case, we showed a sensitivity analysis for the robustness of our results to a violation of this assumption.

The results of this paper also suggest that the research agendas of funding institutions are non-neutral to gender and may exacerbate, or even cause, the gender gap in funding. When a research agenda is set-up, it preselects or pre-allocates funding towards those groups of scientists who are more active on the related topics. Because men and women are not evenly distributed across research topics, even within a given field, research agendas implicitly pre-allocate funding by gender. In fact, we showed how women are active in research topics which are distant from the ones funded by the foundation. Previous literature has also shown how women self-select in college majors and in occupations with lower potential earnings (Sloane et al., 2021) and how topic choice contributes to the underfunding of African-American scientists (Hoppe et al., 2019). This invites reflections on how research agendas are formed. Decisions concerning research agendas inevitably reflect the values, preferences, and priorities of the social and political groups represented by those that make the decisions. They may also be affected by lobbying or influence groups (Hegde & Sampat, 2015). To the extent that lobbies or political and influence groups are male-dominated or reflect gendered preferences, research agendas may mirror a male-dominated set of research priorities. In this sense, choices of research agendas may be endogenous to gender. Making more funding available for male scholars may, in turn, exacerbate the disparity in achievements of males and females and further hamper the rise of female scholars towards the highest academic ranks.

One can correctly object that, altough research priorities are not shaped by gendered preferences, men could be specialized in topics that are more socially relevant, more impactful, or more at the forefront of research, inducing the effect that we observed. If this is the case, the gender gap would be simply a collateral effect of an otherwise wise choice. Thus, we should not seek to re-address the research agendas towards more gender-neutral priorities, but instead stimulate women to move towards more relevant areas. While this is plausible, the problem remains that the judgment of what counts as socially relevant and impactful is necessarily subjective and political.

We hope that our research will stimulate future studies in this important area and will invite reflections by policymakers, granting agencies, scientists, and the general public on how priorities and missions are identified and selected in research agencies. This appears especially relevant considering the recent surge of interest for mission-oriented programs in Europe and the US (Tollefson, 2021).

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Table 1: List of calls and related focal subject categories.

Call Code	Call Title	Focal Subject Categories
AM13	Applied mathematics	Applied Mathematics Electrical and Electronic Engineering Computer Science Applications Computer Vision and Pattern Recognition
BD15	Big Data and Computational Science	Condensed Matter Physics Computer Science Applications Applied Microbiology and Biotechnology Biochemistry
EM11	Energy-Related Materials	Condensed Matter Physics Electrical and Electronic Engineering
EM16	Materials for Energy Applications	Condensed Matter Physics Electrical and Electronic Engineering Chemical Engineering
GMT14	Generic Methods and Tools for Future Production	Electrical and Electronic Engineering Computer Science Applications Control and Systems Engineering
IIS11	Information Intensive Systems: Making good use of ever increasing data volumes	Electrical and Electronic Engineering Software Computer Networks and Communications
IRT11	Innovative Technologies for the Extraction of Metals from Raw Materials	Materials Chemistry Chemical Engineering Condensed Matter Physics
KF10	Clinical research – use of National Quality Registers	Cardiology and Cardiovascular Medicine Cancer Research
RB13	Novel biomarkers of clinical relevance	Biochemistry Cancer Research Genetics Cardiology and Cardiovascular Medicine Immunology
RBP14	Biological Production Systems	Applied Microbiology and Biotechnology Agronomy and Crop Science
RE10	Electronics and Photonics systems	Electrical and Electronic Engineering
RIT10	Software Intensive Systems	Electrical and Electronic Engineering Computer Science Applications Software
RIT15	Smart Systems	Electrical and Electronic Engineering Control and Systems Engineering
RIT17	Cybersecurity and Information Security	Computer Networks and Communications Electrical and Electronic Engineering
RMA11	Materials Science research	Condensed Matter Physics Ceramics and Composites Materials Chemistry

RMA15	Materials Science and Engineering: New methods for synthesis and processing	Condensed Matter Physics Materials Chemistry Ceramics and Composites
RMX18	MED-X; Medicine meets IT, electronics, and materials research	Biochemistry Biomedical Engineering Condensed Matter Physics Electrical and Electronic Engineering Atomic and Molecular Physics, and Optics Cardiology and Cardiovascular Medicine Electronic Optical and Magnetic Materials
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 Infectious Diseases
SB16	Systems Biology	Genetics Biochemistry Cancer Research
SBE13	Molecular Imaging Tissue Engineering and Regenerative Medicine Implanted sensors, Wearable sensors and Lab-on-a-chip New Biomaterials	Biomedical Engineering Biochemistry Electrical and Electronic Engineering Cardiology and Cardiovascular Medicine Analytical Chemistry Condensed Matter Physics Neuroscience
SE13	"Post CMOS" and "More than Moore" electronics, and techniques for high data-rate communications.	Electrical and Electronic Engineering Atomic and Molecular Physics, and Optics

Table 2: Summary of the variables used in the models with explanation and descriptive statistics.

Name of variable	Explanation	Mean	Std. Dev.	Min	Max
Applicant	A dummy variable equal to 1 if the scientist is an *applicant* of the call, and 0 if he/she is a *non-applicant*.	0.44%	0.07	0	1
Budget	The total budget that SSF makes available for the call, in millions of Swedish kronor.	207.15	67.99	80	300
Discontinuity	Number of years with no publications since the year of first publication of the scientist and until the year of the call	4.14	5.03	0	45
Female	A dummy variable equal to 1 if the scientist is a female, and 0 if he is a male.	31.76%	0.47	0	1
Masculine Words	Variable returned by DICTION proportional to the number of masculine words in the call.	3.71	0.72	1.67	5.32
Nordic	A dummy variable equal to 1 if the potential applicant is of Nordic ethnicity.	59%	0.49	0.00	1.00
N. of prior applications	Number of prior applications the applicant has submitted before (potentially) applying to the current call.	0.02	0.17	0	7
N. of YY pubs	Number of papers the scientist has published since beginning of Scopus coverage until the year of the call (included). YY can be:				
	Q1: number of papers published in journals which have a “Q1” SJR Best Quartile	22.30	47.03	0	1,765
	Q2: number of papers published in journals which have a “Q2” SJR Best Quartile	7.86	17.39	0	465
	Q3: number of papers published in journals which have a “Q3” SJR Best Quartile	2.00	6.27	0	377
	Q4: number of papers published in journals which have a “Q4” SJR Best Quartile	1.07	5.52	0	678

	Unranked: number of papers published in journals which are tracked in the SJR database, but do not have a "SJR Best Quartile" associated with them	0.04	0.44	0	115
	Other: number of papers published in journals which are not tracked in the SJR database	4.39	13.54	0	508
Proximity	Proximity between scientist's past research and the call, transformed in z-score.	0	1	-2.59	7.06
Seniority	Is equal to the year of the call minus the year of the first publication of the scientist. It is a proxy for scientist's seniority at the year of the call.	13.62	11.56	0	55
Sweden R&D Expenditure	Gross Domestic Expenditure in R&D in Sweden in the year of the call, in millions of Swedish kronor.	3,236.32	56.65	3,102	3,363
Total Words Analyzed	Number of words in the text of the call.	1,882.11	501.65	925	3,340
University	A dummy variable equal to 1 if the potential applicant is affiliated with a university in the focal years of the call, 0 otherwise.	56%	0.50	0.00	1.00
Call Field	A set of dummy variables coding the following call fields: ICT / Math, Engineering, Physics, Chemistry, Medicine, Biology. An interdisciplinary call may belong to more than one field.				
Call F.E.	A set of dummy variables, one for each call.				
Text Controls	A set of variables that count the number of words from certain DICTION-provided dictionaries, i.e.: Exclusion, Aggression, Leveling Terms, Ambivalence, Human Interest.				

Table 3: Potential applicants, applicants, reviewed, and winners, and related share of females in total sample, by calls, and by field.

	PotApps		Applicants		Reviewed		Winners		Applicants vs PotApps			Reviewed vs Applicants			Winners vs Reviewed	
Call	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**Δ**	**χ^2**		**Δ**	**χ^2**		**Δ**	**χ^2**
AM13	9,178	15.91	64	12.50	30	10.00	6	16.67	-3.41	0.45		-2.50	0.57		6.67	0.37
BD15	19,084	31.25	67	16.42	21	19.05	7	28.57	-14.83	0.01	***	2.63	0.69		9.52	0.62
EM11	6,996	18.07	23	13.04	20	10.00	5	20.00	-5.02	0.53		-3.04	0.26		10.00	0.74
EM16	9,853	22.10	64	31.25	29	37.93	9	44.44	9.15	0.08	*	6.68	0.29		6.51	0.24
GMT14	8,456	16.59	59	6.78	27	7.41	8	12.50	-9.81	0.04	**	0.63	0.86		5.09	0.43
IIS11	8,675	19.04	45	13.33	28	17.86	4	0.00	-5.71	0.33		4.52	0.25		-17.86	1.01
IRT11	6,335	25.87	16	12.50	16	12.50	1	0.00	-13.37	0.22		.	.		-12.50	0.15
KF10	23,292	41.64	45	35.56	16	25.00	5	0.00	-6.09	0.41		-10.56	0.27		-25.00	2.42
RB13	28,273	44.02	133	27.07	30	23.33	9	33.33	-16.96	0.00	***	-3.73	0.60		10.00	0.72
RBP14	2,016	38.05	40	37.50	22	31.82	8	25.00	-0.55	0.94		-5.68	0.41		-6.82	0.27
RE10	7,561	15.55	62	6.45	46	6.52	6	0.00	-9.10	0.05	**	0.07	0.97		-6.52	0.48
RIT10	7,209	14.62	51	9.80	36	11.11	8	0.00	-4.82	0.33		1.31	0.63		-11.11	1.29
RIT15	9,942	17.73	81	9.88	29	13.79	10	20.00	-7.86	0.06	*	3.92	0.38		6.21	0.49
RIT17	6,250	18.75	31	6.45	16	6.25	10	0.00	-12.30	0.08	*	-0.20	0.96		-6.25	1.78
RMA11	9,064	22.11	61	24.59	44	20.45	6	16.67	2.48	0.64		-4.14	0.23		-3.79	0.06
RMA15	12,061	20.00	84	14.29	53	13.21	10	20.00	-5.71	0.19		-1.08	0.71		6.79	0.50
RMX18	40,355	39.91	66	27.27	.	.	6	33.33	-12.63	0.04	**	.	.		.	.
SB12	7,638	43.83	57	33.33	28	35.71	9	33.33	-10.50	0.11		2.38	0.71		-2.38	0.03
SB16	16,145	41.32	61	19.67	25	20.00	9	22.22	-21.65	0.00	***	0.33	0.96		2.22	0.04
SBE13	33,026	39.62	83	22.89	41	17.07	8	25.00	-16.73	0.00	***	-5.82	0.21		7.93	0.44
SE13	6,055	14.07	39	5.13	29	6.90	8	0.00	-8.94	0.11		1.77	0.39		-6.90	0.82
Field																
ICT	58,852	21.59	317	11.36	158	12.03	43	9.30	-10.23	19.71	***	0.67	0.14		-2.72	0.41
ENG	153,556	28.11	668	14.82	331	13.29	88	14.77	-13.29	58.62	***	-1.53	1.21		0.12	0.00
PHYS	142,829	31.86	503	20.28	253	17.39	60	23.33	-11.58	31.17	***	-2.89	2.62		4.83	1.12
CHEM	174,196	35.88	635	22.83	259	20.08	65	27.69	-13.05	47.15	***	-2.76	1.89		7.04	2.36
MED	148,729	41.25	445	26.97	140	23.57	46	26.09	-14.29	37.58	***	-3.39	1.20		1.43	0.06
BIO	122,754	39.40	389	25.45	114	21.93	38	28.95	-13.95	31.81	***	-3.52	1.05		6.20	1.00
Total	277,464	31.76	1,232	19.24	586	16.89	152	18.42	-12.52	89.50	***	-2.34	3.95	**	-0.82	0.12

*p<0.1; **p<0.05; ***p<0.01.
Legend:
PotApps = Potential Applicants.
ICT = Information Communication Technology.
ENG = Engineering.
PHYS = Physics.
CHEM = Chemistry.
MED = Medicine.
BIO = Biology.

Table 4: Correlation Matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	1.000															
(2)	-0.018***	1.000														
(3)	0.038***	-0.120***	1.000													
(4)	0.047***	-0.130***	0.631***	1.000												
(5)	0.025***	-0.105***	0.404***	0.530***	1.000											
(6)	0.005*	-0.052***	0.315***	0.335***	0.435***	1.000										
(7)	0.018***	-0.042***	0.090***	0.092***	0.100***	0.048***	1.000									
(8)	0.021***	-0.126***	0.605***	0.680***	0.446***	0.342***	0.063***	1.000								
(9)	-0.006**	-0.042***	-0.083***	-0.045***	-0.021***	-0.005**	0.013***	-0.009***	1.000							
(10)	0.035***	-0.161***	0.494***	0.514***	0.347***	0.233***	0.077***	0.494***	0.554***	1.000						
(11)	0.116***	-0.040***	0.104***	0.140***	0.072***	0.023***	0.049***	0.063***	-0.009***	0.095***	1.000					
(12)	0.003	-0.082***	-0.033***	-0.012***	-0.002	-0.028***	0.017***	-0.013***	-0.007***	-0.047***	0.003	1.000				
(13)	-0.016***	0.087***	0.007***	-0.030***	-0.029***	0.005**	-0.016***	-0.056***	0.011***	-0.004*	0.030***	-0.132***	1.000			
(14)	0.008***	0.011***	0.029***	-0.003	-0.008***	-0.003	-0.001	-0.029***	-0.004*	0.001	0.064***	0.042***	0.369***	1.000		
(15)	0.013***	-0.072***	-0.022***	-0.001	0.005*	-0.011***	0.015***	0.005**	0.002	-0.023***	0.006***	-0.013***	-0.333***	-0.088***	1.000	
(16)	0.039***	-0.101***	-0.149***	-0.121***	-0.057***	-0.055***	0.018***	-0.108***	0.080***	-0.117***	0.021***	0.125***	-0.018***	0.091***	0.106***	1.000

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

Legend: (1) Applicant, (2) Female, (3) N. of Q1 publications, (4) N. of Q2 publications, (5) N. of Q3 publications, (6) N. of Q4 publications, (7) N. of Not Ranked publications, (8) N. of Not Found publications, (9) Discontinuity, (10) Seniority, (11) N. of prior applications, (12) Total Words Analyzed, (13) Sweden R&D Expenditure, (14) Budget, (15) Masculine Words, (16) Proximity.

Table 5: Test of the baseline assumption H0. Dependent variable: Apply. Logit estimates.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Female	0.511***	0.706***	0.685***	0.685***	0.715***	0.748***	0.744***	0.844**
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
ln N. of Q1 pubs		1.619***	1.405***	1.301***	1.284***	1.308***	1.318***	1.386***
		(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
ln N. of Q2 pubs		1.473***	1.371***	1.324***	1.247***	1.228***	1.231***	1.209***
		(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
ln N. of Q3 pubs		1.144***	1.164***	1.146***	1.109***	1.104***	1.117***	1.092**
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
ln N. of Q4 pubs		0.766***	0.811***	0.815***	0.827***	0.862***	0.862***	0.902**
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
ln N. of unranked pubs		1.775***	1.754***	1.758***	1.407***	1.375***	1.385***	1.272**
		(0.17)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.14)
ln N. of other pubs		0.781***	0.971	0.957	0.981	0.969	0.975	0.900***
		(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Seniority			1.264***	1.300***	1.281***	1.282***	1.276***	1.278***
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Seniority^2			0.994***	0.994***	0.994***	0.994***	0.994***	0.994***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Discontinuity				0.966***	0.972**	0.978*	0.980*	0.978*
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N. of prior applications					2.903***	2.680***	2.659***	2.901***
					(0.17)	(0.15)	(0.15)	(0.18)
University						2.098***	2.089***	1.970***
						(0.14)	(0.14)	(0.13)
Nordic							1.167**	1.149**
							(0.08)	(0.07)
Call FE	No	No	No	No	No	No	No	Yes
Intercept	0.005***	0.001***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of observations	277,464	277,464	277,464	277,464	277,464	277,464	277,464	277,464
Pseudo R-squared	0.0062	0.0680	0.0981	0.0986	0.1237	0.1319	0.1322	0.1534
χ^2	86.23	1,406.37	1,244.93	1,221.42	1,761.63	1,882.67	1,899.36	2,485.58

*** p<.01, ** p<.05, * p<.1

Table 6: Test of H1. Dependent variable: Apply. Logit estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.753***	0.785***	0.782***	0.832**	0.832**	0.832**	1.186
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.42)
ln N. of Q1 pubs	1.308***	1.330***	1.338***	1.356***	1.356***	1.355***	1.355***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
ln N. of Q2 pubs	1.239***	1.221***	1.224***	1.214***	1.214***	1.214***	1.214***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
ln N. of Q3 pubs	1.100***	1.095**	1.107***	1.089**	1.089**	1.089**	1.089**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
ln N. of Q4 pubs	0.846***	0.879***	0.880***	0.903**	0.903**	0.903**	0.903**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
ln N. of unranked pubs	1.368***	1.339***	1.348***	1.304**	1.304**	1.305**	1.303**
	(0.16)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
ln N. of other pubs	0.942	0.933*	0.940*	0.928**	0.928**	0.929**	0.929**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Seniority	1.280***	1.282***	1.276***	1.278***	1.278***	1.278***	1.278***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Seniority # Seniority	0.994***	0.994***	0.994***	0.994***	0.994***	0.994***	0.994***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Discontinuity	0.972**	0.978*	0.980*	0.978*	0.978*	0.978*	0.978*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N. of prior applications	2.983***	2.757***	2.730***	2.697***	2.697***	2.695***	2.696***
	(0.18)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
Sweden R&D Expenditure	0.994***	0.995***	0.995***	0.999**	0.999**	0.999**	0.999**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Budget	1.002***	1.002***	1.002***	1.001	1.001	1.001	1.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
University		2.049***	2.042***	1.974***	1.974***	1.975***	1.975***
		(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)
Nordic			1.160**	1.175**	1.175**	1.175**	1.175**
			(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Masculine Words						0.970	0.985
						(0.04)	(0.04)
Female # Masculine Words							0.909
							(0.08)
Intercept	15132.280***	4029.672***	3576.172***	0.022*	0.022*	0.030	0.027
	(25352.48)	(6727.72)	(5997.32)	(0.05)	(0.05)	(0.07)	(0.06)
Field FE	No	No	No	Yes	Yes	Yes	Yes
Text Controls	No	No	No	No	Yes	Yes	Yes
Number of observations	277,464	277,464	277,464	277,464	277,464	277,464	277,464
Pseudo R-squared	0.1309	0.1385	0.1388	0.1463	0.1463	0.1463	0.1464
χ^2	1,991.98	2,102.78	2,121.40	2,442.06	2,442.06	2,443.87	2,452.06

*** p<.01, ** p<.05, * p<.1

Table 7: Proximity by application and gender.

	PotApps	Applicants	Δ	t	
Total	+0.00	+0.58	+0.58	0.03	***
	Male	**Female**			
Total	+0.07	-0.15	-0.22	0.00	***
Field					
ICT	+0.40	+0.13	-0.27	0.01	***
ENG	+0.21	-0.03	-0.24	0.01	***
PHYS	+0.05	-0.16	-0.20	0.01	***
CHEM	-0.04	-0.19	-0.15	0.00	***
MED	-0.19	-0.25	-0.06	0.00	***
BIO	-0.07	-0.20	-0.13	0.01	***
Call					
AM13	+0.43	+0.45	+0.02	0.03	
BD15	+0.13	-0.29	-0.42	0.02	***
EM11	+0.09	-0.10	-0.19	0.02	***
EM16	+0.03	-0.17	-0.19	0.02	***
GMT14	+0.41	+0.46	+0.05	0.04	
IIS11	+0.35	+0.15	-0.21	0.04	***
IRT11	-0.09	-0.11	-0.02	0.02	
KF10	-0.49	-0.46	+0.03	0.01	***
RB13	-0.23	-0.22	+0.01	0.01	
RBP14	+0.03	-0.02	-0.04	0.04	
RE10	+0.30	+0.04	-0.25	0.03	***
RIT10	+0.42	+0.51	+0.09	0.05	*
RIT15	+0.61	+0.60	-0.01	0.04	
RIT17	+1.16	+1.39	+0.22	0.06	***
RMA11	+0.08	+0.05	-0.03	0.02	
RMA15	+0.26	+0.16	-0.10	0.02	***
RMX18	-0.20	-0.29	-0.09	0.01	***
SB12	-0.24	-0.23	+0.01	0.01	
SB16	-0.18	-0.30	-0.12	0.01	***
SBE13	+0.07	-0.06	-0.13	0.01	***
SE13	+0.64	+0.48	-0.16	0.04	***

*** p<.01, ** p<.05, * p<.1

Table 8: Testing of H2a. Dependent variable: Proximity. OLS estimates.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Female	-0.216 ***	-0.290 ***	-0.288 ***	-0.288 ***	-0.286 ***	-0.277 ***	-0.277 ***	-0.166 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln N. of Q1 pubs		-0.203 ***	-0.244 ***	-0.215 ***	-0.217 ***	-0.219 ***	-0.219 ***	-0.196 ***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln N. of Q2 pubs		-0.043 ***	-0.066 ***	-0.052 ***	-0.055 ***	-0.058 ***	-0.058 ***	-0.067 ***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln N. of Q3 pubs		0.076 ***	0.069 ***	0.077 ***	0.075 ***	0.073 ***	0.073 ***	0.047 ***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln N. of Q4 pubs		-0.023 ***	-0.027 ***	-0.022 ***	-0.020 ***	-0.013 ***	-0.013 ***	0.027 ***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln N. of unranked pubs		0.309 ***	0.293 ***	0.297 ***	0.282 ***	0.279 ***	0.279 ***	0.173 ***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln N. of other pubs		0.008 ***	-0.018 ***	-0.006 **	-0.006 **	-0.008 ***	-0.008 ***	-0.022 ***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Seniority			0.021 ***	0.010 ***	0.009 ***	0.011 ***	0.011 ***	0.014 ***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Seniority²			0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Discontinuity				0.012 ***	0.012 ***	0.013 ***	0.013 ***	0.010 ***
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N. of prior applications					0.271 ***	0.249 ***	0.250 ***	0.158 ***
					(0.01)	(0.01)	(0.01)	(0.01)
University						0.130 ***	0.130 ***	0.064 ***
						(0.00)	(0.00)	(0.00)
Nordic							-0.004	0.034 ***
							(0.00)	(0.00)
(Intercept)	0.070 ***	0.576 ***	0.523 ***	0.495 ***	0.501 ***	0.419 ***	0.421 ***	0.728 ***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Call FE	No	No	No	No	No	No	No	Yes
R^2	0.0103	0.0811	0.0871	0.0879	0.0900	0.0941	0.0941	0.1757
Adj. R^2	0.0103	0.0811	0.0871	0.0879	0.0900	0.0940	0.0940	0.1756

p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N	262,278	262,278	262,278	262,278	262,278	262,278	262,278	262,278

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

Table 9: Testing of H2b-H2c. Dependent variable: Apply.

	(1)	(2)	(3)	(4)	(5)
	H2b	H2b	H2c	H2b	H2c
Link function	**Logit**	**Logit**	**Logit**	**Probit**	**Probit**
Female	0.827 **	0.939	0.986	-0.025	-0.003
	(0.06)	(0.07)	(0.08)	(0.03)	(0.03)
ln N. of Q1 pubs	1.415 ***	1.680 ***	1.679 ***	0.206 ***	0.206 ***
	(0.06)	(0.08)	(0.08)	(0.02)	(0.02)
ln N. of Q2 pubs	1.231 ***	1.345 ***	1.348 ***	0.108 ***	0.109 ***
	(0.05)	(0.06)	(0.06)	(0.02)	(0.02)
ln N. of Q3 pubs	1.088 **	1.046	1.048	0.019	0.020
	(0.04)	(0.04)	(0.04)	(0.01)	(0.01)
ln N. of Q4 pubs	0.893 ***	0.848 ***	0.848 ***	-0.061 ***	-0.061 ***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
ln N. of unranked pubs	1.231 *	1.100	1.098	0.066	0.065
	(0.14)	(0.12)	(0.12)	(0.05)	(0.05)
ln N. of other pubs	0.894 ***	0.912 **	0.913 **	-0.036 **	-0.036 **
	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)
Seniority	1.288 ***	1.290 ***	1.288 ***	0.087 ***	0.087 ***
	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Seniority^2	0.994 ***	0.994 ***	0.994 ***	-0.002 ***	-0.002 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Discontinuity	0.975 **	0.941 ***	0.941 ***	-0.020 ***	-0.020 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N. of prior applications	2.818 ***	2.634 ***	2.632 ***	0.478 ***	0.477 ***
	(0.17)	(0.16)	(0.16)	(0.03)	(0.03)
University	2.004 ***	1.826 ***	1.828 ***	0.212 ***	0.213 ***
	(0.14)	(0.13)	(0.13)	(0.03)	(0.03)
Nordic	1.176 **	1.158 **	1.157 **	0.056 **	0.056 **
	(0.08)	(0.08)	(0.08)	(0.02)	(0.02)
Proximity		2.104 ***	2.148 ***	0.286 ***	0.300 ***
		(0.05)	(0.05)	(0.01)	(0.01)
Proximity * Female			0.895 **		-0.064 ***
			(0.05)		(0.02)
(Intercept)	0.000 ***	0.000 ***	0.000 ***	-4.087 ***	-4.094 ***
	(0.00)	(0.00)	(0.00)	(0.08)	(0.08)
Call FE	Yes	Yes	Yes	Yes	Yes
Null Deviance	15,323.50	15,323.50	15,323.50	15,323.50	15,323.50
Null df	262,277	262,277	262,277	262,277	262,277
Residual Deviance	12,946.39	12,314.32	12,310.65	12,271.21	12,263.48
Residual df	262,244	262,243	262,242	262,243	262,242
χ^2	2,377.11	3,009.18	3,012.86	3,052.30	3,060.02
p-value	0.0000	0.0000	0.0000	0.0000	0.0000
pseudo-R^2	0.1551	0.1964	0.1966	0.1992	0.1997
N	262,278	262,278	262,278	262,278	262,278

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

Table 10: Testing of H2b-H2c. Mediation analysis.

	(1)				(2)			
	Estimate	**95% CI Lower**	**95% CI Upper**	**p-value**	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-value**
ACME (control)	-0.054%	-0.059%	-0.049%	0.000	-0.056%	-0.062%	-0.050%	0.000
ACME (treated)	-0.051%	-0.058%	-0.044%	0.000	-0.042%	-0.051%	-0.033%	0.000
ADE (control)	-0.027%	-0.092%	0.033%	0.415	-0.036%	-0.097%	0.027%	0.306
ADE (treated)	-0.025%	-0.083%	0.030%	0.415	-0.022%	-0.078%	0.036%	0.475
Total Effect	-0.078%	-0.137%	-0.022%	0.008	-0.078%	-0.135%	-0.018%	0.011
Prop. Mediated (control)	68.751%	38.793%	213.729%	0.008	70.800%	40.554%	277.780%	0.011
Prop. Mediated (treated)	65.240%	32.501%	225.765%	0.008	52.860%	25.804%	234.890%	0.011
ACME (average)	-0.052%	-0.058%	-0.047%	0.000	-0.049%	-0.055%	-0.043%	0.000
ADE (average)	-0.026%	-0.088%	0.031%	0.415	-0.029%	-0.089%	0.032%	0.389
Prop. Mediated (average)	66.996%	35.599%	219.734%	0.008	61.830%	33.780%	261.080%	0.011

Figure 1: Funnel plot. Alternative sample of potential applicants.

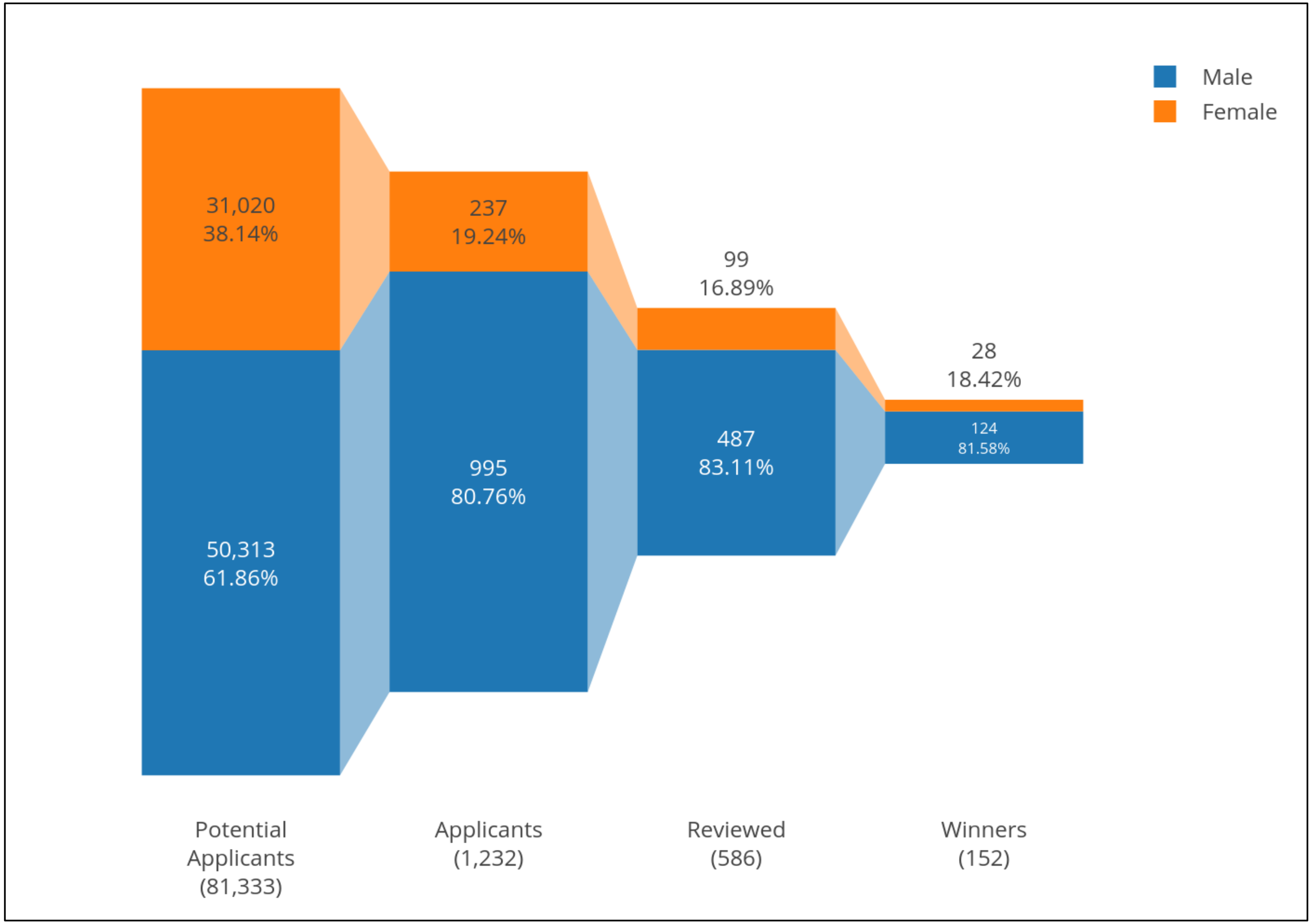

Figure 2. Testing of H2b-H2c. Sensitivity analysis. Alternative sample of potential applicants.