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Training across the academy: The impact of R&D funding on graduate students

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ABSTRACT

This paper measures the impact of external R&D funding on the career trajectory and research productivity of graduate students across the divisions of life sciences, math & physical sciences, engineering, and social sciences & psychology. We contribute to the understanding of the production of science by examining the training regimen for graduate students. We exploit variation between 3,678 awardees and honorable mentions of the U.S. National Science Foundation's Graduate Research Fellowship Program. We find consistent evidence that the award increases degree completion, placement in a post-doctoral or academic research position, research productivity and impact, and network size. We further explore the role of the graduate advisor in this training process and find the award does not disrupt the apprenticeship model, but instead, increases the student's interaction with their advisor.

"It was a wonderful experience being given the award and it made my first few years of grad school incredibly easier, both because of the funding and because of the extra time that I had to focus on developing my research interests and not on being a teaching assistant." – *National Science Foundation Graduate Research Fellow*

"I met young scientists and faculty from Harvard, Johns Hopkins, and literally all over the U.S. It expanded my knowledge and contact base, my suite of techniques, and my confidence." – *National Science Foundation Graduate Research Fellow*

1. Introduction

Graduate students within the fields of science and engineering (S&E) provide a critical source of human capital for research production at higher education institutions. Since 2015, the National Center for Science and Engineering Statistics (NCSES) reports that, on average, 670,000 students are enrolled annually in S&E graduate programs across the U.S. alone. These graduate programs emulate an apprenticeship model that actively integrates students into the knowledge production process (Latour & Woolgar, 2013; Stephan, 2012; Carayol & Matt, 2004). Students are often part of faculty-led labs and collaborative teams as they develop their research and teaching skills (Conti & Liu, 2015; Bozeman & Corley, 2004). This training defines a formative stage for students that shapes opportunities for their subsequent professional trajectory within S&E-related industries (Pezzoni et al., 2012). Despite the standard structure of this training model, relatively little research examines this early career stage (Graddy-Reed et al., 2018; Shibayama, 2019).

To address this limitation, we leverage research and development (R&D) funding to examine graduate training. Funding is a major component for scientific activity across all ranks. This spans from graduate students, post-doctoral fellows, faculty, and senior research personnel. R&D funding increases access to resources and thereby grants greater flexibility to manage and advance research portfolios (Stephan, 2012). The U.S. federal government leads in R&D funding for basic research ($21.9 billion in 2015); this accounts for 53 percent of higher education basic research.[1] The public sector generally allocates these funds in a competitive, merit-based manner, which not only provides tangible financial resources to conduct research but can also provide

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[1] Retrieved January 22, 2020 from Table 4-3 https://www.nsf.gov/statistics/2018/nsb20181/assets/nsb20181.pdf.

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intangible signals of prestige and reputational benefits (Azoulay, Stuart, & Wang, 2014).

However, the treatment effect of R&D allocation for graduate students is arguably different compared to senior scholars. Most prior work examines the impact of R&D funding among faculty and star researchers (Jacob & Lefgren, 2011a; Azoulay et al., 2011; Arora & Gambardella, 2005; Hemmatian & Barden, 2018) and even post-doctoral fellows (Jacob & Lefgren, 2011b) – all of whom are in later career stages. Generally, there is evidence of a nominal impact on measures of research productivity whereby the funding provides resource and signaling benefits. However, for graduate students, access to competitive extramural funding affects their training regimen as well. This setting is understudied in the literature; yet it has important implications on our understanding of the production of science. On one hand, it may enhance their graduate training by granting the student greater flexibility and independence to establish their research identity. On the other hand, graduate students have yet to develop and hone their research skills. In turn, the R&D funding – and independence that comes with it – may disrupt the standard training model that is designed to develop these foundational skills.

Graduate students are not only part of the knowledge economy, but also train to hold positions of leadership in S&E-related industries at later career stages (Zolas et al., 2015). It is insufficient to extrapolate from prior studies that examine the role of public R&D funding on senior scholars. As future leaders, it is essential to understand the role of R&D funding on the students' training and professional development. This is the central focus of our study.

We trace the professional trajectories of 3,678 scientists and engineers over a standardized 16-year timeframe – spanning the years leading to their graduate school matriculation, graduate training, and first professional placement. The U.S. National Science Foundation (NSF) Graduate Research Fellowship Program (GRFP), serving as the largest graduate R&D program, provides the context for this study. We use qualitative data from a survey of GRFP awardees and honorable mentions to validate this setting. For the empirical analysis, we estimate the innovation production function (e.g. Adams & Griliches, 2000). This measures the impact of public funding for early-career researchers across a range of outcomes including degree completion, career placement, and research productivity. For productivity, we consider the quantity and impact of research publications and draw upon bibliometric measures to estimate the student's network. Moreover, unique to this setting, we assess how the external funding affects graduate training in terms of the student's research independence and their relationship with their advisor.

To construct this individual-level panel dataset, we employ a multi-step matched sampling approach to improve identification and exploit funding variation around the GRFP award cutoff. We begin with the complete set of competitive awardees and honorable mentions from 1995 to 2005. Awardees receive funding while honorable mentions are acknowledged as meritorious without funding. Given the dearth of extramural funding at the pre-candidacy stage (Graddy-Reed et al., 2018),[2] honorable mention recipients generally follow the more standard training model and are supported instead by research and teaching assistantships. We coarsen the sample along an extensive set of observable characteristics to ensure awardees and honorable mentions are comparable at the baseline prior to GRFP acknowledgement. Altogether, these efforts enable us to approximate causal effects. Moreover, while prior research has focused on a single discipline or field, we examine a sample of students from all four S&E divisions – engineering, life sciences, math & physical sciences, and social sciences & psychology.

We first estimate a series of logistic regressions to examine the impact of the award on a student's likelihood of completing their PhD and the type of position they first receive post-graduation. Regarding degree completion, our results indicate that receiving an award increases the probability of completing their PhD by 2.5 percentage points, on average. Regarding first placement post-graduation, receiving an award increases the probability of taking a post-doctoral fellowship by 5.7 percentage points yet has no statistically significant impact on a tenure-track position. More generally, it positively affects the probability of taking an academic research position by 4.3 percentage points, on average.

We then turn to research productivity. We estimate a series of fixed effects models on outcomes related to peer-reviewed publications, citations, and co-author networks. We further explore these results by looking at a sub-sample of students for whom their advisor has both awardees and honorable mentions. We consistently find evidence that receiving the award increases publications, citations, and co-author network size. However, we find the award has more muted impact for top performers; yet it still boosts their subsequent citations. In addition, the award also increases the probability that a student co-authors with their advisor; this offers important insight on graduate training effects.

Together, our results examining a prominent early career S&E fellowship report that R&D funding positively, but modestly, affects student outcomes. Further, we find that such funding does not disrupt the apprenticeship model. Instead, the fellowship increases interaction with one's advisor.

2. Theoretical framing

The public sector provides a significant level of R&D funding under the premise that scientific research activity has inherent public good characteristics that bolster innovation (Arrow, 1963; Nelson, 1959) and offer knowledge spillovers (Audretsch & Feldman, 1996; Feldman & Kelley, 2006). However, much of the cumulative extant literature on this topic has examined its impact among more senior scholars, overlooking graduate student achievements.

In brief, Jacob and Lefgren (2011a) examine 20 years of proposal activity for standard U.S. National Institutes of Health (NIH) R01 research grants and find the award is associated with an increase of 1.2 publications over a five-year period. This is equivalent to a seven percent increase in research production. Azoulay et al. (2011) follow senior investigators of the Howard Hughes Medical Institute and find the source of funding influences the nature of the scientific activity with funding financed by foundations producing higher impact than by federal sources. Within chemistry, Rosenbloom et al. (2015) document a robust positive return of R&D investment on knowledge production. Turning to engineering, Goldfarb (2008) examines the effect of government contracting and finds evidence that maintaining a relationship with the grant officer diminished the senior researcher's productivity by 25 percent. Within the social sciences, Arora and Gambardella (2005) find a modest positive effect for R&D investment in the field of economics. However, they argue the research would have been conducted regardless of the funding outcome. The breadth of these findings from these studies prompts the question of whether – and in what context – public R&D is allocated optimally.

Only recently has attention turned to graduate students. Graddy-Reed et al. (2018) find students in the life sciences produce an additional two-thirds of a publication ten years following the NSF GRFP award. Moreover, students without prior publication activity drive the main effect. In another study, Graddy-Reed et al. (2019) find evidence that R&D grants yielded differential research outcomes for graduate students by gender with men reporting a positive effect from the award and women showing no evidence of an effect. Both of these studies indicate that R&D funding affects graduate students' research productivity; however, they do not provide sufficient insight into how the R&D funding may influence graduate training more broadly. A broader lens should extend beyond standard metrics of research production to

[2] Among their sample of 562 graduate students, only one secured other competitive extramural funding from NIH.

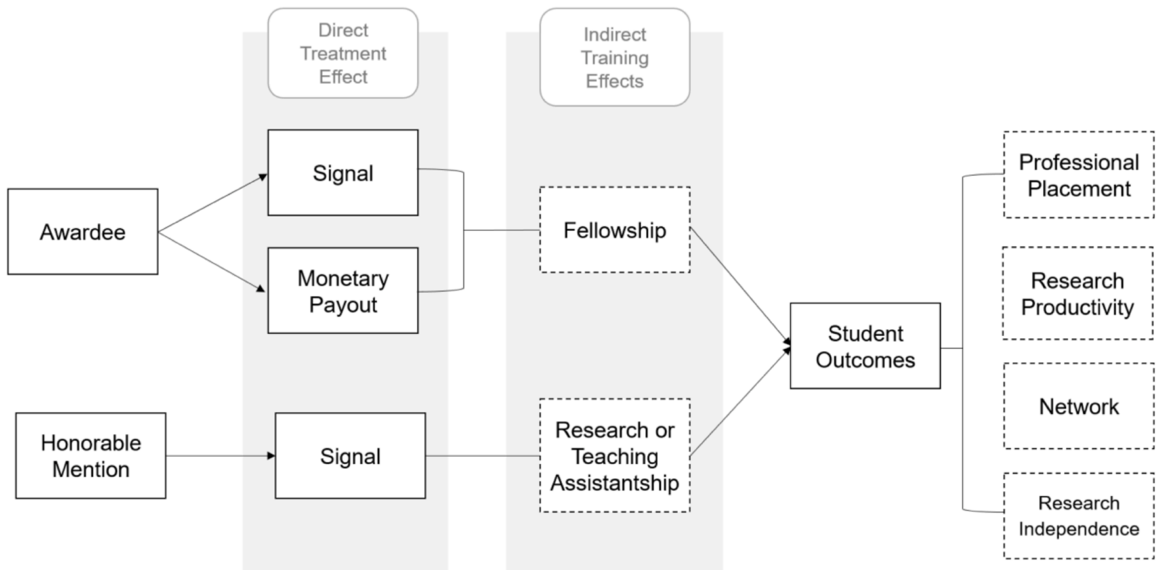

Fig. 1. Treatment Effects of External R&D Funding for Graduate Students.

include degree completion, initial placement, research output in terms of both quantity and impact, collaborations with their advisor, and network development.

From one angle, competitive extramural funding may enhance the student's professional trajectory. Tangibly, the funding provides resources for the student to conduct independent research. This offers reprieve from research and teaching assistantship responsibilities that are common with the standard graduate training model. In 2018, the U. S. Survey of Earned Doctorates reports that the majority of S&E graduate students finance their training with these assistantship positions with 36 percent hired as research assistants and 21 percent hired as teaching assistants.[3] These responsibilities often require considerable time commitments that can detract from time devoted to developing the students' research program.

By design, the external grant relieves constraints from assistantships and is intended to support students as they build a research identity. Here, students have greater independence and flexibility to execute their research program. This can allow research exploration in high-risk and even interdisciplinary topics that may lead to more transformative scientific contributions. Moreover, students have resources to attend workshops and conferences to acquire additional skills and build their professional network. Research autonomy and exploration are essential components of academic training and are tied to longer-term performance outcomes (Shibayama, 2019; Conti & Visentin, 2015).

Within the physical and biological sciences, students join a lab for the duration of their training (Conti & Liu, 2015; Agarwal et al., 2017). Generally, the leading faculty member devotes considerable time to securing funds to support research continuity for their members (Owen-Smith, 2001). If the student secures their own extramural funding, this may relieve some grant-writing pressures for the faculty. In turn, the faculty may have more time to devote to research with their lab members rather than "chase" the next grant. This may offer an opportunity for greater research synergy between the faculty advisor and their student.

Beyond these tangible benefits, extramural funding may also provide intangible opportunities for the student. Securing competitive funding – especially from a credible funding institution – may yield a level of prestige and reputation (Partha & David, 1994). At this early-career stage, external validation in their research project may not only instill confidence for the student, but also signal research potential to their larger community of scholars. This may present opportunities for the student to build a broader research network, which is an essential component for collaborative research activity. Across all S&E fields, team-based science has become an increasingly prominent feature of research production (Wuchty et al., 2007). Altogether, these factors suggest that external funding enhances the students' graduate training experience and professional opportunities.

From another contrasting angle, the R&D grant may induce tradeoffs that negatively affect their training and professional trajectory. While the extramural resources are designed to grant the recipient independence, the fellowship can disrupt the standard training model. Blume-Kohout and Adhikari (2016) find that the training model – comparing research assistant positions versus fellowships – affects professional placement options. With a focus on biomedical sciences, they find that the former more likely leads to a research-oriented career given that research assistant positions are more emblematic of apprenticeship models. The assistantship position defines a close relationship between the student and their faculty mentor; this provides an opportunity to acculturate collaborative research practices for early career scientists. Fellowships, on the other hand, can crowd out these mentorship opportunities. Among fields with stronger norms of research collaboration, this can isolate recipients from research groups (Mendoza et al., 2014).

While the more standard research and teaching assistantship positions demand considerable time commitments, they are designed to help students develop fundamental skills. Research assistantship positions often place the student on their advisor's research project exposing them to various tasks including conducting literature reviews, building datasets, analyzing results, and drafting manuscripts. These skills are foundational for subsequent research-oriented positions. At this early stage, graduate students likely have yet to receive adequate training to lead a project across these myriad tasks. Research independence – without sufficient training and mentorship – may compromise the quality of the student's output.

It is important to reiterate that the nature of S&E research has become increasingly collaborative (Wuchty et al., 2007). Students often establish their initial network with their graduate advisor (Bozeman & Corley, 2004). If the graduate student pursues an independent project, this may affect the socialization and research collaboration process that begins at this early stage. Broström (2019) finds that changes to collaboration dynamics can disproportionately hinder productivity for

[3] Source: National Center for Science and Engineering Statistics, 2018 Survey of Earned Doctorates (Table 35)

early career scientists as team size increases. Moreover, this effect likely varies across academic disciplines where the level of collaboration varies. This may be especially counter-effective for lab-based disciplines that are more prevalent among biological sciences, physical sciences, and engineering, which together account for a large share of the S&E graduate student population.[4] Extramural funding may present a hurdle if it isolates the student from research networks that have access to shared facilities available through their advisor's lab. With that said, costs related to the socialization process may be less within social sciences. These fields often require smaller teams or are completely independent; and the resource demands for infrastructure and equipment are significantly less[5]. In sum, while prior studies find extramural funding benefits the scientists and engineers at later career stages, it is worth questioning whether this funding model and the impact it has on graduate training is optimal at the early career stage when the student has a more limited set of research skills.

2.1. Treatment effect

Fig. 1 provides an illustration of the treatment effects for our setting centered on graduate students. The first column – Direct Treatment Effect – generally aligns with prior studies that examine the effect of R&D funding for senior scholars. Receipt of the external funds provides tangible monetary resources. Moreover, the competitive selection yields a signal of prestige and reputational benefits for awardees. However, unique to our setting, even acknowledgement of an honorable mention may yield reputational benefits for students. Here, the status effect for honorable mentions contrasts to settings with senior scholars. Studies have found that individuals at later career stages are more reticent to divulge their status as a runner-up and thus do not gain reputational benefits (Azoulay, Graff Zivin & Manso, 2011; Cohen et al., 2019; Kerr, Lerner & Schoar, 2014).

The second column – Indirect Training Effects – highlights further unique features for graduate students; specifically, how external R&D funding affects the students' training regimen. Award recipients pursue a fellowship, while honorable mentions are more likely to follow the standard apprenticeship model as a research or teaching assistant. From one angle, external funding is designed to accelerate the student's training and research productivity. However, from another angle, there remains a concern that this resource disrupts the apprenticeship model that offers foundational skills needed for this profession. We set up an empirical analysis to examine the impact of funding and subsequent training models on student outcomes and research productivity.

3. Empirical context

The NSF GRFP provides the context for this study. The competitive program awards three years of support for graduate training – the costs include an annual stipend ($34,000) and educational allowance paid to the graduate institution ($12,000). The full allocation of the award in 2021 was $138,000.[6] In this section, we discuss the benefits of the program structure for constructing a robust research design and then report qualitative evidence to validate this context. We review each in turn.

3.1. Program structure

The eligibility requirements for this program allow us to set up valid identification for the quantitative analysis. First, we focus on early-stage graduate students rather than selecting scientists and engineers at a later professional stage. Regarding the latter, although there are more observables to proxy for ability, there is evidence of large-scale research differentials among senior researchers (Azoulay et al., 2010). This poses empirical challenges in terms of accounting for unobserved endogeneity related to individual research potential. Contrastingly, even though graduate students have fewer observable measures, they have a less developed skill set. We posit the research differential is smaller at this earlier professional stage.

Second, there is less material to review given the GRFP proposal requirements; this feature likely increases uncertainty in the allocation of the GRFP award. This stands in contrast to the majority of NSF programs. To elaborate, students with less than 12-months of graduate training are eligible to apply as Principal Investigator (PI) for GRFP funding. Given that this applicant base has limited research experience, the solicitation requires the following: (i) two-page research statement; (ii) three-page personal statement; (iii) three to five reference letters; and (iv) higher education academic transcripts. Rather than providing a 15-page project description, which is standard at NSF, the abbreviated format of the proposal and early-career stage of the applicant increases the level of uncertainty in selecting awardees. Moreover, NSF requests that senior scholars identify applicants with "demonstrated potential for significant research achievements in STEM."[7] At this stage of the review process, panelists explicitly distinguish the top 20 percent that are meritorious from the rest. Among this set, NSF then convenes panels to sort the competitive proposals into awardees and honorable mentions (Freeman et al., 2009).

Third, while NSF restricts public access of application data (to protect the status of non-awardees), this graduate training program provides the exception. Specifically, NSF annually publicizes the complete list of awardees and honorable mentions. Although awardees receive the R&D allocation, NSF acknowledges honorable mentions as attaining a "significant national academic achievement."[8] We draw upon the list of GRFP award recipients and honorable mentions across both a range of S&E fields and U.S. research institutions not only to identify early-career scientists and engineers with research potential, but also to exploit variation in R&D funding allocation. This serves as the baseline for the research design.

3.2. Survey

To inform our theoretical framework, we surveyed a random sample of GRFP awardees, honorable mentions, and their advisors (Appendix A). Here, we draw from their responses to an open-ended question about their experience with the program. We use this data for exploratory purposes to validate the conceptualization of the treatment effect as presented in Fig. 1, which we then test with our quantitative analysis detailed in Section 5.

Their recollection confirms both the benefits and tradeoffs to the program identified above in terms of graduate training with implications on the students' placement, research output, and overall career outcomes. This evidence further bolsters our claims that the indirect training effects in this setting are unique to prior scholarship focused prominently on senior researchers. Notably, this setting offers important insights on the production of science for early career researchers.

Regarding benefits, some awardees confirmed the award empowered them to build their own research identity. For example, one awardee noted,

[4] Retrieved April 6, 2020: https://www.nsf.gov/statistics/2017/nsf17306/static/report/nsf17306.pdf

[5] Retrieved January 22, 2020: http://www.nsf.gov/statistics/nsf10305/.

[6] Retrieved February 18, 2021 from GRFP Program Solicitation, NSF 20-587

[7] Retrieved April 6, 2020 from https://www.nsf.gov/pubs/2016/nsf16588/nsf16588.htm

[8] Retrieved April 6, 2020 on Page 7: https://www.nsf.gov/pubs/2016/nsf16588/nsf16588.pdf

> "The GRFP award was key in allowing me to choose my own research directions in grad school, which allowed me to spend a lot of time working on developing a large model of my own." – *Awardee A*

With less time constraints, the student was able to devote necessary effort towards investigating and developing their research niche. The GRFP award also provided the student flexibility to explore diverse research interests. Another awardee stated,

> "Being a recipient of the GRFP award was extremely helpful to my professional development during graduate school and also afforded me the flexibility to pursue dynamic interdisciplinary research interests." – *Awardee B*

Such external funding prevents students from feeling constrained to a specific research area, allowing them to work across disciplines that are beyond their specific field of study. Additionally, the benefits to a student's research identity are not limited to awardees. An honorable mention commented:

> "Applying for the program helped me to clarify my research interests and receiving the honorable mention helped increase my confidence in my ideas." – *Honorable Mention A*

This suggests the act of submitting a research proposal as well as receiving the signal as a distinguished scholar from NSF can enhance a student's research career even without corresponding funding.

In addition, receiving the GRFP increases access to workshops and conferences that enhance a student's network. Drawing from one of the initial illustrative quotes in the Introduction, one awardee commented,

> "I met young scientists and faculty from Harvard, Johns Hopkins, and literally all over the U.S. It expanded my knowledge and contact base, my suite of techniques, and my confidence." – *Awardee C*

Moreover, awardees found the grant enhanced their research identity, collaboration efforts, as well as their career outcome. One stated,

> "The GRFP allowed me to conduct higher-risk higher-reward research as part of my doctoral studies. Our work was ultimately successful. The fellowship certainly helped me secure my present faculty position." – *Awardee D*

While another awardee wrote,

> "[The GRFP] increased my success as a graduate student and likely improved my ability to get [a] postdoctoral position and funding after that." – *Awardee E*

The award has the potential to improve placement and increase access to follow-on funding; this is likely a benefit caused by the signal of the award and subsequent research production.

The benefits of the award are not only recognized by graduate students, but also by their advisors. Advisors acknowledge the effect of the award on student productivity. One advisor stated,

> "[I] have had students supported by NSF fellowships – I have no doubt that this support (vs. for example TAships) increased their research/publication rates" – *Advisor A*

Further, the award's benefits may extend beyond the student by supporting new research trajectories for the advisor as well. Another advisor added,

> "A student in my lab was awarded the GRFP and it is a hugely productive opportunity to branch out my research in a new direction" – *Advisor B*

This suggests that the fellowship cultivates a productive research-oriented relationship between the student and their mentor.

While the GRFP appears to provide several benefits that contribute to a student's future success, survey respondents also commented on tradeoffs – albeit to a lesser extent than perceived benefits. Among survey respondents, 63 percent commented on benefits from the program; 31 percent were neutral; and 7 percent discussed tradeoffs. Recipients of both distinctions – awardee and honorable mention – detail some of the costs of their experience with the GRFP concerning their training and career prospects. By design, the award incentivizes students to pursue independent research at the possible expense of training via assistantship positions. An awardee expressed this limitation stating,

> "My department was not supportive of my proposal. There was no peer support or networking among the awardees so it felt isolating." – *Awardee F*

Without standard training support, a student may be placed in a leadership role before they have the tools to succeed. Furthermore, the GRFP has the potential to limit students' motivation to seek additional R&D funding. The extended duration of the award may result in complacency. An honorable mention recipient warned of this tradeoff,

> "I am really glad I did NOT get a GRFP (and only an Honorable Mention) as it forced me to raise all of my own funding through other means which resulted in me being an independent entrepreneur and highly successful." – *Honorable Mention B*

The monetary value of the award is substantial, but it is not enough to aid in the generation of research beyond graduate training. Lastly, the signal of an honorable mention is not necessarily beneficial. One recipient's response highlighted indifference,

> "As an honorable mention, the program did not impact me much, other than the time consumed in the application process." – *Honorable Mention C*

While receiving an honorable mention is an anticipated career benefit by enhancing reputation and prestige, it may be negligible given the effort demanded by the application process. Taken together, these costs demonstrate the benefits of the program are not universally perceived.

These survey responses illustrate how public R&D funding may influence graduate training in terms of research independence, mentorship, access to networks, and placement. Moreover, both awardees and honorable mentions recount benefits and costs to their distinction. In the subsequent sections, we examine whether these outcomes are more systematic through quantitative analysis of a larger, representative sample.

4. Data and sample

4.1. Initial sample construction

We scraped GRFP records for the population of awardees and honorable mentions between 1995 and 2005.[9] We then augmented the records accordingly: (i) identifying the gender of the applicant based on trends of U.S. birth records from 1965-1980; (ii) identifying the unique Integrated Postsecondary Education Data System (IPEDS) number for the set of institutions (baccalaureate and graduate); and (iii) classifying the field of graduate study following the National Research Council's (NRC) taxonomy of doctoral programs.[10] Moreover, we removed applicants with common last names – notably, those with more than five

[9] In 1995, the program began reporting the complete list of honorable mentions. NSF does not disclose detail on the complete list of applicants; NSF only publicizes the honorable mentions. For each proposal, NSF reports the following: applicant name, baccalaureate institution, field of study, proposed and current institution, award year, and award type.

[10] Retrieved April 6, 2020 from http://sites.nationalacademies.org/PGA/Resdoc/PGA_044521

occurrences. This follows prior work to reduce false positives and eases the process of identifying the correct individual across third party sources (Jacob & Lefgren 2011a; Graddy-Reed et al., 2018). Altogether, we constructed an initial sample of 14,466 applicants.[11]

We then employed an initial coarsened exact matching (CEM) approach to define the sample. Among the set of awardees, we identified up to two honorable mentions per awardee that directly matched along all of the following variables: (i) gender of applicant; (ii) type of baccalaureate institution (drawing from the Carnegie university classifications: e.g. liberal arts, very high research institution); (iii) graduate institution *and* academic field (i.e. Chemistry department at Stanford); and (iv) year of GRFP acknowledgement (1995 – 2005). Importantly, this direct match sampling approach controls for the graduate training environment yet varies by external R&D allocation. To enhance this sample, we also relaxed the GRFP award year and matched either one year before or after the awardee's acknowledgment. We provide further detail in Appendix B. Altogether, this sampling approach yielded an initial sample of 5,340 students – 2,681 awardees and 2,659 honorable mentions.

For this sample of 5,340 students, we gathered additional data from a series of third-party sources to trace graduate training activity, professional placement, and research production. First, we incorporated data from Proquest, the largest central repository of dissertations and theses. This provided detail on the student's degree conferment (including year), advisor, committee, and graduate institution for 4,040 students (75.7 percent). Second, we conducted systematic online searches to identify and classify the student's first professional placement following degree completion (including start and graduation year). We gathered data for 4,273 students (92.9 percent). Third, we pulled complete reference detail for 90,908 unique publications for 4,005 students (75 percent) from Scopus, the largest collection of bibliometric data. Fourth, we pulled additional institutional detail from the National Research Council's (NRC) 2010 Survey of Doctoral Programs (Ostriker, 2015), the NSF Higher Education Research and Development (HERD) survey, and IPEDS. We matched 4,907 students (92 percent) to NRC, 5,205 students (97.5 percent) to HERD, and 4,897 students (91.7 percent) to IPEDS. We triangulated and validated the data across the various sources to further increase the overall match rate for each metric. This approach yields higher response rates in contrast to standard survey designs (Clarke et al., 2008). This mirrors concurrent efforts to triangulate data sources among doctoral recipients (Chang et al., 2019).

We construct a longitudinal panel tracing each student over a standardized 16-year timeframe – defined by the five years leading up to the GRFP proposal submission ($-5 \leq t \leq -1$), the GRFP "treatment" year ($t = 0$), and the ten years following ($1 \leq t \leq 10$). We intentionally extend the post period to account for the notable time lag that is characteristic of the publication process (Powell, 2016). Appendix B details these sampling and data construction efforts.

4.2. Variables

We include a range of dependent variables to trace the graduate student's training performance. First, we examine *Degree Completion* as measured by a binary variable. We confirm this outcome with detail from Proquest and online searches. Second, we measure the student's first placement following their graduate training. Given the nature of the empirical setting, we account for placement in a series of prominent research-oriented positions. These include the following: (i) *Research Position*; (ii) *Post-Doctoral Position*; (iii) *Academic Research Position*; and (iv) and *Academic Tenure Track Position*. The first placement indicator includes the broadest categorization of positions with a research focus; this spans both academic and non-academic contexts. The second indicator more narrowly includes post-doctoral positions and research fellowships across both academic and non-academic contexts. We narrow the institutional context for the third and fourth placement indicators to academic-based positions. *Academic Research Positions* includes a broader set of research-oriented positions within higher education institutions, while *Academic Tenure Track Positions* strictly trace research faculty positions. The referent group for each of these indicators is the remaining sample.

As a third set of dependent variables, we include a series of research productivity measures that we derive from Scopus bibliometric records.[12] First, we estimate *Cumulative Publications – weighted by author* to measure the quantity of research activity. We track the cumulative count of peer-reviewed articles over the 16-year panel for each student to compute the numerator. We then divide by the count of total authors for the corresponding set of publications. This follows prior scholarship tracing research productivity as a cumulative rather than annual metric (Jacob & Lefgren, 2011a; Jacob and Lefgren, 2011b; Azoulay et al., 2010). We weight by the number of authors to account for disciplinary differences in collaboration practices and publishing across our sample. Second, we estimate *Cumulative Citations – weighted by publications* to measure the impact of research activity. We designate a standard post-publication time span by relying on the total five-year forward citation count among the cumulative set of peer-reviewed articles.

Third, we include a metric of the student's *Cumulative Co-Author Network*. Specifically, we compute the student's collaborative network based on the unique set of co-authors over the 16-year panel. Here, we account for co-authors across research publications – that includes peer-reviewed articles along with books, conference proceedings, and chapters – to estimate the size of their professional research network. We normalize the metric by computing the natural log.

Award receipt of the GRFP serves as the key explanatory variable in this study. Operationally, we draw upon variation in external R&D allocation (awardees vs. honorable mention) over time (pre vs. post GRFP conferment). We are interested in the interaction – *Award * Post* – that estimates the impact of GRFP allocation on the range of student outcomes. These students receive both national recognition with the award and external R&D funding for three years of their graduate training. This waives them of research or teaching assistantship responsibilities during this time. We assume honorable mentions secure assistantship positions in lieu of the fellowship. Not only is this the most prominent and standard training model for S&E graduate training, we confirm this structure from our survey responses of awardees, honorable mentions, and their advisors. Moreover, we base this on the assumption that there is a dearth of funding opportunities for graduate students at this early training stage (Graddy-Reed et al., 2018). We remove students that receive both honorable mention status in one year and award recognition in a subsequent year to ensure a clear cutoff between these two groups.

4.3. Identification

Despite our initial matching efforts, discrepancies remain between awardees and honorable mentions prior to receipt of the GRFP. Appendix Table C1 reports key statistics for the sample. Specifically, 15 percent of awardees have publications prior to the GRFP acknowledgment compared to 12 percent of honorable mentions. Regarding the level of publication activity, awardees have an average of 0.20 of a prior publication compared to 0.17 for honorable mentions. Together, this reflects a growing trend of students producing publications pre-PhD (Waaijer et al., 2016). Honorable mentions are also more likely to

[11] 25,317 awardees and honorable mentions applied between 1995 and 2005. 23,660 provided complete information in the NSF GRFP database. We removed 6,467 due to common names, 734 due to duplicate records, and 1,993 with incomplete data from the additional data gathering effort.

[12] For research productivity measures, we examine alternative functional forms as extensions (Appendix Table C3).

attend a public institution – both for their baccalaureate and graduate training. The relative comparability for most measures across the two groups is reflective of the initial matching efforts in the sample selection process (Appendix B); however, there remain differences.

To address these differences, we coarsen the data again using a more extensive set of variables gained from our third-party data collection efforts detailed in Section 4.1. To improve balance along observables in the pre-period (Blackwell et al., 2009; Iacus et al. 2012), we use variables related to graduate student productivity (Graddy-Reed et al., 2017). Specifically, we directly match on the year of GRFP application, any prior publications, field, graduate institution type, baccalaureate institution type, the student's gender, and the gender of the student's advisor. We use the CEM procedure to construct strata of observations with statistically indistinguishable values between the two groups. This reduces the sample to 3,764 students (70.5 percent of our initial sample). We present detail on this second coarsening procedure in Appendix B (Improved Matching).

As a final step of the sample construction, we remove extreme outliers to avoid estimation of spurious results. We remove student observations that exceed three standard deviations above their division mean for the following measures: prior publication count, total publications, unique co-authors, and total authors of publications. This reduced the sample by 157 students. We use the CEM sample of 3,678 students for the empirical models.

As a diagnostic assessment of this balance check, we report trend lines of the three productivity-based dependent variables for the CEM sample. Fig. 2 reports the annual average count of cumulative publications; Fig. 3 reports the annual average count of cumulative 5-year forward citations; and Fig. 4 reports the annual count of cumulative unique co-authors. In all figures, we present the trends between awardees (yellow) and honorable mentions (black). We label the standardized 16-year timeframe on the x-axis to reflect the five years leading up to the GRFP event (t=0) and the 10 years following. For all three figures, the pre-trends exhibit strong, relatively flat, parallel trends. At the cost of reducing the sample size, the second coarsening procedure further improves balance between the awardees and honorable mentions.

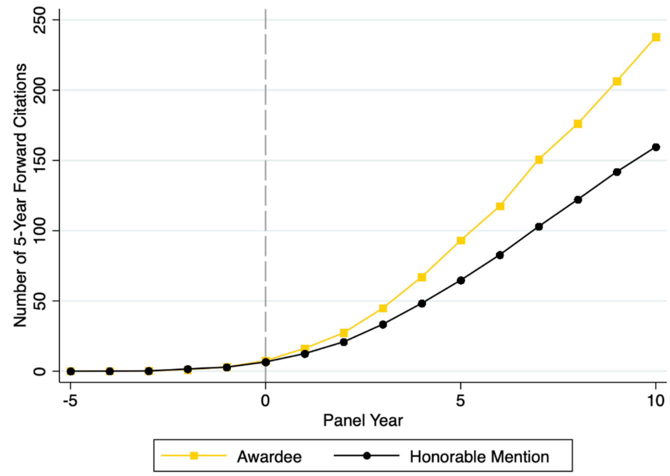

Fig. 3. Annual Average Cumulative Count of 5-Year Forward Citations.

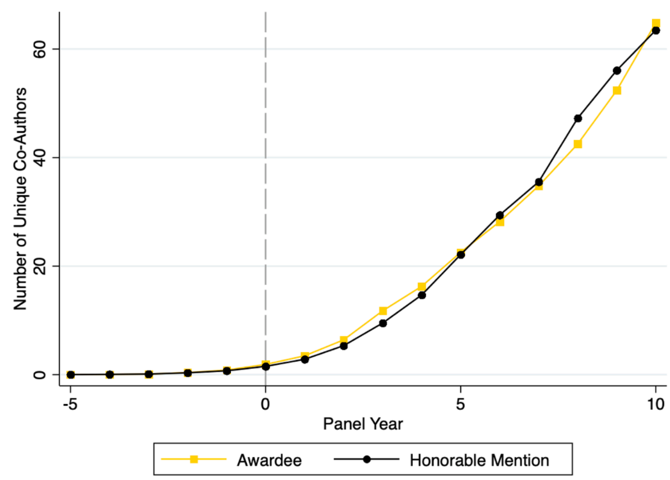

Fig. 4. Annual Average Count of Co-Author Network.

4.4. Descriptive statistics

Table 1 reports the descriptive statistics for the CEM sample, stratified by award status. Regarding career trajectory, the majority of students across award status complete their degree (85 percent). Moreover, they place in a research-active position (86 percent) following graduate training with a large share remaining in academic institutions (58 percent). Awardees are more likely to stay in academia, specifically in a research position. Similarly, awardees are more likely to place first in a post-doctoral fellowship, while there is no difference in tenure-track initial placements.

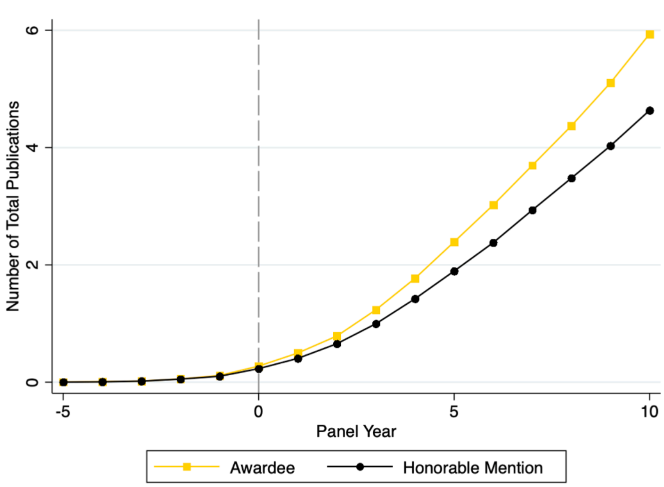

Fig. 2. Annual Average Cumulative Count of Peer-Reviewed Publications.

With respect to productivity, overall, 75 percent of the sample publishes at least once over their 16-year timeframe with an average of 5.29 publications in total. While awardees and honorable mentions report comparable publishing rates prior to GRFP conferment, awardees demonstrate higher rates of publication over the extended panel for a difference of approximately 1.3 additional publications. At the extremes, awardees are also more likely to be top-publishers with 12 percent of awardees in the top ten percent compared to seven percent of honorable mentions.

Regarding impact, the overall sample averages nearly 200 citations over the panel yet the rate for awardees exceed honorable mentions significantly with approximately 238 citations compared to 160 for honorable mentions. These trends hold when we weight by publication count as well; awardees exceed honorable mentions by roughly 3.7 additional citations per publication.

As for networks, the students have approximately 64 unique co-authors over the 16-year panel. Of note, the standard deviations are extremely large due to variation in co-authorship practices across fields even after removing outliers; thus, we adjust the functional form to the natural logarithm for the empirical estimations. Finally, awardees also appear to be more likely to publish with their advisors for a longer period, yet the ratio of joint publications to total is larger for honorable

Table 1
Descriptive Statistics by Award Status.

	(1) CEM Sample	(2) Awardees	(3) Honorable Mentions	(4) Diff. SS
Ever Publish in 16-Year Timeframe	0.75	0.79	0.72	***
Any Publications Prior to GRFP	0.07	0.08	0.07	
Total Number of Publications (0 - 58)	5.29	5.94	4.63	***
	(6.56)	(7.04)	(5.97)	
Student PI in Top 10% of Division of Total Publications	0.1	0.12	0.07	***
Total Number of Author-Weighted Publications (0 - 2)	0.26	0.27	0.25	**
	(0.20)	(0.20)	(0.20)	
Total Number of Unique Co-Authors (0 - 30,452)	64.14	64.81	63.47	
	(652.37)	(535.34)	(751.25)	
Total Number of Research Outputs (0 - 112)	7.51	8.36	6.66	***
	(9.23)	(9.63)	(8.74)	
Ever Publish with Advisor	0.57	0.59	0.55	***
Ratio of Publications with Advisor to Total (0 - 1)	0.46	0.45	0.48	**
	(0.37)	(0.36)	(0.37)	
Number of Panel Years Co-Authoring with Advisor (0 - 11)	2.83	2.95	2.71	**
	(2.47)	(2.51)	(2.43)	
Total Number of 5-Year Forward Citations (0 - 7,605)	198.7	237.91	159.62	***
	(430.46)	(512.46)	(324.45)	
Publication-Weighted Total 5-Year Forward Citations (0 - 691.36)	32.33	34.09	30.4	**
	(42.91)	(46.41)	(38.63)	
Division				
Engineering	0.3	0.3	0.31	
Life Sciences	0.16	0.16	0.17	
Math & Physical Sciences	0.31	0.32	0.31	
Social Sciences & Psychology	0.22	0.22	0.22	
Female Student PI	0.34	0.35	0.33	
Advisors with Multiple Students in Sample	0.47	0.49	0.44	***
Completed a PhD	0.85	0.87	0.82	***
First Job Placement Position Type (3,213 obs.)				
Research-related	0.86	0.86	0.87	
Post-Doctoral Fellow	0.44	0.47	0.41	***
Academic Institution	0.58	0.61	0.54	***
Academic Research	0.51	0.54	0.48	***
Tenure-Track Faculty	0.11	0.11	0.11	
Observations	3,678	1,836	1,842	

Notes: Means or proportions presented on CEM sample. Standard deviations for means in parentheses. Ranges reported next to variable name for continuous measures. Col. 4 is statistical significance of difference between awardees and honorable mentions calculated from t-tests. First job placement types are not mutually exclusive; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

mentions. Award status appears to affect the relationship and training with advisors. We address this further in Section 7.

We also report the descriptive statistics by division in Appendix Table C2 (engineering (ENG), life sciences (LS), math & physical sciences (MPS), and social sciences & psychology (SSP)). It is interesting to note how weighting productivity outcomes balances the variables. Students in MPS have an average of 7.44 publications over the 16-year panel compared to 4.36 in ENG. Yet the rates of publications weighted by the number of authors are more comparable – 0.25 for MPS and 0.23 for ENG. Similarly, while SSP has the lowest cumulative publication count of 3.05, it has the largest count weighted by authors with 0.39. Thus, while lab-based fields have more publications, the average contribution of a scientist is relatively consistent across divisions. We report similar comparable trends weighting the citation counts.

This is not all to say the divisions are otherwise comparable. There are interesting differences between disciplines that warrant mention. Notably, the mentoring model takes different forms across divisions. While roughly 60 percent of the full sample co-authors with their advisor, 78 percent of LS students do, compared to just 34 percent of SSP students. Yet the overall *count* of joint publication is led by MPS with 0.17 and followed by LS with 0.15 and 0.12 for ENG. Students in SSP have only an average of 0.08 joint publications over the panel. Similarly, SSP has the lowest ratio of joint to total publications with 0.27 compared to an overall average of 0.46.

Altogether, we report a variety of functional forms for the research-related outcomes, using author-weighted publications, publication-weighted citations, and logged co-author networks. This enables us to control for disciplinary differences in publication and collaborative practices. This balances the measures across the divisions, allowing us to provide a more general understanding of the role of R&D funding across the fields of S&E.

5. Empirical methods

We estimate a series of models to assess the award's impact on training and productivity outcomes. First, we estimate a series of logistic regressions for the outcomes of degree completion and first professional placement post-graduation (Eq. 1).

$$\Pr(Y_i) = \mathrm{f}(Award_i, Controls, \varepsilon_i) \tag{1}$$

Operationally, we use the data in wide form (one row per student observation). We include a robust set of control variables at the PI, program, and university levels. At the PI-level, we include publications prior to GRFP acknowledgement, student gender, gender match between student and advisor, and whether the student attended a public baccalaureate institution. Graduate Institution indicators include whether it is a public, flagship, or land grant institution. Graduate Program controls include rank, size, average publications and citations per faculty, average GRE, and total GRFP acknowledgements in the two years prior. Finally, we include dummy indicators for the year of GRFP application, academic division, and region of graduate institution.

We then estimate a series of fixed effect models for the research-related outcomes around publications, citations, and network size (Eq. 2). This model leverages the structure of the panel dataset that traces students over a standardized 16-year timeframe from the five years prior to the GRFP proposal submission year and the following 10-

Table 2
Logistic Regression Estimations on Degree Completion & First Placement.

	(1) Completed PhD	(2) Research Position	(3) Post-Doc Position	(4) Academic Research Position	(5) Academic Tenure Track Position
GRFP Award	**0.025*****	-0.012	**0.057*****	**0.043****	-0.010
	(0.009)	(0.013)	(0.018)	(0.019)	(0.012)
Any Publications Prior to GRFP	0.029	**0.058***	0.007	0.023	**0.046***
	(0.023)	(0.031)	(0.034)	(0.035)	(0.026)
Female Student PI	-0.013	**-0.035***	0.006	0.026	**0.029***
	(0.018)	(0.020)	(0.031)	(0.032)	(0.017)
Advisor-Student Gender Match	0.002	-0.015	-0.022	0.010	0.005
	(0.017)	(0.019)	(0.030)	(0.031)	(0.016)
Public BA Institution	**-0.023****	-0.011	**-0.033***	**-0.067*****	-0.016
	(0.010)	(0.013)	(0.019)	(0.019)	(0.013)
Average Number of Faculty Publications	**0.008***	**0.020*****	**0.025*****	-0.003	**-0.030*****
	(0.004)	(0.006)	(0.007)	(0.008)	(0.007)
Average Citations per Faculty Publication	0.006	-0.003	**0.027*****	0.011	-0.009
	(0.005)	(0.006)	(0.009)	(0.009)	(0.007)
Average GRE Scores	**0.001*****	0.000**	**-0.001*****	-0.000	**0.001*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prior GRFP Program Activity	-0.001	-0.001	**-0.004*****	**-0.003****	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Top Tercile Program Rank	-0.033	-0.037	0.070	0.027	-0.046
	(0.025)	(0.035)	(0.053)	(0.053)	(0.031)
Largest Quartile Program Size	-0.002	-0.005	0.007	-0.009	-0.005
	(0.012)	(0.015)	(0.022)	(0.022)	(0.013)
Observations	2,855	2,617	2,617	2,617	2,617
Year Applied, Institution, Region, & Division Controls	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-637.93	-916.44	-1631.03	-1690.20	-742.62
LR Chi2	157.64	75.46	361.65	224.56	378.57
Prob > chi2	0.0000	0.0001	0.0000	0.0000	0.0000

Notes: Marginal effects presented from logistic regression estimations of Eq. 1 on CEM sample. Data in wide form (one row per student). The column header reports the dependent variable; the outcomes are the binary indicators for completing the PhD or not (column 1) and the type of professional placement first received after graduation (columns 2 – 5). Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 3
Fixed Effects Estimations on Research Productivity.

	(1) Pubs, Author-Weighted	(2) Citations, Pub-Weighted	(3) Co-Author Network (LN)
Award * Post-GRFP	**0.029*****	**4.504*****	**0.194*****
	(0.005)	(1.056)	(0.039)
Constant	0.093***	11.227***	1.105***
	(0.002)	(0.352)	(0.013)
Student-Year Observations	54,457	54,570	54,570
Number of Students	3,638	3,638	3,638
Adjusted R-Squared	0.534	0.497	0.763

Notes: Fixed effects results from regression estimations of Eq. 2 on CEM sample. The column header reports the dependent variable. Each outcome reflects cumulative counts over time. Col. 1 – Pubs, Author-Weighted – reports the quantity of peer-reviewed articles weighted by the number of authors. Col. 2 – Citations, Pub-Weighted – reports the quality of research productivity based on the 5-year forward citation count weighted by the number of peer-reviewed articles. Col. 3 – Co-Author Network (LN) – reports the student's network size in logged form based on the number of co-authors among research publications that includes peer-reviewed articles along with books, conference proceedings, and chapters. We omit the panel year of GRFP acknowledgement (t = 0). Standard errors in parentheses are clustered by the student-matched groups; *** p<0.01, ** p<0.05, * p<0.1.

year post period. We omit the GRFP year to ensure a clear cutoff pre-post treatment. We utilize a linear model with multiple levels of group fixed effects (Guimaraes & Portugal, 2010; Correia, 2018) to account for student (*i*), group (*j*), and time (*t*) trends over the 16-year standardized timeframe. The groups refer to the strata derived from the coarsening procedure detailed in Section 4.1. We cluster the standard errors by group.

$$Y_{ijt} = \mathrm{f}(Award_i * Post_t,\ \alpha_i,\ \mu_{jt},\ \varepsilon_{ijt}) \tag{2}$$

We aim to set up the most robust natural experiment feasible. This includes not only leveraging the merit review process that acknowledges awardees and honorable mentions as meritorious, but also we utilized coarsened exact matching procedures to improve the match when comparing awardees and honorable mentions. These design features, along with the model specifications outlined above give us confidence in approximating causal claims with observational data.

6. Results – direct treatment effect

6.1. Degree attainment & professional placement

Table 2 reports the marginal effects from the logistic regressions of Eq. 1. Column 1 reports for the outcome of *Degree Completion*, while columns 2 through 5 report for the first professional placement post-graduation. Overall, GRFP award receipt increases the student's probability of completing their PhD by 2.5 percentage points, on average (Standard Error (SE) 0.009). Also of note, attending a public baccalaureate institution is negatively associated with completing the PhD, by roughly the same impact – a decrease of 2.3 percentage points (SE 0.010).

Post-graduation, receiving the GRFP award positively affects placement in a *Post-Doctoral Position* and *Academic Research Position*. GRFP award receipt increases the student's probability of placing in a *Post-*

Table 4
Fixed Effects Estimations on Top-Performers and Average Student Sub-Samples.

	Top-Performer Sub-Sample:Top 10% of Publishers (1)	(2)	(3)	Average Sub-Sample:Excluding Top-Performer & Non-Publishers (4)	(5)	(6)
	Pubs, Author-Weighted	Citations, Pub-Weighted	Co-Author Network (LN)	Pubs, Author-Weighted	Citations, Pub-Weighted	Co-Author Network (LN)
Award * Post-GRFP	-0.018	**7.495***	-0.073	**0.025*****	**4.243****	**0.074***
	(0.017)	(4.074)	(0.153)	(0.006)	(1.709)	(0.042)
Constant	0.144***	21.768***	2.357***	0.127***	14.916***	1.372***
	(0.007)	(1.638)	(0.062)	(0.002)	(0.577)	(0.014)
Student-Year Observations	2,756	2,760	2,760	33,498	33,615	33,615
Number of Students	184	184	184	2,241	2,241	2,241
Adjusted R-Squared	0.612	0.538	0.875	0.575	0.491	0.804

Notes: Fixed effects results from regression estimations of Eq. 2 on CEM sample. Col. 1 – 3 report for the top-performer sub-sample that includes students who are in the top ten percent of peer-reviewed publication counts based on their corresponding division. Col. 4 – 6 report for the average student in the sample that omits top-performers and non-publishers over the 16-year panel. The dependent variables are those of Table 3. We omit the panel year of GRFP acknowledgement (t = 0). Standard errors in parentheses are clustered by the student-matched groups; *** p<0.01, ** p<0.05, * p<0.1.

Table 5
Fixed Effects Estimations on Co-Authoring with Advisors.

	(1) Any Joint-Advisor Pubs	(2) Joint-Advisor Pubs	(3) Ratio of Joint-Advisor Pubs
Award * Post-GRFP	**0.042*****	**0.174*****	0.003
	(0.011)	(0.059)	(0.032)
Constant	0.247***	0.816***	0.489***
	(0.004)	(0.020)	(0.016)
Student-Year Observations	54,570	54,570	19,714
Number of Students	3,638	3,638	2,566
Adjusted R-Squared	0.649	0.603	0.832

Notes: Fixed effects results from regression estimations of Eq. 2 on CEM sample. The column header reports the dependent variable. Col. 1 – Any Joint-Advisor Pubs – is the binary indicator of whether the student has any publications with their advisor in the panel. Col. 2 – Joint-Advisor Pubs – reflects the cumulative counts of joint-advisor publications over time. Col. 3 – Ratio of Joint-Advisor Pubs – is the ratio of publications joint with the advisor over the total cumulative count over time. We omit the panel year of GRFP acknowledgement (t = 0). Standard errors in parentheses are clustered by the student-matched groups; *** p<0.01, ** p<0.05, * p<0.1.

Doctoral Position by 5.7 percentage points (SE 0.018) and in an *Academic Research Position* by 4.3 percentage points (SE 0.019). These results are consistent with the differences shown in Table 1. While there appears to be no impact of the award on research or tenure-track positions, publications prior to receiving the GRFP both positively affect these placement types. It is interesting to note that female students are less likely to stay in research overall, but they are more likely to initially place in a tenure-track position.

6.2. *Research productivity & networks*

Table 3 reports the coefficients from the fixed effects estimations of Eq. 2. Overall, the GRFP award estimates positive and significant within-student changes after controlling for within-group, time-specific dummy trends for each outcome. Specifically, awardees have 0.029 (SE 0.005) additional author-weighted publications. This suggests the award does increase the quantity of publication activity.[13] Given the overall sample average of 0.26 author-weighted publications, this marginal effect reflects a significant share. Similarly, for the measure of impact, the GRFP award estimates a relatively large effect of an additional 4.5 (SE 1.056) publication-weighted citations. We also find a large positive effect for *Cumulative Co-author Network,* with an increase of 19.4 percent for GRFP awardees (SE 0.039).

6.2.1. *Robustness and sensitivity checks*

We validate these findings with a series of robustness and sensitivity analyses. First, we adjust the computation and functional forms of the productivity-based outcomes (Appendix Table C3). Specifically, we use a broader set of research-based publications to account for different publication practices across disciplinary fields (Bikard et al., 2015; Sauermann & Haeussler, 2017). For example, the field of computer science values conference proceedings as equivalent as or even higher than peer-reviewed publications in the academic promotion process. Other fields like sociology and political science acknowledge books.

We re-estimate Eq. 2 with research publications that not only includes peer-review articles, but also conference proceedings, books, and chapters using the unweighted cumulative count (col. 1). We find positive results on the outcome – Cumulative Research Output (0.722 SE 0.135).[14] We also estimate the weighted productivity metrics based on *annual*, rather than cumulative, publication activity (Rosenbloom et al., 2015; Conti & Liu, 2015). Operationally, we estimate the three-year average of author-weighted annual publications (col. 2) and three-year average of publication-weighted annual citations (col. 3). The results are consistent with the primary results reported in Table 3. In addition, we estimate the impact of the award using the raw (un-logged) count of co-author network (col. 4). The effect is not consistent with our primary results due to the wide range of the raw count.

Additionally, we examine the award impacts on author position (col. 5 – 7). Specifically, we estimate the effect on the cumulative count of peer-reviewed publications with the student PI in either the first or last author position or in sole-authored pieces. Across all three estimations, the award shows a positive impact. However, it should be noted that

[13] We explore descriptive statistics to examine the timing of this effect. Appendix Figure C1 reports publication trends for the annual average of new publications. The two groups show a significant divergence three years post-GRFP.

[14] Results are robust with Cumulative *Publication* Output as the dependent variable (0.615 SE 0.094) and are available upon request. Both dependent variables based on cumulative output are unweighted; this contrasts with the primary dependent variable – Publications, author-weighted (Table 3 col. 1).

these results vary in meaning by division. Different fields have varying practices for listing authors and different likelihoods of sole-authoring. Yet, on average, the award increases each of these measures.

In addition to varying the functional form of the dependent variables, we adjust the sample of analysis in a number of manners. By design of selecting a sample among GRFP awardees and honorable mentions, we identify students with a higher incidence of remaining research-active following graduate training. However, not all students pursue this path (86 percent place in research positions). This introduces selection concerns when examining productivity-based outcomes. As a second extension, we exclude students that do not place in a research position following degree completion and re-estimate Eq. 2. We find robust and slightly larger estimates for the three dependent variables (Appendix Table C4). Third, we confirm that programmatic shifts at NSF over our period (1995 – 2005) do not confound the results. In 1997, NSF expanded their merit review criteria to include broader impacts (in addition to intellectual merits). We split the sample based on this institutional change using the year of GRFP acknowledgement and find consistent results.

Fourth, we assess the potential role of peer effects. Recall, we initially identified direct matches between awardees and honorable mentions in terms of student gender, baccalaureate type, and graduate institution and field. Moreover, we matched on the GRFP year of acknowledgement and then subsequently adjusted by one calendar year to find an additional plausible match (refer to Appendix B – Initial Sample Selection). The former match defines the *Within-Cohort Sample* and the latter defines *Non-Cohort Sample*. This empirical choice has theoretical implications. While both allow us to control for the research environment (namely the graduate department), we acknowledge the Within-Cohort Sample may introduce an additional level of competition between the student pair when comparing similar students within the same graduate cohort. Appendix Table C5 reports the results for the two subsamples – Non-Cohort Sample and Within-Cohort Sample, respectively – for the productivity-based dependent variables. We report consistent and robust results across both samples. The comparability of these results further confirms the primary results and indicates that peer effects are not driving the effect.

Lastly, while we remove extreme outliers from the sample, we are still interested in how the award affects top-performers. To ensure sufficient sample size, we define top-performers as those students in the top ten percent of publication activity for their academic division and re-estimate Eq. 2. We report these results in Table 4. For this sub-sample (col. 1 – 3), the award no longer exhibits a positive impact within a student on the quantity of publications produced. However, there is weak evidence of a larger impact on the citations of those publications – approximately an additional 7.5 citations per publication (SE 4.074). There is also no longer a significant effect of the award on the size of a student's network. Interestingly, these results suggest the average student, rather than the more productive set of students, drives the positive effects of the fellowship (refer to col. 4 – 6).

7. Results – indirect training effect

Our primary results indicate that receiving external R&D funding positively affects student outcomes in terms of placement, productivity, and network. However, we have yet to examine a key component in any doctoral student's training – their relationship with their advisor. As motivated earlier, we argue there may be discrepancies between the fellowship versus assistantship training models. Here, we investigate the student-advisor relationship through their joint collaboration. This serves as a useful proxy for the mentorship the student receives while training. This section reveals insight on the indirect training effects as reflected in the second column in Fig. 1.

As reported in Table 1, the descriptive statistics indicate that over half the students publish with their advisor (57 percent). Moreover, the mean for awardees exceeds honorable mentions. However, we also compute the ratio of joint publications with their advisor to total publications and find that honorable mentions have higher ratios than awardees (0.48 compared to 0.45). On average, students start publishing this joint work approximately four years following the GRFP acknowledgement. This reflects a time when many students are completing their degrees. Students remain active collaborators with their advisors for roughly three years with awardees maintaining a slightly longer joint relationship than honorable mentions (2.95 years compared to 2.71 years, respectively).

To examine this activity more systematically, we re-estimate Eq. 2 on measures of joint-advisor work. Specifically, we estimate whether the student has any publications with their advisor, the level of joint publication activity, and the ratio of joint-to-total publications. Table 5 presents the results. We find evidence that receiving the GRFP award increases the probability a student co-authors with their advisor and increases the raw count of joint publications. However, we do not find evidence that this increases the concentration of joint work, relative to overall publications.

To examine this relationship with greater nuance, we leverage a useful feature of the sample. As reported in Table 1, 47 percent of students work with an advisor that has multiple students in our sample. More specifically, 32 percent of the students work with an advisor that mentored students with both awardee and honorable mention status. We define this sample as the *Within-Advisor Student Sample*. This sample provides an even stronger design where we control for the advisor and vary the graduate student-training model by award status. By design, both the awardee and honorable mention work with the same advisor and share similar baseline characteristics as specified by the coarsening procedure in Section 4.3; however, the awardee relies on the external fellowship for funding support while the honorable mention likely is supported via a standard research or teaching assistantship position.

As an initial diagnostic, we estimate a series of t-tests to assess whether students from the Within-Advisor Student Sample differ compared to those from our primary CEM sample that do not have an advisor that mentored both an awardee and honorable mention (Appendix Table C6, col. 1 – 3). We identify a series of interesting differences. First students from the Within-Advisor Student Sample have a higher likelihood of degree completion (95 percent compared to 91 percent). Second, students in the Within-Advisor Student Sample receive more forward citations both in total and weighted by number of publications (245 versus 206 and 36 versus 31, approximately). Interestingly, though not statistically different due to the wide range, students in the Within-Advisor Student Sample have *smaller* networks of co-authors – with an average of 53 versus 79. There are also notable differences between the samples with respect to the graduate programs (Panel B of Appendix Table C6). Students in the Within-Advisor Student Sample are more likely to be in a top ranked department where faculty have a higher number of average publications and citations. These programs also have higher average GRE scores and more experience with the GRFP program.

We then parse apart differences of the Within-Advisor Student Sample by accounting for award status (Appendix Table C6, col. 4 – 6). Generally, we report similar trends to the overall sample where the awardee reports greater performance outcomes. Interestingly, the fellowship appears to accelerate the pace of graduate training for awardees compared to honorable mentions as they complete their degrees slightly faster (5.29 years post GRFP compared to 5.49), publish earlier with their advisors (3.64 years post GRFP compared to 4.01), and spend more time co-authoring with their advisor (3.07 years compared to 2.75).

Of note, awardees have an even smaller co-authoring network compared to honorable mentions that share the same advisor (though this difference is not statistically significant due to the wide range). On the one hand, this suggests that honorable mentions may benefit from traditional training models as they gain access to larger collaborative networks, yet their productivity levels, in terms of quantity and impact,

Table 6
Fixed Effects Estimations on Within-Advisor Student Sample.

	(1) Pubs, Author-Weighted	(2) Citations, Pub-Weighted	(3) Co-Author Network (LN)	(4) Any Joint-Advisor Pubs	(5) Joint-Advisor Pubs	(6) Ratio of Joint-Advisor Pubs
Award * Post-GRFP	**0.022***	**6.604*****	**0.271*****	**0.074*****	0.170	-0.043
	(0.011)	(2.452)	(0.081)	(0.024)	(0.141)	(0.062)
Constant	0.102***	13.467***	1.204***	0.272***	1.007***	0.542***
	(0.004)	(0.838)	(0.028)	(0.008)	(0.048)	(0.032)
Student-Year Observations	13,241	13,275	13,275	13,275	13,275	4,951
Number of Students	885	885	885	885	885	652
Adjusted R-Squared	0.540	0.475	0.758	0.647	0.628	0.816

Notes: Fixed effects results from regression estimations of Eq. 2 on CEM sub-sample of students whose advisors have at least one awardee and honorable mention in the sample. The dependent variables are those of Table 3 (col. 1 – 3) and Table 5 (col. 4 – 6). We omit the panel year of GRFP acknowledgement (t = 0). Standard errors in parentheses are clustered by the student-matched groups; *** p<0.01, ** p<0.05, * p<0.1.

are not as strong. On the other hand, awardees report stronger performance with smaller networks. One possible explanation for these trends is that the external grant and independence that come with it limits the awardees access to larger networks. Another possible explanation may be that networks become more exclusive as productivity increases. This is a ripe area for future research.

We explore these trends more systematically by re-estimating Eq. 2 with the Within-Advisor Student Sample. We report the results in Table 6. Columns 1, 2, and 3 report the results for the primary productivity-based dependent variables from Table 3. Columns 4, 5, and 6 examine the collaborative outcome variables from Table 5. Regarding the former set of outcomes, we find robust results with larger effect sizes for all three primary dependent variables. The improved matching of the Within-Advisor Student Sample further supports the positive impact of the award.

Regarding collaborations with the advisor, we again find that the award increases the probability of having any publications with the advisor. Yet the level of joint publications is no longer statistically different for awardees. The ratio is still not statistically different as well. Thus, we do not find evidence that the increase in productivity is driven from increased collaboration with the advisor.

As noted above, awardees within-advisor spend a longer time co-authoring with their advisor than their honorable mention peers (3.07 years compared to 2.75). We explore this difference further by estimating the effect of the award on the time (in years) of co-authoring with advisor while controlling for a series of student and program characteristics. Interestingly, award status does not significantly affect this relationship. These results and additional timing-related results on graduate training are presented in Appendix Table C7.[15]

8. Discussion

We introduced this paper directing attention to an under-studied setting – S&E graduate training. To advance this scholarship, we leverage R&D funding to examine this topic. For graduate students, access to competitive extramural funding may enhance their training by granting students greater flexibility and independence to establish their research identities. However, graduate students have yet to develop and hone their research skills at this early career stage. Consequently, the R&D funding may disrupt the apprenticeship model that cultivates these foundational skills. We track the professional trajectories of 3,678 scientists and engineers over a 16-year timeframe to provide insight on this matter.

Overall, we find evidence that the GRFP increases student outcomes in terms of improved degree completion, placement into a post-doctoral or academic research position,[16] and increased publications and citations as well as expanded co-author networks. While we are unable to tease apart explicitly how the monetary award versus the signal drives the effects, this suggests that the external funding produces positive direct treatment effects for the students. This is in alignment with prior scholarship focused on senior researchers.

Additionally, we find evidence that the external funding also positively affects the student's graduate training. Specifically, the results show that the award does not appear to isolate graduate students from their training but instead increases the likelihood of publishing with their advisor. Yet, this is where the impacts on training end. Looking at our sample of awardees and honorable mentions with the same advisor, we find that awardees do not have a statistically higher number of publications joint with their advisor, nor is there a significant difference in the ratio of joint publications compared to the total number, nor the length of time spent co-authoring with their advisor.

While we find a positive effect of the award on the growth of their network, there are interesting differences among average co-author size across sample and award status. Overall, awardees and honorable mentions have similar average raw counts of co-authors, both near the overall mean of 64. Yet, for the sample of students with shared advisors, there is preliminary evidence of smaller networks. When we look within the shared advisor sample, the difference persists with awardees having an average of 49 unique co-authors to 57 for honorable mentions. The differences of these network sizes are not statistically different, likely due to the large range.[17] It is interesting to note that awardees of the Within-Advisor Student sample have a much smaller standard deviation as well (99 compared to 392 of honorable mentions). These differences warrant future research. With the rise of collaborative research, the smaller networks of awardees may indicate the role of prestige and the "circling of the wagons" in the publication process. If awardees are

[15] We find that awardees time to degree is approximately 0.133 years faster – roughly two months earlier than honorable mentions. We further explored this relationship by examining if time spent co-authoring with an advisor was tied to an initial post-doc placement. Of the Within-Advisor Sample, students with an initial post-doc placement co-authored with their advisors for an average of 3.45 years compared to 2.6 years for non-post-docs.

[16] The positive finding for professional placement contrasts with the findings reported in Blume-Kohout and Adhikari's (2016) study. They report that research assistantships in the biomedical sciences improve professional placement in a research-oriented position compared to NIH-funded traineeships and fellowships. The differences between their study and ours may reflect differences across the research setting and design. We examine training differences that begin at the pre-candidacy stage. Moreover, our context spans all four S&E divisions – engineering, life sciences, math & physical sciences, and social sciences & psychology.

[17] The range spans from – from zero to 30,452. Even with omitting extreme outliers, the practices of certain fields to list every lab member on publications greatly increases the range and thus standard deviation. Recall, to account for the broad distribution of this measure, we winsorize the data. Specifically, we remove observations that exceed three standard deviations from the mean of the student's corresponding academic division. We then log the variable.

granted access into small, more prestigious circles, this would result in smaller, yet impactful, co-author networks. Thus, the value of the award may be even larger when prestige is considered. However, it is also possible that the larger networks of honorable mentions are explained by multiple research assistantships that provide students with the opportunity to meet more faculty within their department.

In sum, the results of these estimations show strong support for the positive impact of external R&D funding on the career trajectory of graduate students. In line with prior research, such funding is associated with increased research productivity and network size for researchers at an earlier stage of their careers. Our unique sample of early-stage researchers allows us to examine graduate training and explore a multitude of outcomes, from degree completion and first professional placement to research productivity, impact, and network size. We offer important advancements toward understanding the production of science by directing attention to this understudied population of researchers. Graduate students, like more experienced researchers, experience increases in their research productivity. Moreover, we find the award also positively affects graduate training.

CRediT authorship contribution statement

Alexandra Graddy-Reed: Funding acquisition, Conceptualization, Project administration, Methodology, Formal analysis, Writing - original draft. **Lauren Lanahan:** Funding acquisition, Conceptualization, Project administration, Data curation, Writing - original draft. **Jesse D'Agostino:** Data curation, Investigation, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Survey methodology

To collect data on the students' experiences with the NSF GRFP, we distributed a survey via Qualtrics to GRFP awardees, honorable mentions, and their advisors. The survey requested that respondents confirm their demographic information. In addition, we included an open response question regarding respondent's experience with the program.

To distribute the survey, we followed the following steps. First, we randomly selected half of our student sample (awardees and honorable mentions) and half of the corresponding advisor sample. This included 4,804 individuals – 3,000 students and 1,804 advisors. Second, we searched for their email address online via LinkedIn pages as well as institutional and personal webpages. We identified 2,917 emails (60.7 percent) – 1,304 student emails and 1,613 advisor emails.

Third, we distributed the survey via email using Qualtrics in September of 2019. We sent three subsequent reminders to improve the response rate. After the fourth attempt to collect a response, we ended the data collection. We obtained 747 survey responses – 439 student responses and 308 advisor responses. This reflects a 25.6 percent overall response rate with a 33.7 percent response from students and a 19 percent response from advisors.

For this analysis, we used the 114 student responses to the open-ended question to evaluate individual experiences with the program. We coded the responses as overall positive (63.12 percent), overall negative (7 percent) or neutral (30.7 percent), including neither positive or negative reactions and designated key words within each response to determine the impact of the program on graduate training. No responses had both positive and negative comments. Two authors coded the responses to produce an inter-rater reliability rate of 93.9 percent.

Appendix B. Details on Sampling and Data Construction

Initial sample selection

Here, we detail step 3 listed in Fig. B1.

For the direct match, we used coarsened exact matching (CEM) to identify up to two honorable mentions per awardee that directly matched along all of the following variables: (i) gender of applicant; (ii) type of baccalaureate institution (drawing from the Carnegie university classifications: e.g. liberal arts, very high research institution); (iii) graduate institution *and* academic field (i.e. Chemistry department at Stanford); and (iv) year of GRFP acknowledgement (1995 – 2005). We identified 3,447 students – 1,748 awardees and 1,699 honorable mentions. This defines the Within-Cohort Sample.

Second, we re-ran the direct match sampling procedure, but relaxed the year of GRFP acknowledgement and allowed the honorable mention to receive acknowledgement two years either before or after the awardee. This approach pulled 3,833 students – 1,978 awardees and 1,846 honorable mentions. This defines the Non-Cohort Sample.

Taken together, this sampling approach yielded a matched sample of 5,340 *unique* students – 2,681 awardees and 2,659 honorable mentions. We label this as the Initial Sample in Fig. B1.

Additional data collection

As summarized in the manuscript, for our sample of 5,340 students, we gathered additional data from a series of third-party sources to trace graduate training activity, professional placement, and research production. First, with information on the student's name, field, and graduate institution, we identified the student in Proquest. This database serves as the largest central repository of dissertations and theses. This source provides additional detail on the student's degree conferment (including year), advisor, committee, and graduate institution. We retrieved data from this source for 4,040 students (75.7 percent of the initial sample).

Second, we conducted systematic online searches to confirm degree completion for missing values in ProQuest and identified the student's first professional placement (including start and end year). The first professional placement excludes temporary summer internships or fellowships following graduation. We drew upon publicly available data in LinkedIn and institutional, advisor, and professional webpages. In addition, we confirmed the gender of the student and their advisor; and identified name changes (where applicable). We gathered data for 4,273 students (92.9 percent of the initial sample). Inter-rater reliability across the research team for a random sample of student records exceeded 90 percent.

Third, we identified the list of students in Scopus to track their publication activity. This data source, a subsidiary of Elsevier, houses

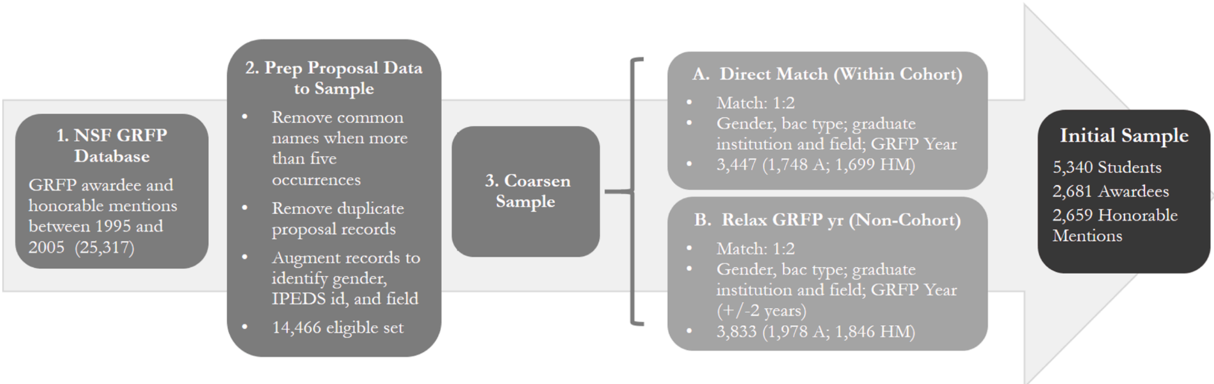

Fig. B1. Sample Selection Process.

Table B1
Variables by Source.

Data Source	Variables
NSF GRFP	Year Applied
	Award Status
	Baccalaureate Institution
	Graduate Institution
	Academic Field & Division
Proquest	PhD Completion Status
	Advisors
Elsevier Scopus	Publications & Research Outputs
	Publication Co-Authors
	Citations
Web Search	PI Gender
	Advisor Gender
	First Placement After Graduation
IPEDS	Baccalaureate Institution Governance Structures
	Graduate Institution Governance Structures
NRC	Graduate Program Characteristics
	Division

Notes: Graduate program characteristics includes: Faculty Publication & Citation Activity, Average GRE Scores, Program Rank & Size.

the largest collection of bibliometric data. We pulled complete reference detail for 90,908 unique publications for 4,005 students in the sample (75 percent of the initial sample). In addition, as a measure of impact we pulled forward citation counts five years following each publication, respectively. We limited this timeframe to reduce right censoring for the most recent cohort. Moreover, we assume students without a record of publication activity in Scopus did not publish. For the final dataset, we only include publication activity that falls within each student's standardized 16-year window.

Fourth, we pulled in additional institutional detail on the student's baccalaureate and graduate institution. We matched the student's graduate program (analogous to their reported university-field) to the National Research Council's (NRC) 2010 Survey of Doctoral Programs to gather additional detail on faculty research activity, GRE scores, faculty and student demographics, resources, and program rank (Ostriker, 2015). This survey reports program-level detail from 2000 – 2006, which overlaps with the second half of the timeframe for this study. The NSF Higher Education Research and Development (HERD) survey provides detail on annual federal R&D allocations by academic division. Lastly, we used the institution's IPEDS id to gather additional characteristics on the research rank and governance. We matched 4,907 students (92 percent of the initial sample) to NRC, 5,205 students (97.5 percent of the initial sample) to HERD, and 4,897 students (91.7 percent of the initial sample) to IPEDS.

Altogether, we identified complete data for 3,295 students. This includes 1,766 awardees and 1,529 honorable mentions. In Table B1, we map the variables used in empirical analyses to their respective data source.

Improved matching & removing outliers

We further reduced the imbalance between awardees and honorable mentions – shown in Appendix Table C1 – by using coarsened exact matching (CEM) a *second* time. This approach is designed to ensure balance across the observable characteristics between the treated and control groups by constructing strata of observations with statistically indistinguishable values between the two groups. We rely on the extended set of observable measures gathered as part of the data detailed above in the additional data collection section. The indicators used include: (i) year of GRFP application, (ii) any prior publications, (iii) academic field, (iv) graduate institution type, (v) baccalaureate institution type, (vi) the student's gender, and (vii) the gender of the student's advisor. This reduced the sample to 3,764 students (70.5 percent of the initial sample). Of note, we utilize the strata derived from this coarsening procedure as the group indicators in the fixed effect specification of Eq. 2.

As a final step, we removed extreme outliers to avoid estimation of spurious results. Operationally, we removed student observations that exceed three standard deviations above the mean for the following measures: prior publication count, total publications, unique co-authors, and total authors of publications. This reduced the sample by 157 students.

Final CEM sample

In review, we coarsened the original GRFP sample by relying on data available from the GRFP proposal record. This provided an initial sample of 5,340 students. Second, we collected additional data on training, placement, and productivity from multiple third-party sources. Third, we coarsened a second time to improve balance by drawing upon the larger list of variables obtained from the additional data collection step; this reduced the sample to 3,764 students. Fourth, we removed outlying observations (157 students). We use the final CEM sample of 3,678 students for the empirical analysis.

Appendix C. Empirical extensions

Tables C1, C2, C3, C4, C5, C6,C7 and Fig. C1

Table C1
Pre-Trend Descriptive Statistics of Initial Sample by Award Status.

	(1) Full Sample	(2) Awardees	(3) Honorable Mentions	(4) Diff. SS
Ever Publish in 16-Year Timeframe	0.75	0.79	0.7	***
Any Publications Prior to GRFP	0.13	0.15	0.12	***
Total Number of Pre-GRFP Publications (0 - 6)	0.19	0.2	0.17	**
	(0.55)	(0.56)	(0.54)	
Female Student PI	0.37	0.39	0.35	***
Division				
Engineering	0.29	0.29	0.29	
Life Sciences	0.21	0.2	0.22	
Math & Physical Sciences	0.28	0.29	0.28	
Social Sciences & Psychology	0.22	0.22	0.22	
Baccalaureate Institution				
Public	0.46	0.42	0.49	***
Liberal Arts	0.07	0.07	0.07	
R1 Research University	0.89	0.89	0.89	
Graduate Institution				
R1 Research University	0.95	0.95	0.95	
Public	0.44	0.41	0.47	***
Flagship	0.29	0.27	0.31	***
Land Grant	0.38	0.38	0.38	
Female Advisor	0.18	0.17	0.18	
Average Number of Faculty Publications (0.01 - 10.16)	2.6	2.59	2.61	
	(1.76)	(1.76)	(1.77)	
Average Citations per Faculty Publication (0.45 - 11)	3.27	3.27	3.27	
	(1.82)	(1.82)	(1.82)	
Average GRE Scores in Program (545 - 800)	764.92	765.02	764.82	
	(37.80)	(37.60)	(38.01)	
Graduate Department Prior GRFP Activity (0 - 38)	7.72	7.92	7.5	**
	(6.89)	(7.04)	(6.73)	
Observations	5,285	2,652	2,633	

Notes: Means or proportions presented. Standard deviations for means in parentheses. Ranges reported next to variable name for continuous measures. Statistical significance of difference (Diff. SS) between awardees and honorable mentions calculated from t-tests presented in column 4; *** p<0.01, ** p<0.05, * p<0.1.

Table C2
Descriptive Statistics by Academic Division.

	(1) CEM Sample	(2) ENG	(3) LS	(4) MPS	(5) SSP
Ever Publish in 16-Year Timeframe	0.75	0.72	0.88	0.79	0.66
Any Publications Prior to GRFP	0.07	0.04	0.12	0.12	0.01
Total Number of Publications (0 - 58)	5.29	4.36	5.86	7.44	3.05
	(6.56)	(5.12)	(4.95)	(8.90)	(3.93)
Total Number of Author-Weighted Publications (0 - 2)	0.26	0.23	0.18	0.25	0.39
	(0.20)	(0.13)	(0.11)	(0.19)	(0.29)
Total Count of Unique Co-Authors (0 - 30,452)	64.14	36.04	40.1	139.53	13.13
	(652.37)	(46.13)	(44.51)	(1159.34)	(22.06)
Total Number of Research Outputs (0 - 112)	7.51	8.14	6.15	10.24	3.79
	(9.23)	(9.56)	(5.15)	(11.57)	(5.02)
Ever Publish with Advisor	0.57	0.59	0.78	0.59	0.34
Ratio of Publications with Advisor to Total (0 - 1)	0.46	0.59	0.54	0.43	0.27
	(0.37)	(0.38)	(0.32)	(0.35)	(0.34)
Total Number of 5-Year Forward Citations (0 - 7,605)	198.7	135.28	270.39	306.69	78.31
	(430.46)	(294.40)	(390.16)	(618.46)	(155.26)
Publication-Weighted Total 5-Year Forward Citations (0 - 691.36)	32.33	28.16	44.43	35.37	21.44
	(42.91)	(41.25)	(46.26)	(49.48)	(20.84)
Female Student PI	0.34	0.2	0.53	0.19	0.6
Female Advisor	0.11	0.06	0.13	0.04	0.26
Completed a PhD	0.85	0.77	0.93	0.86	0.87
First Job Placement (3,213 obs.)					
Research	0.86	0.87	0.87	0.9	0.81
Post-Doctoral Fellow	0.44	0.31	0.67	0.52	0.33
Academic Institution	0.58	0.37	0.66	0.61	0.72
Academic Research	0.51	0.32	0.58	0.56	0.63
Tenure-Track Faculty	0.11	0.04	0.03	0.09	0.29
Observations	3,678	1,106	604	1,155	813

Notes: Col. 1 reports for CEM sample (as reported in Table 1). Col. 2 – 5 report for sub-samples based on academic division – engineering (ENG), life sciences (LS), math and physical sciences (MPS), and social sciences and psychology (SSP). Means or proportions presented. Standard deviations in parentheses. Ranges reported next to variable name for continuous metrics.

Table C3
. Fixed Effects Estimations with Alternate Outcome Functional Forms.

	Alternate Functional Forms				Author Position		
	(1) Cumulative Research Output	(2) 3-Yr Avg. of Annual Pubs, Author-Weighted	(3) 3-Yr Avg. of Annual Cites, Pub-Weighted	(4) Co-Author Network (count)	(5) First Author Cum Pubs	(6) Sole Author Cum Pubs	(7) Last Author Cum Pubs
Award * Post-GRFP	**0.722*****	**0.018*****	**3.218*****	-1.876	**0.291*****	**0.071*****	**0.110*****
	(0.135)	(0.003)	(0.601)	(12.463)	(0.046)	(0.017)	(0.026)
Constant	2.235***	0.048***	6.297***	19.721***	0.572***	0.063***	0.191***
	(0.045)	(0.001)	(0.208)	(4.156)	(0.015)	(0.006)	(0.009)
Student-Year Observations	54,570	46,844	47,294	54,570	54,570	54,570	54,570
Number of Students	3,638	3,638	3,638	3,638	3,638	3,638	3,638
Adjusted R-Squared	0.629	0.416	0.320	0.270	0.598	0.403	0.442

Notes: Fixed effects results from regression estimations of Eq. 2 on CEM sample. The column header reports the dependent variable. Col. 1 – 4 reports alternate functional forms of dependent variable. Col. 1 reports the cumulative count (unweighted) of research publications. Col. 2 reports the three-year average of author-weighted annual publications (peer-reviewed only). Col. 3 reports three-year average of publication-weighted annual citations (peer-reviewed only). Col. 4 reports the student's network size based on the number of co-authors among research publications. Col. 5 – 7 reports cumulative count (unweighted) measures of publications for a variety of author positions. Col. 5 is the first author position, Col. 6 is of sole-authored, and Col. 7 is in the last author position. We omit the panel year of GRFP acknowledgement (t = 0). Standard errors in parentheses are clustered by the student-matched groups; *** p<0.01, ** p<0.05, * p<0.1.

Table C4
Fixed Effects Estimations on Research Active Sample.

	(1) Pubs, Author-Weighted	(2) Citations, Pub-Weighted	(3) Co-Author Network (LN)
Award * Post-GRFP	**0.035*****	**4.645*****	**0.211*****
	(0.005)	(1.371)	(0.049)
Constant	0.099***	12.723***	1.227***
	(0.002)	(0.458)	(0.016)
Student-Year Observations	39,598	39,705	39,705
Number of Students	2,647	2,647	2,647
Adjusted R-Squared	0.533	0.496	0.769

Notes: Fixed effects results from regression estimations of Eq. 2 on CEM sample. The column header reports the dependent variable. The dependent variables are those of Table 3. Sample reflects students who first place in a research-active position post-graduation. We omit the panel year of GRFP acknowledgement (t = 0). Standard errors in parentheses are clustered by the student-matched groups; *** p<0.01, ** p<0.05, * p<0.1.

Table C5
Fixed Effects Estimations on Peer Effects & Cohort Spillovers.

	Non-Cohort Sample			Within-Cohort Sample		
	(1) Pubs, Author-Weighted	(2) Citations, Pub-Weighted	(3) Co-Author Network (LN)	(4) Pubs, Author-Weighted	(5) Citations, Pub-Weighted	(6) Co-Author Network (LN)
Award * Post-GRFP	**0.032*****	**4.386*****	**0.216*****	**0.027*****	**4.164*****	**0.172*****
	(0.006)	(1.247)	(0.047)	(0.006)	(1.360)	(0.048)
Constant	0.091***	11.143***	1.079***	0.095***	11.670***	1.138***
	(0.002)	(0.438)	(0.016)	(0.002)	(0.463)	(0.016)
Student-Year Observations	38,146	38,220	38,220	35,304	35,400	35,400
Number of Students	2,548	2,548	2,548	2,360	2,360	2,360
Adjusted R-Squared	0.522	0.483	0.759	0.533	0.497	0.763

Notes: Fixed effects results from regression estimations of Eq. 2 on CEM sample. The column header reports the dependent variable. The dependent variables are those of Table 3. Sample stratified by matching approach detailed in Appendix B of either within or out of cohort (Fig. B1). We omit the panel year of GRFP acknowledgement (t = 0). Standard errors in parentheses are clustered by the student-matched groups; *** p<0.01, ** p<0.05, * p<0.1.

Table C6
Descriptive Statistics of Within-Advisor Student Sample by Award Status.

	CEM Sample with Advisors			Within-Advisor Sample		
	(1) Not Within	(2) Within-Advisor	(3) Diff. SS	(4) Awardees	(5) Honorable Mentions	(6) Diff. SS
Panel A: Publication Activity						
Any Publications Prior to GRFP	0.08	0.1	**	0.09	0.1	
Ever Publish in 16-Year Timeframe	0.82	0.81		0.86	0.76	***
Total Number of Publications (0 - 58)	5.67	6.05		6.81	5.25	***
	(6.76)	(6.52)		(6.69)	(6.24)	
Total Number of Author-Weighted Publications (0 - 2)	0.26	0.25	**	0.26	0.24	
	(0.20)	(0.19)		(0.19)	(0.18)	
Total Number of Unique Co-Authors (0 - 30,452)	78.9	52.8		48.95	56.87	
	(810.04)	(282.52)		(99.33)	(392.13)	
Total Number of Research Outputs (0 - 112)	8.16	8.34		9.27	7.36	***
	(9.38)	(9.41)		(9.36)	(9.38)	
Total Number of 5-Year Forward Citations (0 - 7,605)	205.95	244.55	**	280.28	206.85	***
	(465.97)	(405.82)		(429.95)	(375.42)	
Publication-Weighted Total 5-Year Forward Citations (0 - 691.36)	30.68	36.43	***	38.45	34.02	*
	(44.66)	(39.45)		(43.26)	(34.29)	
PI in Top 10% of Division of Total Publications	0.1	0.11		0.15	0.08	***
	(2.13)	(1.93)		(1.53)	(2.28)	
Ever Publish with Advisor	0.62	0.64		0.67	0.6	**
Ratio of Publications with Advisor to Total (0 - 1)	0.47	0.49		0.47	0.51	
	(0.37)	(0.36)		(0.36)	(0.37)	
First Year of Panel to Co-Author with Advisor (-3 - 10)	4.15	3.81	***	3.64	4.01	**
	(2.44)	(2.37)		(2.22)	(2.53)	
Last Year of Panel to Co-Author with Advisor (-3 - 10)	6.94	6.73	*	6.71	6.76	
	(2.44)	(2.20)		(2.17)	(2.24)	
Number of Panel Years Co-Authoring with Advisor (0 - 11)	2.79	2.92		3.07	2.75	*
	(2.46)	(2.50)		(2.53)	(2.45)	
Panel B: PI Demographics & Program Characteristics						
Female Student PI	0.35	0.3	***	0.31	0.28	
Number of Advisees of Advisor within Sample (1 - 11)	1.28	3.56	***	3.73	3.39	***
	(0.60)	(1.85)		(1.96)	(1.70)	
Completed a PhD	0.91	0.95	***	0.96	0.93	**
Years to Degree Post-GRFP (0 - 19)	5.57	5.39	**	5.29	5.5	*
First Job Placement (3,213 obs.)						
FP: Research	0.87	0.89		0.9	0.88	
Post-Doctoral Fellow	0.46	0.48		0.51	0.44	**
Academic Institution	0.6	0.58		0.63	0.53	***
Academic Research	0.54	0.53		0.58	0.47	***
Tenure-Track Faculty	0.12	0.1	*	0.11	0.1	
Graduate Program Characteristics						
Top Tercile Program Rank	0.96	0.98	***	0.98	0.97	
Largest Quartile Program Size	0.69	0.71		0.71	0.71	
Average Number of Faculty Publications (0.01 - 10.16)	2.57	3.04	***	3.09	3	
	(1.77)	(1.88)		(1.96)	(1.80)	
Average Citations per Faculty Publication (0.45 - 11)	3.15	3.41	***	3.46	3.36	
	(1.69)	(1.70)		(1.75)	(1.65)	
Share of Female Faculty (0 - 0.67)	0.17	0.17		0.17	0.16	
	(0.11)	(0.11)		(0.11)	(0.11)	
Average GRE Scores (545 - 800)	764.25	771.54	***	771.09	772	
	(39.59)	(33.81)		(34.96)	(32.60)	
Prior GRFP Program Activity (0 - 38)	7.48	9	***	9.07	8.91	
	(6.95)	(6.92)		(7.07)	(6.76)	
Observations	2,252	1,077		553	524	

Notes: Means or proportions presented on CEM sample. Standard deviations for means in parentheses. Ranges reported next to variable name for continuous metrics. Statistical significance of difference between sample calculated from t-tests presented in col. 3 and 6; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C7
OLS Estimation Results on Timing Measures.

	(1) Years Co-authoring with Advisor	(2) Time to Degree from GRFP	(3) Time to Degree from PhD Start
GRFP Award	0.285	**-0.208*** **	**-0.133***
	(0.198)	(0.076)	(0.074)
Any Publications Prior to GRFP	**0.504***	**-0.862*** **	**-0.241***
	(0.295)	(0.142)	(0.134)
Female Student PI	-0.213	-0.049	0.116
	(0.366)	(0.130)	(0.125)
Advisor-Student Gender Match	0.434	-0.127	0.022
	(0.351)	(0.125)	(0.122)
Public BA Institution	-0.210	0.123	0.017
	(0.206)	(0.079)	(0.077)
Average Number of Faculty Publications	**0.186** **	-0.028	-0.025
	(0.083)	(0.031)	(0.030)
Average Citations per Faculty Publication	**0.169***	-0.023	0.049
	(0.096)	(0.036)	(0.035)
Average GRE Scores	**-0.012** **	-0.001	**-0.003** **
	(0.005)	(0.002)	(0.002)
Prior GRFP Program Activity	-0.023	-0.008	-0.009
	(0.017)	(0.006)	(0.006)
Top Tercile Program Rank	1.089	0.227	0.045
	(0.753)	(0.218)	(0.217)
Largest Quartile Program Size	0.285	**0.203** **	0.149
	(0.256)	(0.092)	(0.092)
Constant	9.206**	5.910***	7.880***
	(4.337)	(1.209)	(1.231)
Observations	611	2,799	1,939
Adjusted R-Squared	0.0847	0.0571	0.0553
Year Applied Region Division Fixed Effects	Yes	Yes	Yes

Notes: OLS regression. Data in wide form (one row per student). The column header reports the dependent variable. For Col. 1, dependent variable is length of time (in years) of student co-authoring with advisor; this sample restricted to Within-Advisor Student Sample. Col. 2 and 3 report for the CEM sample (for observations with complete data). For Col. 2, the dependent variable is length of time (in years) from GRFP to degree completion. For Col. 3, the dependent variable is length of time (in years) from graduate program start to degree completion. The latter is not known for all students so reflects a smaller sample size. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

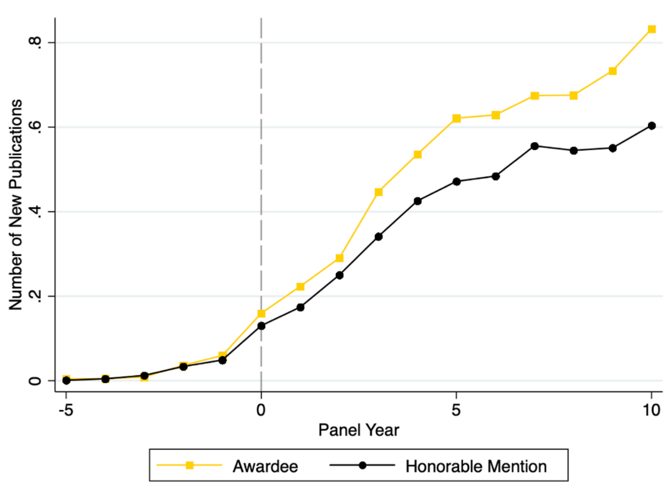

Fig. C1. Annual Average Count of New Peer-Reviewed Publications.

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