Mediators of Academic R&D Funding: An Analysis of Institutional Determinants on R&D Grant Funding for Emerging Researchers

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Abstract

Considerable attention on understanding university research and development focuses on the research activity among senior scholars, with more recent attention focused on the dynamics of innovation within labs and scientific teams. Less attention, however, has focused on the role of academic institutions in training graduate students. This study directs attention to this important, yet often overlooked, population of science and engineering emerging researchers who not only provide critical support for their academic advisors, but also are actively defining and building their own research trajectories. We examine the effect of institutional characteristics on research funding grant success for emerging researchers. This paper draws upon the National Science Foundation’s Graduate Research Fellowship Program (GRFP) to define an elite set of science and engineering graduate students with demonstrated research promise – as indicated by award receipt or publicized acknowledgement of honorable mention. We augment this dataset with program-level survey data presented as part of the National Research Council’s Data-Based Assessment of Research-Doctorate Programs in the United States. Given the closeness in quality of GRFP award and honorable mention submissions, we examine whether additional factors, external to the proposal itself, mediate funding assignment. We find evidence that a series of leadership, peer, programmatic, and university characteristics are associated with grant funding outcomes for emerging researchers. Notably, faculty and student research quality improve the likelihood of award success, while the signal of being at a public institution decreases the likelihood of award receipt. Moreover, while we find that larger programs are more likely to have graduate students receive awards, the larger, lower-ranked programs exhibit inefficiencies in scaling the activity. When viewed as a signal of resources, this implies that larger programs may face coordination costs that are detrimental to the rate of graduate student success. This paper presents a baseline in understanding the antecedent factors that lead to emerging researcher success.
1. Introduction

With over $63 billion invested annually in US university science and engineering (S&E) research and development (R&D), the market for research is substantial.¹ The S&E fields comprise the research foundation for the major knowledge- and technology-intensive industries, which are estimated to account for 40 percent of US GDP.² In an effort to understand the broad implications of these investments, considerable research on academic R&D has focused on the research activity among senior scholars, with more recent attention focused on the dynamics of innovation within labs and scientific teams. Less attention, however, has focused on the role of academic institutions in training new entrants into the S&E innovative workforce.

The population of S&E graduate students – referred to here as emerging researchers – defines the next generation of innovators with significant economic potential. These individuals are at the beginning of their research careers and receive formal and informal training from their graduate programs.³ As they progress through their academic apprenticeship, these students are expected to develop and pursue their own research agenda. However, unlike their mentors, emerging researchers have few opportunities to secure external funding support for their research.

The National Science Foundation’s (NSF) Graduate Research Fellowship Program (GRFP) provides a rare opportunity for emerging researchers to obtain a substantial and prestigious award. The grant is unique and relatively sizeable in value, providing the most promising students with three years of guaranteed funding to pursue their own research agenda with no service obligation to their program. In 2015, approximately 16,000 applicants submitted proposals,⁴ 12.8 percent were

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² [http://www.nsf.gov/statistics/seind14/content/overview/overview.pdf](http://www.nsf.gov/statistics/seind14/content/overview/overview.pdf) (pg. O-3)
³ Here and henceforth, programs are analogous to academic departments.
⁴ [https://www.nsfgrfp.org/applicants](https://www.nsfgrfp.org/applicants)
awarded competitive funding, and 11.8 percent were deemed near-misses\textsuperscript{5} and given formal recognition as honorable mentions due to their exceptional proposal quality.

Heralded nationally and internationally, NSF administers the ‘gold standard’ of merit review.\textsuperscript{6} Under standard proposal submission, NSF administers single-blinded peer review panels – composed of experienced senior researchers in the respective academic field – that evaluate several dimensions of a comprehensive research proposal, weighing its intellectual value as well as its broader impacts.

While consideration of GRFP proposals follows the same general merit review process, student proposals differ in important ways from others submitted to NSF. GRFP proposals are abbreviated in length (one third the length of regular, standard proposals), demand less technical information, and weigh applicant quality and experience differently given their status as early-stage researchers-in-training. In contrast, standard proposals are designated for more senior researchers, who have who accumulated more training and research experience. Their submissions are longer in length, allowing for greater explication of the project, in addition to demonstration of project feasibility. Relative to standard proposals, the lack of these features for the GRFP is likely to increase the degree of uncertainty that a student-applicant is able to execute the research proposal. Faced with this ambiguity, reviewers may turn to other, more tangible pieces of information to help inform their evaluation of emerging researcher proposals. The GRFP provides a unique opportunity to examine considerations of the merit review process that extend beyond the research idea as articulated in the proposal – notably, the potential mediating factors of an applicant’s unique research environment.

\textsuperscript{5} NSF defines honorable mentions as “meritorious applicants who do not receive Fellowship awards. This is considered a significant national academic achievement and provides access to cyber-infrastructure resources.” GRFP Program Solicitation, NSF 15-597, \url{http://www.nsf.gov/pubs/2015/nsf15597/nof15597.htm}

\textsuperscript{6} \url{http://www.acs.org/content/dam/acsorg/policy/publicpolicies/promote/peerreview/peer-review.pdf}
Following the merit review process, NSF publishes the names of both awardees and honorable mentions. While honorable mentions do not receive the financial award, they do receive public recognition that carries merit. Panels review applicants in their field and make recommendations to NSF regarding who should receive the award. NSF then “determines the successful applicants from these recommendations, with Fellowships and Honorable Mentions offered based on the GRFP portfolio within the context of NSF’s mission.” Given the closeness in quality of GRFP award and honorable mention submissions, we can examine whether additional external factors to the proposal itself influence award assignment. More specifically, in this paper we ask: are there institutional academic characteristics (program- and university-level) that mediate the likelihood of an individual’s assignment to award rather than honorable mention? Given the increased level of uncertainty that is inherent in an emerging researcher’s GRFP proposal, we argue that program and university traits influence award and honorable mention assignment in two ways. First, a student’s academic institution may directly impact likelihood of an award, as the perceived quality of the institution serves as an indicator of the proposal’s quality and potential for success. Second, institutions also may indirectly impact likelihood of award assignment as they could provide resources and support to the student principal investigator (PI), which she can utilize to improve the quality of her application.

Emerging researchers not only provide critical support for their mentors and advisors, but are also actively defining and building their own research trajectories. As they progress through their graduate training, they face notable hurdles, including limited research funding opportunities and a scarce labor market for prospects beyond graduate training (Stephan, 2012; Roach & Sauermann, 2010). Moreover, the constant threat of ever-diminishing public research funding only compounds

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9 http://www.aas.org/fy16budget/federal-rd-fy-2016-budget-overview#rd
both challenges. Nevertheless, this population comprises a workforce with considerable innovative and economic potential. Thus, we argue it is essential to understand the role of institutional characteristics for securing funding, especially for a population of researchers for which such opportunity is scarce.

Our paper proceeds as follows: section two overviews the research context for this analysis – including both an overview of the GRFP and population of interest, emerging researchers. Section three presents the institutional framework, highlighting the implications of institutional features as mediators for R&D receipt. Section four presents the research design detailing the data, sample, and methods. Section five presents the results while section six provides discussion of them; section seven offers concluding remarks.

2. Research Context: Emerging Researchers

Beyond faculty, research scientists, and postdoctoral fellows, graduate students participate in the process of knowledge and technology creation in their training and research (Stephan, 2012). While much of the extant literature focuses on the activities of senior S&E scholars (e.g. Azoulay et al., 2007; Zucker & Darby, 1996; Thursby & Thursby, 2004; Bercovitz & Feldman, 2008; Stuart & Ding, 2006) with some more recent focus on post-docs (Roach & Sauermann, 2010; Miller & Feldman, 2014) and laboratory personnel (Conti & Lui, 2015), we focus on the large, yet understudied group of emerging researchers: S&E graduate students. Similar to senior scholars, graduate students are eligible to pursue competitive research grant funding. Moreover, receipt of an external funding award, especially from a prestigious source like the US NSF, National Institutes of Health, or the European Science Foundation, not only distinguishes the merit of these graduate students, but can also play a pivotal role in helping support emerging researchers as they conduct original research. This is especially critical within the S&E fields where the costs of research are substantial.
and continue to rise (Stephan, 2012: chapter 3). This initial award holds the potential to help dramatically shape an emerging researcher’s long-term research trajectory not only through the resource support, but also through the award recognition.

Our attention to graduate students addresses the call from Lane and Betruzzi (2011) for more scholarship on the activities of students – representing the future workforce and generators of scientific, social, and economic activity. The National Science Board estimates that in 2013 approximately 615,000 individuals enrolled in US-based S&E graduate programs. The economic impact of this population is not only defined by the sheer supply of graduate students, but also by the productive endeavors these researchers may pursue. This population of researchers is often more willing to tackle risker research undertakings compared to established faculty (Cetina, 2009). While these riskier projects do not guarantee results, there is evidence that, like postdoctoral fellows (Roach & Sauermann, 2010; Miller & Feldman, 2014), emerging researchers – even in their formative training experiences – contribute noticeability to program output (Conti & Lui, 2015). The graduate experience is a pivotal time where only the most successful emerge from this training stage to advance professionally (Freeman et al., 2001). Greater scrutiny in understanding how these researchers develop a professional research trajectory is needed.

A recent discussion in *Nature* has highlighted this latter point (Gould, 2015; Callier & Polka, 2015; Woolston, 2015). Notably, the 2015 *Nature* survey drew upon over 3,400 responses globally from early-career researchers to gain a better sense of the prospects for professional placement for STEM graduates, spanning industry and academia. Not only do the results find that the level of graduate enrollment far exceeds the market and opportunity for professional research positions, but

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10 “Capturing activities of students is similarly critical; they not only form the workforce of the future but generate scientific, social, and economic activity. Characterizing the funding and outcomes of interdisciplinary research within and across federal agencies will require being able to describe the structure of proposals, awards, and publications.”

also that students are unaware of these career limitations when they initially enroll. While concerning for current student cohorts, this survey overlooks a fundamental component of this equation: the role of institutions in training emerging researchers. Before we can effectively assess the role and implications of STEM training on professional placement, more attention is needed on the training component itself. Hence, we focus this analysis on graduate training and examine how the academic institution influences early-stage student resource access.

To elaborate, progression to the next career stage – where and how – often hinges upon the success emerging researchers attain during their training. Success can be represented in a multitude of ways, from publication experience to technical skill attainment (Agarwal & Ohyama, 2013). In this paper, we explore student research success measured as early-stage receipt of research grant funding. We define this by drawing upon data from one of the most prestigious research funding programs designed for emerging researchers in the US, NSF’s GRFP. This program has a demonstrated history of supporting promising graduate students in NSF-supported science, technology, engineering, mathematics, and social science disciplines. Award recipients receive a generous three-year fellowship to conduct their own research. In 2015, NSF offered $138,000 for the full award – $34,000 as an annual student stipend and $12,000 as an annual educational allowance to the institution.12

Applicants are subject to a competitive, single-blind merit review process where a panel of field-related experts with no institutional or personal conflicts of interest reviews the proposal’s intellectual merit and broader impacts.13 For the GRFP, NSF uses a “holistic” review, which they define as “a flexible, individualized way of assessing an applicant's interests and competencies by which balanced consideration is given to experiences, attributes, and academic achievements and, when considered in combination, how the applicant has demonstrated potential for significant

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research achievements in STEM and STEM education.” The full application includes the personal, relevant background, and future goals statement (3 pages), the graduate research statement (2 pages), transcripts, and three letters of reference.

The GRFP contains a number of features that are particularly useful in answering our research question. First, the program is designed specifically to support emerging researchers; applicants are only eligible for a three-year period that ends the fall of their second year of graduate school. Second, as a signal of quality, both GRFP recipients and honorable mentions are publicized, collectively representing the top quarter of applicants. Honorable mentions are competitive applicants who are recommended by the panelists to NSF, but who were just shy of receiving the funding. This publicized acknowledgement is revered as a signal of intellectual merit and research promise. We draw upon this data not only to identify promising emerging researchers, but also to exploit this narrow margin between award and honorable mention status.

While the merit review component mirrors the other NSF funding mechanisms, the GRFP application notably differs. The standard, collaborative, career, dissertation, workshop, and even larger center proposals are all approximately three times longer in length, allowing for greater explication of research proposition. Proposals often include initial proof of concept – with the data building efforts often well underway. Moreover, PIs applying for additional NSF funding are required to detail the outcomes of their prior research. Meanwhile, unlike the GRFP, these later-stage proposals do not require a personal statement or three reference letters. While NSF has tailored the GRFP application requirements given the nature of the funding opportunity for emerging researchers, we argue that this comparatively abbreviated format and reliance on external references heightens the level of uncertainty for proposal review. In light of this, the GRFP provides

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a unique opportunity to examine how institutional factors—external to the research proposal itself—influence the likelihood of award receipt.

Winning a GRFP fellowship carries significant weight for graduate students, with the potential to affect student experiences differentially depending on a student’s individual characteristics in addition to the academic program and wider academic discipline to which the student belongs. Annually, roughly $330 million is obligated for awards to support approximately 2,000 emerging researchers. Notably, the GRFP allows the emerging researcher to spend more time devoted exclusively to her own evolving research agenda without worrying about other common time commitments like teaching or research assistantships. It is unclear whether this “free time” will necessarily result in improved research output and productivity, although evidence from external postdoctoral fellowship funding suggests it might (Conti & Lui, 2015). With additional resources, award winners may indeed attempt riskier, yet more rewarding projects (Owen-Smith & Powell, 2001).

To our knowledge, only a handful of studies have used the GRFP database (Chapman & McCauley, 1993; Bartolone et al., 2014; Le & Bartolone, 2015). The former academic study examined whether the award yielded a Pygmalion or Galatea effect in terms of professional placement. The latter two comprise recent NSF contracted reports of the GRFP to provide the following: (i) descriptive information on GRFP goals; (ii) evidence of program impact on employment and professional productivity; and (iii) an understanding of how universities implement the program. While this full set of research focuses primarily on programmatic outcomes, additional work remains to examine how institutional factors mediate these outcomes.

As “natural incubators”, academic programs (and their respective university) constitute a prime location for innovation by connecting a relatively steady stream of potential innovators (students) with human and physical capital (Etzkowitz, 2003). Both as part of nested- and knowledge-creating organizations, academic programs encourage innovation in part by giving autonomy to its personnel, allowing researchers to experiment and push research boundaries forward (Amar, Hentrich, & Hulpic, 2009). Yet, little attention has been directed towards understanding how the academic research organization fuels innovative potential through one of its critical resources: emerging researchers.

We argue that program and university traits and support may mediate a student’s probability of assignment to a GRFP award through direct and indirect means. In other words, we argue that contrary to the objectives of the NSF proposal merit review, the contents of the research idea presented in the proposal are not the sole determinants of award receipt. The abbreviated nature of the proposal leads reviewers to seek out other sources of relevant information that can better signal the merit of each application. Specifically, the applicant’s research environment, through components that can be observed by the proposal review panel (i.e. direct) and those that cannot (i.e. indirect), additionally influences the likelihood of grant receipt (Figure 1). Direct measures include quality signals attached to an applicant’s program – including both the faculty and student body attributes – and more, broadly, the university. Indirect measures refer to additional resource opportunities and support for research activities that could improve the quality of a student’s proposal.
The same institutional qualities and resources can have both direct and indirect effects on ultimate student GRFP award/honorable mention status. For example, the publication record and research portfolio of faculty in a given program may be readily familiar to a reviewing panelist, and in this manner may have a direct impact on probability of award – as opposed to honorable mention – assignment – hence serving as an additional indicator of proposal quality. At the same time, high faculty research and publication activity in the applicant’s program can create the potential for knowledge spillovers that may indirectly impact award assignment. Students observe the actions of their leaders and vicariously learn what activities are deemed legitimate as researchers (Bercovitz & Feldman, 2008). Through a process of social learning, students then emulate the behaviors considered most appropriate and even adopt value systems that resemble those of their leaders (Bandura 1977, 1986; Shamir et al., 1993). As Jones cogently argued in his review of inventor activity, “if one is to stand on the shoulders of giants, one must first climb up their backs…” (2009: 284). This is particularly salient during graduate training.

Peer productivity can have similar direct and indirect effects. Bercovitz and Feldman (2008) find that peer groups act in tandem with leaders and serve as an important reference. In graduate training, students often look to the behaviors of other graduate students who share similar research interests or experiences as inspiration for how to approach problems and make decisions (Bandura,
1986; Duflo & Saez, 2000; Sorensen, 2002, Ellison & Fudenberg, 1993). Within an academic program, this means that actions taken by one student hold important spillover effects for her peers. For example, programs with a high volume of graduate research assistants may spur more productive research output – in the form of publications, grant proposals, and even collaborative projects – than programs with a higher volume of graduate teaching assistants. A student’s research experience may inspire other students to seek out similarly prestigious and beneficial research positions. The experience may also inspire a student to pursue additional innovative projects that may require knowledge and resource input from other graduate students, helping them to establish their own research foothold. This is important because, as recent empirical work suggests, collaboration – as opposed to isolated production – has become an increasingly important element in inventive output (Aggarwal, Hsu, & Wu, 2015; Wuchty, Jones, & Uzzi, 2007; Singh & Fleming, 2010; Jones, 2009). An astute reviewer may be aware of the student productivity of various departments and may use the signal of an applicant’s department to inform her recommendation for award receipt.

From another angle, diversity may spur the creation of knowledge spillovers. This includes diversity of personnel, ideas, and backgrounds, which has the ability to foster productivity, research agendas, and perspectives (Autio et al., 2014; Amin & Cohendet, 2000). Organizations can be diverse in a multitude of ways based on the composition of their personnel including technical skill sets, experience levels, normative ideologies, and general demographic characteristics. In the case of technical skill sets, if the program fosters interdisciplinary interaction (as opposed to only within-discipline interactions), students are likely to draw upon a broader set of skills and analytical perspectives for approaching a research problem (Lattuca, 2001). Critics to this argument, however, highlight that team diversity can also lead to higher coordination costs (Aggarwal, Hsu, & Wu, 2015; Williams & O’Reily, 1998). Within an academic program, these coordination costs could arise with
interdisciplinary research agendas and even when researchers from different backgrounds interact (Jacobs & Frickel, 2009).

Program resources and support may also indirectly affect assignment as they may improve application quality (Salancik & Pfeffer, 1978). Program resources can serve a critical role in connecting human and physical capital with one another more efficiently and effectively. These resource supports are intended to aid not only faculty, but graduate students as well, who are often in need of more structured guidance and mentorship as they learn to navigate the world of research. Recent research has noted the importance of comprehensive support mechanisms in supporting emerging researchers as they pursue a variety of diverse career paths (Agrawal & Ohyama, 2013). Within the higher education literature, others have noted the significance of intra-departmental policies and practices in encouraging graduate student persistence and performance. The evidence suggests that regular evaluations of student progress and an emphasis on apprenticeship and collaboration leads to better student outcomes (Nerad & Cerny, 1993; de Valero, 2001). Though some of these program characteristics may have a direct impact on GRFP award status, it seems most probable that program-specific research support is likely to have a stronger indirect effect in helping applicants craft stronger proposals.

In addition to program signals, we argue that the academic institution may mediate the application outcome. While more distant to the PI than the specific program signal, we argue that university ranking and type of institutional control not only signal research quality, but also relative capacity to provide resource support. Regarding the latter, a relatively nascent stream of literature has focused on the role of institutional control on research output (Aghion et al., 2010; Whaley & Hicks, 2014); however, we argue that this signal also influences receipt of external public funding as well through direct and indirect channels.
4. Research Design

Upon review, both awardees and honorable mentions pass a high threshold of quality that distinguishes them from non-recipients. However, there is a less clear distinction between the ultimate winners and the near-misses. First, panel reviewers have recommended both sets of students. Second, we argue that given the brevity of the application compared to a traditional NSF proposal and the fact that the GRFP targets emerging researchers in early-career-stage research, there is a higher degree of ambiguity or uncertainty on behalf of proposal reviewers. Thus, while proposal (and inherently student) quality is an important factor in the assignment of award status, it is also driven directly and indirectly by program and university characteristics, of which reviewers are likely to be aware. Such characteristics can both directly offer signals to reviewers about the legitimacy of the research potential and further distinguish student quality, and they indirectly offer resources that would impact application quality.

With any study, there are shortcomings. For this analysis, while we do have the complete list of awardees and honorable mentions since inception of the GRFP, detail on each individual applicant is limited. Thus, we rely on the distinguishing characteristic that these applicants are comparable given this top quarter of publicized proposals were recommended by the panelists to NSF. In addition, we use doctoral program rankings to proxy for the innate student quality of the application to match comparable doctoral programs that have graduate student honorable mentions only to those with at least one awardee. We then assess what institutional characteristics influence assignment through direct and indirect means.

The premise of the analysis is to assess what programmatic characteristics impact receipt of a prestigious research award by eligible students – considering factors beyond the merit review of the research proposal itself. There is an endogeneity concern that high quality students select into high quality programs and universities; thus, the underlying student quality may be driving the award
outcomes, not the academic organization’s characteristics. Critical to the research design, however, is the fact that both GRFP award recipients and honorable mentions are distinguished by reviewing panelists as having high merit and research potential. Moreover, while NSF has firm guidelines about restricting application data with the public, this program provides an exception: awardees and honorable mentions for all years of the GRFP program are publicly provided. We draw upon this data not only to identify promising emerging researchers, but also to exploit this variation as the counterfactual and control for a baseline of student quality. We augment this approach with both a set of university and program controls and program ranking stratifications. The latter approach allows us to define similar subsamples with comparable prestige and quality to assess moderated effects of program rank. Both of these aspects of the model are discussed in Section 4.3.

4.1 Data

We use data from two separate databases: the NSF’s GRFP grant database and the National Research Council’s (NRC) data on research doctorate programs, which is eponymous with academic departments. The NSF GRFP data is a time series dataset that is structured at the proposal-level and includes institutional affiliation and field of study for the population of awardees and honorable mentions, respectively. We compute annual, program-level counts of student GRFP award receipts and GRFP honorable mentions, indexed by academic field and university.

The NRC is a decennial survey assessment of the quality of US research doctoral programs. The first and second rounds were conducted in 1983-84 and 1995-96, respectively. However, the most recent survey (2005-2006), published in 2010, offers the most rigorous and current assessment of graduate program quality (Hicks, 2009; Schmitt, 2013). The NRC survey data contain detailed information on program characteristics for a representative sample of US doctoral programs. This survey includes data on a series of program-level measures ranging from faculty publications,
citations, grants, and diversity to characteristics of the graduate student population including average GRE scores, type of financial support, and socio-demographic characteristics. The data also contain information on characteristics of the doctoral program such as the number of PhD’s granted over five years, median time to degree, student completion rate, and various types of student activities available for supporting students (Ostriker et al., 2011). Over 5,000 doctoral programs that span 62 academic fields from 212 universities were surveyed (see Appendix D in Ostriker et al., 2011).

We recognize that the GRFP can be awarded to both research masters and doctoral students. However, given the nature of the NRC data, we rely on statistics from doctoral programs to obtain the most detailed level study of graduate programs. Moreover, the NRC study provides a representative database of doctoral-research programs (Ostriker et al., 2011), which is revered as the most comprehensive data source on US graduate programs. As highlighted in the study’s methodology, the chairman of the NRC reached out to the population of presidents and chancellors of US universities that offer doctoral degrees to encourage participation in this survey. While data on the response rate is not publicly available, the NRC highlights that the small proportion of those not participating either had very few doctoral programs or were undergoing administrative reorganization (Ostriker et al., 2011; pg. 5).

In the past, the NRC survey has placed precedence on academic program review to promote academic standards (Ostriker et al., 2011), with much scholastic attention on the NRC study stemming from discussion of higher education ranking methodology (e.g. Brooks, 2005; Dill, 2006; Dill & Beerkens, 2012; Schmitt, 2013). Less attention, however, has been directed towards utilizing the data for higher education empirical analyses despite the richness of the data.

We merged the NSF GRFP and NRC databases based on a numeric university-field crosswalk. We referred to the publicly available National Center for Education Statistics (NCES) Integrated Postsecondary Education Data System (IPEDS) and NRC’s S&E fields to assign a unique
institution and field identification, respectively. We draw upon the individual’s listed field and institution to match the program, and then rely on the NRC data to approximate the graduate program’s characteristics. The level of analysis is at the program, indexed by the academic field, $i$, and university, $n$. Appendix A details the data building and merging processes.

4.2 Sample

The sample of NRC programs with any GRFP award and/or honorable mention activity by students from 2005 to 2008 defines the dataset. Given the S&E scope of the NSF GRFP program, we exclude 21 academic fields from the NRC survey that comprise the Arts and Humanities division, have a health-related focus, or demonstrate no GRFP activity. The 41 remaining S&E academic fields constitute four broad divisions of Engineering, Life Sciences, Math & Physical Sciences, and Social & Behavioral Sciences, as defined by the National Academy’s Board on Higher Education and Workforce (Table 1).

<table>
<thead>
<tr>
<th>Academic Division</th>
<th>Academic Field</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engineering</td>
<td>Aerospace Engineering; Biomedical Engineering and Bioengineering; Chemical Engineering, Civil and Environmental Engineering, Electrical and Computer Engineering; Materials Science and Engineering, Mechanical Engineering, Operations Research, Systems Engineering, and Industrial Engineering</td>
</tr>
<tr>
<td>Life Sciences</td>
<td>Animal Sciences; Biochemistry, Biophysics, and Structural Biology; Biology/Integrated Biology/Integrated Biomedical Sciences; Cell and Developmental Biology; Ecology and Evolutionary Biology; Entomology; Forestry and Forest Sciences; Genetics and Genomics; Immunology and Infectious Disease; Microbiology; Neuroscience and Neurobiology; Nutrition; Pharmacology, Toxicology, and Environmental Health; Physiology; Plant Sciences</td>
</tr>
<tr>
<td>Mathematics and Physical Sciences</td>
<td>Applied Mathematics; Astrophysics and Astronomy; Chemistry; Computer Sciences; Earth Sciences; Mathematics; Oceanography, Atmospheric Sciences, and Meteorology; Physics; Statistics and Probability</td>
</tr>
<tr>
<td>Social and</td>
<td>Anthropology; Communications; Economics; Geography;</td>
</tr>
</tbody>
</table>
Regarding the timeframe of 2005-2008, the NSF GRFP program reports annual data on proposal activity while the NRC data is a cross-section. Although administered as a decennial survey, the NRC data reflect programmatic trends over several years. More specifically, the most recent 2010 survey contains program data from years 2000 to 2006. In an effort to most accurately estimate the effect of institutional factors on the performance of emerging researcher grant success, we draw upon NSF GRFP data over a four-year period, 2005 to 2008, notably a timeframe that overlaps the tail end of NRC data collection. We exclude the years after 2008 where the Great Recession had significant impact on the economy, affecting both NSF funding and GRFP activity.\(^{15}\)

The primary unit of analysis is the program (indexed by academic field \(i\) and university \(n\)). Our full sample includes 1,033 S&E graduate programs from 142 universities.\(^{16}\) This sample of programs secured 1,984 awards and 3,642 honorable mentions, for a total of 5,626 GRFP accolades from 2005 to 2008. Table 2 provides descriptive statistics of GRFP activity for the full sample and the sub-samples stratified by academic division.

### Table 2: Distribution of GRFP Activity for Full Sample and by Academic Division

<table>
<thead>
<tr>
<th>S&amp;E Graduate Programs with GRFP Activity</th>
<th>Full Sample</th>
<th>ENG</th>
<th>LS</th>
<th>MPS</th>
<th>SBS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Academic Fields</td>
<td>1,033</td>
<td>318</td>
<td>333</td>
<td>158</td>
<td>224</td>
</tr>
<tr>
<td>Number of Universities</td>
<td>41</td>
<td>8</td>
<td>15</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Total Number of Awards &amp; Honorable Mentions</td>
<td>5,626</td>
<td>1,599</td>
<td>1,753</td>
<td>891</td>
<td>1,383</td>
</tr>
<tr>
<td>Program Mean Count</td>
<td>5.45</td>
<td>5.03</td>
<td>5.26</td>
<td>5.64</td>
<td>6.17</td>
</tr>
<tr>
<td><strong>GRFP Awards</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Programs with Awards</td>
<td>643</td>
<td>213</td>
<td>183</td>
<td>104</td>
<td>143</td>
</tr>
</tbody>
</table>

\(^{15}\) The number of GRFP awards roughly doubled from 2009 to 2010 (1248 and 2051, respectively). Moreover, the ratio of honorable mentions to awards decreased from an average of 1.63 (2000 – 2009) to 0.89 (2010 – 2014).

\(^{16}\) We drop from 1,034 to 1,033 programs as one program with only honorable mentions lacks reporting for cohort size, a key variable used in the derivation of one of our outcomes described below.
Share of Programs with Awards | 62%  | 67%  | 55%  | 66%  | 64%
Total Number of Awards       | 1,984 | 659  | 571  | 296  | 458
Program Mean Count           | 3.09  | 3.09 | 3.12 | 2.85 | 3.20

**GRFP Honorable Mentions**

| Number of Programs with Honorable Mentions | 906  | 266  | 305  | 135  | 200  |
| Share of Programs with Honorable Mentions | 88%  | 84%  | 92%  | 85%  | 89%  |
| Total Number of Honorable Mentions      | 3,642| 940  | 1,182| 595  | 925  |
| Program Mean Count                      | 4.02 | 3.53 | 3.88 | 4.41 | 4.63 |

*Notes: Stratification by academic division; ENG – Engineering, LS – Life Sciences, MPS – Math & Physical Sciences, SBS – Social & Behavioral Sciences; Sample includes only programs with GRFP activity (award and/or honorable mention) between 2005 - 2008*

The Life Sciences division accounts for the largest share of the sample with 333 programs from 15 academic fields. This is followed by the Engineering (318), Social & Behavioral Sciences (224), and Math & Physical Sciences (158) divisions. The average count of total GRFP activity by program over the four-year period fluctuates across divisions with an aggregate mean of 5.45 for the full sample, a minimum of 5.03 for programs in the Engineering division, and a maximum of 6.17 for the Social & Behavioral Sciences.

In terms of award activity, the Engineering and Math & Physical Sciences divisions have the largest share of programs with awards (67 percent and 66 percent, respectively) while the Social and Behavioral Sciences division has the highest average number of awards per program (3.20). There is a larger pool of honorable mentions with 88 percent of programs containing at least one graduate student who received this distinction and an average of 4.02 per program. This varies across the divisions with 84 percent of programs from the Engineering division having honorable mentions up to 92 percent of programs from the Life Sciences division. Social and Behavioral Sciences again has the largest average count with 4.63 honorable mentions per program.
4.3 Methods

To examine the effect of institutional spillovers on demonstrated success among emerging researchers, we estimate three empirical models at the program-level of analysis.

*Step 1: Any Award Success*

As discussed in Section 4.2, our sample contains those programs with any demonstrated GRFP success, either award or honorable mention, from 2005 – 2008. By restricting the NRC sample to the 1,033 programs containing students who experienced some form of GRFP activity, we focus our attention on a set of programs that are justifiably more similar and thus comparable to one another. In order to experience success in having students obtain any GRFP recognition, these programs necessarily contain emerging researchers who actively choose to seek graduate research funding from NSF. Students in this sample are likely to be of higher quality, research-oriented, and to share more characteristics with one another than with those students from programs that experience no graduate student GRFP activity at this time.

Within this sample, we examine the effect of a set of institutional spillover factors on their graduate applicants gaining a competitive advantage. By competitive advantage, we mean the difference between a program containing students that win honorable mentions *exclusively* and those that contain students who win at least one formal award. Our first outcome of interest is a binary variable for whether a program experiences any GRFP award activity.

Of our sample of programs with any GRFP activity, 38 percent (390 programs) have students who only obtain honorable mentions, with the remaining 62 percent (643) contain at least one student in receipt of a GRFP award (the share of programs with only awards is 12 percent (127)). Equation 1 is a binary model estimating the effect of the series of institutional spillovers on a
program experiencing any GRFP award activity from 2005 to 2008 where \( i \) denotes the academic field and \( n \) indexes the university.

\[
\Pr(\text{Any GRFP Award}_{in} = 1|\mathbf{x}) = f(\beta_0 + \beta_1 \text{Leadership Quality & Composition}_{in} + \\
\beta_2 \text{Peer Quality & Composition}_{in} + \beta_3 \text{Program Support & Traits}_{in} + \beta_4 \text{University Traits}_{n} + \\
\lambda_i + \epsilon_{in}) \quad [1]
\]

The binary outcome of interest is any GRFP award for students in the graduate program from 2005 to 2008, where one indicates that at least one award was received, and a zero indicates that only honorable mentions were received during this time period. The institutional factors of interest are divided into 4 categories. The first, Leadership Quality and Composition, is measured with a vector of variables, \( \beta_1 \), to capture the program’s faculty-based characteristics. These include faculty publications and external grant activity to proxy for faculty quality, as well as measures of the share of female, interdisciplinary, and non-Asian minority faculty to account for faculty composition.

We include a similar set of student measures for Peer Quality and Composition, \( \beta_2 \). These include the average GRE quantitative scores to proxy for student quality, and measures of the share of female, non-Asian minority students, and the percent of students with academic plans to estimate student composition. Program Support and Traits are estimated with a vector, \( \beta_3 \), which includes whether there is student workspace, proposal support, and an above average number of student support programs; it also includes median time to degree and the program size by quartile. University Traits are included with \( \beta_4 \), a vector containing the region, whether it is a public institution, and university rank by tercile, based on Barron’s university rankings.\(^{17}\) The full list of variables and their functional form is detailed in Section 4.5 below.

Last, we include a field fixed effect (\( \lambda_i \)). This refers to the 41 S&E fields from the NRC study. In following with Gardner’s (2009) argument, “disciplines have their own qualities, cultures,

codes of conduct, values, and distinctive intellectual tasks that ultimately influence the experiences of faculty, staff, and most especially students within their walls” (pg. 386). Inclusion of academic field fixed effects controls for unobserved time-invariant variation across academic disciplines and therefore offers more conservative estimates of the models. This allows us to control for differences in academic culture and structure. The complete list and frequency of fields are provided in Appendix Table A1.

Step 2: Concentration of Awards

We next use the same sample to assess how these characteristics impact the share of students in a program that receive an award (Equation 2). This continuous variable stands in contrast to the binary outcome presented in Step 1.

\[
\text{Awards}_{in}/\text{Cohort}_{in} = f(\beta_0 + \beta_1 \text{Leadership Quality and Composition}_{in} + \beta_2 \text{Peer Quality and Composition}_{in} + \beta_3 \text{Program Support and Traits}_{in} + \beta_4 \text{University Traits}_{n} + \lambda_i + \epsilon_{in}) \tag{2}
\]

The outcome variable is a continuous measure that accounts for the relative amount of award activity. The variable represents the share of the average eligible cohort that receives the GRFP award contingent on the program having any GRFP activity. The numerator is the average annual award count\(^{18}\) and the denominator is the average first year cohort size reported in the NRC multiplied by two. The cohort size is doubled due to the fact that students are eligible in their first and second year of graduate school. Because receipt of a GRFP is a relatively rare event, the average share of award activity is quite small at 2.1 percent with a range of 0 to 41 percent.

We maintain the relative activity of this continuous outcome measure, but normalize the distribution by standardizing the variable so that it has a mean of 0 and a standard deviation of 1,

\(^{18}\) Given that we rely on four years of GRFP activity for the analysis, we divide the total number of GRFP awards by four to compute the annual average.
Moreover, the variable is standardized within the corresponding academic division the program belongs too (i.e., one of the four, such as Engineering or Life Sciences) to account for variation across broad academic divisions. Thus, we are estimating how these factors impact the relative concentration of awards. The same set of vectors used in Step 1 are employed in Step 2 as well, along with the academic field fixed effects.

**Step 3**

Recognizing that 38 percent of programs do not contain any students who have obtained a GRFP award between 2005 and 2008, for Step 3 we restrict the sample to programs with any GRFP award activity (643 programs). We then estimate Equation 2 with the restricted sample to assess how the set of university and program characteristics impact the share of students in a program that receive an award, contingent on the program having at least one awarded student. The outcome variable is again a standardized measure of the continuous ratio measuring the share of awards to eligible cohort size, by academic division. Given that we remove the set of programs with no award activity, the average concentration of award activity for this subsample increases from 2.1 percent to 3.5 percent.

4.4 Stratification

Variation in student quality between honorable-mention-only programs and those with one awarded student or more poses the greatest threat of endogeneity in our analysis. Critically, we draw upon applicants just shy of funding to control for those who have passed similar benchmarks during merit review. However, we take additional steps to account for differences student quality by including a set of program rank stratifications. In addition to estimating with the full sample for each step, we stratify the sample by program rank, initially grouping the academic programs in terciles.
where ranks 1, 2, and 3 denote high, mid, and low rank in the respective field. We use the R ranking produced by the NRC. We do this in order to match comparable programs to address the potential for confounding factors related to institutional quality that might attract higher quality students (Hegde, 2005). Moreover, what matters for top rank programs may be different from what matters for lower-ranked programs that will not be competing for the same group of students. Taken together, this approach measures the *moderated* effect of program quality.

We operationalize this using the NRC’s R ranking – a regression based ranking derived from a faculty survey of peer programs. The NRC also reports S ranking – a general survey approach. Correlations indicate significant overlap between the two measures, thus we rely on the R ranking, which methodologically better captures program perception and reputation (Ostriker et al., 2011). We estimate two bins from the tercile rankings – rank 1 (high) and rank 2 and 3 (mid and low). We combined the lower two terciles given the small sample sizes (this is particularly salient in Step 3 with the restricted sample).

4.5 Variables

Four vectors of variables are included to estimate the role of institutional spillover factors on a program having students obtain a GRFP award in a program. Appendix Table A2 details the variables in each vector. To ease interpretation and compare the relative influence of each variable, all *continuous* variables are standardized so they have a normal distribution with a mean of 0 and a standard deviation of 1, \([x_{in1} - \bar{x}_1]/\sigma_1\], where the slope coefficient is \(\hat{\beta}_1\). This allows us to compare effects across the regressors to assess the probability of having an award (Step 1) or the relative concentration of awards (Steps 2 & 3) from a one standard deviation increase of each continuous variable.
As with the award concentration (the outcome variable for Steps 2 and 3), each variable is standardized with respect to the program’s corresponding academic division to account for academic divisional differences. While programs within a university often adopt similar policies and norms, there is a stronger convergence among programs that are across universities within the same academic field (Friedman & Friedman, 1982). Programs in the same field residing within different higher education institutions compete across the discipline over students, faculty, funding, and publications to gain legitimacy and prestige.

The following measures are standardized: average number of faculty publications; percent of faculty with grants; demographics of faculty that include percent female, percent non-Asian minority, and percent interdisciplinary; average GRE quantitative score; percent of students with research fellowships; demographics of students that include percent female and non-Asian minority, respectively; and median time to degree. Additionally, we include a set of binary indicators: student workspace; student proposal support; above-field-average in student support programs; program size dummies (with the smallest bin as the referent); public university; and university rank (with the low bin – formally representing Competitive and Less Competitive institutions – as the referent). The binary variables offer interpretations of differential effects.

4.6 Descriptive Statistics

Table 3 presents the descriptive statistics of the GRFP performance outcome variables and covariates for the full set of programs and then subsequent stratified subsamples by academic division. This includes the full sample of programs with any GRFP activity. Table 3 reports the base-

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19 Barron’s university rankings are in the following descending order: Most Competitive (Q1); Highly Competitive (Q2); Very Competitive (Q3); Competitive (Q4); and Less Competitive (Q5). We classify Q1 and Q2 as High; Q3 as Mid; and Q4 and Q5 as Low.
line statistics; however, we include the standardized measures in the set of regressions for comparative purposes when interpreting marginal effects.

<table>
<thead>
<tr>
<th>Table 3: Descriptive Statistics of Covariates</th>
<th>Full Sample</th>
<th>ENG</th>
<th>LS</th>
<th>MPS</th>
<th>SBS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GRFP Performance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Programs Receiving Any Awards</td>
<td>0.62</td>
<td>0.67</td>
<td>0.55</td>
<td>0.66</td>
<td>0.64</td>
</tr>
<tr>
<td>Award Concentration</td>
<td>0.022</td>
<td>0.02</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Range: 0 - 0.42</td>
<td>(0.04)</td>
<td>(0.02)</td>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Award Concentration Given Award</td>
<td>0.035</td>
<td>0.03</td>
<td>0.05</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>Range: 0.0011 - 0.42</td>
<td>(0.04)</td>
<td>(0.02)</td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.03)</td>
</tr>
<tr>
<td><strong>Leadership Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Publications per Faculty</td>
<td>1.78</td>
<td>1.96</td>
<td>1.82</td>
<td>2.94</td>
<td>0.65</td>
</tr>
<tr>
<td>Range: 0.01 - 10.16</td>
<td>(1.28)</td>
<td>(1.32)</td>
<td>(0.71)</td>
<td>(1.63)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>Faculty with Grants, Percent</td>
<td>78.13</td>
<td>84.29</td>
<td>86.74</td>
<td>86.47</td>
<td>50.70</td>
</tr>
<tr>
<td>Range: 0 - 100</td>
<td>(19.92)</td>
<td>(11.29)</td>
<td>(10.89)</td>
<td>(10.08)</td>
<td>(20.89)</td>
</tr>
<tr>
<td>Female Faculty, Percent</td>
<td>20.27</td>
<td>10.99</td>
<td>23.62</td>
<td>14.02</td>
<td>32.89</td>
</tr>
<tr>
<td>Range: 0 - 100</td>
<td>(12.38)</td>
<td>(6.51)</td>
<td>(9.33)</td>
<td>(8.04)</td>
<td>(12.13)</td>
</tr>
<tr>
<td>Interdisciplinary Faculty, Percent</td>
<td>26.16</td>
<td>30.39</td>
<td>26.61</td>
<td>22.61</td>
<td>21.98</td>
</tr>
<tr>
<td>Non-Asian Minority Faculty, Percent</td>
<td>4.38</td>
<td>4.59</td>
<td>3.27</td>
<td>2.70</td>
<td>6.91</td>
</tr>
<tr>
<td>Range: 0 - 54.55</td>
<td>(4.79)</td>
<td>(4.94)</td>
<td>(3.34)</td>
<td>(3.36)</td>
<td>(6.07)</td>
</tr>
<tr>
<td><strong>Peer Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average GRE Quantitative Score</td>
<td>726.68</td>
<td>768.05</td>
<td>705.12</td>
<td>737.57</td>
<td>692.31</td>
</tr>
<tr>
<td>Range: 485.83 - 800</td>
<td>(51.93)</td>
<td>(23.93)</td>
<td>(46.36)</td>
<td>(42.96)</td>
<td>(52.56)</td>
</tr>
<tr>
<td>Female Students, Percent</td>
<td>41.31</td>
<td>24.28</td>
<td>49.94</td>
<td>38.72</td>
<td>54.46</td>
</tr>
<tr>
<td>Range: 0 - 90.91</td>
<td>(17.36)</td>
<td>(11.15)</td>
<td>(11.67)</td>
<td>(12.09)</td>
<td>(14.47)</td>
</tr>
<tr>
<td>Range: 0 - 100</td>
<td>(10.11)</td>
<td>(11.71)</td>
<td>(9.13)</td>
<td>(7.91)</td>
<td>(10.05)</td>
</tr>
<tr>
<td>Students with Academic Plans, Percent</td>
<td>55.32</td>
<td>35.96</td>
<td>67.18</td>
<td>60.12</td>
<td>61.77</td>
</tr>
<tr>
<td>Range: 0 - 100</td>
<td>(20.46)</td>
<td>(16.36)</td>
<td>(16.23)</td>
<td>(16.16)</td>
<td>(13.34)</td>
</tr>
<tr>
<td><strong>Program Support &amp; Traits</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student Workspace Provided</td>
<td>0.80</td>
<td>0.80</td>
<td>0.88</td>
<td>0.97</td>
<td>0.58</td>
</tr>
<tr>
<td>Student Proposal Support Provided</td>
<td>0.69</td>
<td>0.50</td>
<td>0.80</td>
<td>0.65</td>
<td>0.84</td>
</tr>
<tr>
<td>Number of Student Programs</td>
<td>16.50</td>
<td>16.17</td>
<td>16.65</td>
<td>16.27</td>
<td>16.90</td>
</tr>
<tr>
<td>Range: 0 - 18</td>
<td>(1.79)</td>
<td>(1.83)</td>
<td>(1.67)</td>
<td>(2.31)</td>
<td>(1.32)</td>
</tr>
<tr>
<td>Median Time to Degree, Years</td>
<td>5.59</td>
<td>5.01</td>
<td>5.60</td>
<td>5.52</td>
<td>6.44</td>
</tr>
<tr>
<td>Range: 2 - 12</td>
<td>(1.05)</td>
<td>(0.89)</td>
<td>(0.76)</td>
<td>(0.64)</td>
<td>(1.26)</td>
</tr>
<tr>
<td>Program Size Quartiles</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Though between-division differences are small in some areas, some stark differences arise between the four subgroups. For instance, programs in the Engineering, Life Sciences, and Math & Physical Sciences divisions demonstrate much greater levels of external grant receipt by faculty than the Social & Behavioral Sciences. Moreover, programs in the Math & Physical Sciences division report an average of 2.94 annual publications per faculty in contrast to the mean of 1.78. Programs in the Social & Behavioral Sciences division have higher rates of female and non-Asian minority faculty. As for student characteristics, GRE scores from students in the Engineering and Math & Physical Sciences division exceed the mean, while the share of female students lags.

Turning to program features, student workspace is less prominent in the Social & Behavioral Sciences division, yet proposal support notably lags for Engineering. The length of the program in the Social & Behavioral Sciences division is 6.44 years; this exceeds the full sample with an average of 5.59 years. The variable program size refers to the quartile ranking of a program, given the full
sample of NRC programs in the 2010 release of data (5,004 programs from 212 universities). Our sample of 1,033 programs, roughly 40 percent are classified as the largest (Q4). As for region, over a quarter of the programs are from universities located in the Northeast and West. Lastly, roughly two-thirds of the programs are within public universities, and the majority of programs are housed within most & highly competitive institutions (high ranked) institutions according to the Barron’s ranking.

4.7 Post-Specification Tests

We run a series of post-specification tests and robustness checks to assess the fit of the various models. For the binary model in Step 1 (Equation 1), we fit the models to logit and probit distributions. In addition, we run the model as a linear probability model (LPM) with an OLS distribution to assess the consistency and the efficiency of the results. For the OLS model, we clustered the standard errors by academic field. We present the results from the logit distribution as the primary model; however, the probit and LPM results are included in Appendix Table A3. While perfect prediction was present for a handful of unique programs, the convergence rates were relatively high for the maximum likelihood estimation models with 99.5 percent convergence for the full sample, 98.4 percent for the rank 1 sample, and 96.7 percent for the rank 2 and 3 sample.

For all models, we both excluded and included academic field fixed effects; this reflects the 41 S&E fields from the NRC study. In addition, we tested the functional form of the covariates. While we present the standardized values for the set of continuous measures, we also estimated the continuous regressors as: (i) baseline measures; (ii) location quotients relative to broad academic division base; and (iii), binary, tercile, and quartile rankings of the baseline measures by division. While the baseline measures offer the most direct measure, the wide distribution across the continuous measures (e.g. average faculty publications vs. average GRE scores) makes interpretation
of the coefficients less meaningful. Moreover, given that the baseline values are in level form, additional estimations are needed to benchmark the marginal effects relative to the larger sample. While the set of coefficients across these three approaches are robust to the primary results, we present the results with the standardized notation not only to allow for comparison across regressors, but also to normalize the interpretation of the marginal effects. In addition, as a robustness check, we also standardized the continuous variables across the full sample by program rank (rather than division). Both alternatives produced similar findings to the standardized form by academic division. Due to the theoretical importance of discipline (Gardner 2009), we present the results standardized by academic division.

5. Results

Results are presented below for each of the three steps – the logistic estimation of Equation 1 in Section 5.1, the OLS estimation of Equation 2 in Section 5.2, and the OLS estimation of Equation 2 for the subsample of programs with award activity in Section 5.3.

5.1 Step 1: Any Award Activity

We estimate Equation 1, a binary model of any GRFP award success on academic institutional characteristics. Table 4 presents the marginal effects from the logistic regressions for the full sample in column 1 and the stratified sample by program rank (rank 1 in column 2 and ranks 2 and 3 in column 3). The average marginal effects for the standardized continuous regressors are interpreted such that a one standard deviation increase is associated with a change in the probability of having at least one student in the program secure GRFP award recognition from 2005 to 2008. The binary regressors are interpreted as the differential effect in the probability of having any award success. The comparison of the marginal effects for the logit, probit, and linear probability models
are presented in Appendix Table A3. The results are consistent across models. The coefficients from the primary logistic regression are presented in the Appendix Table A4.

**Table 4: Marginal Effects of Logistic Estimation of Equation 1, Step 1**

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Full Sample</th>
<th>(2) Rank 1</th>
<th>(3) Rank 2 &amp; 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Leadership Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized Average Publications per Faculty</td>
<td><strong>0.072</strong>*</td>
<td><strong>0.079</strong>*</td>
<td>0.075</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.028)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>Standardized Percent of Faculty with Grants</td>
<td>-0.002</td>
<td>0.026</td>
<td>-0.018</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.024)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Standardized Percent Female Faculty</td>
<td>-0.011</td>
<td>0.009</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.020)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Standardized Percent of Interdisciplinary Faculty</td>
<td><strong>0.030</strong></td>
<td><strong>0.031</strong>*</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.018)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Standardized Percent Non-Asian Minority Faculty</td>
<td>0.000</td>
<td>0.008</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.021)</td>
<td>(0.022)</td>
</tr>
<tr>
<td><strong>Peer Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized Average GRE Quantitative Score</td>
<td><strong>0.067</strong>*</td>
<td><strong>0.085</strong>*</td>
<td><strong>0.070</strong>***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.029)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Standardized Percent Female Students</td>
<td>-0.005</td>
<td>-0.022</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.027)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Standardized Percent Non-Asian Minority Students</td>
<td>0.013</td>
<td>0.024</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.024)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Standardized Percent of Students with Academic Plans</td>
<td>0.008</td>
<td>-0.014</td>
<td><strong>0.046</strong>*</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.022)</td>
<td>(0.024)</td>
</tr>
<tr>
<td><strong>Program Support &amp; Traits</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student Workspace Provided (Binary)</td>
<td>0.022</td>
<td>-0.008</td>
<td>0.066</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.045)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Student Proposal Support Provided (Binary)</td>
<td>0.012</td>
<td>0.041</td>
<td>-0.029</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.041)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>Above Field Average in Student Support Programs (Binary)</td>
<td><strong>0.083</strong>*</td>
<td><strong>0.110</strong>*</td>
<td>0.074</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.039)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Standardized Median Time to Degree</td>
<td>-0.008</td>
<td>-0.013</td>
<td>-0.016</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.023)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Program Size Quartiles (Referent: Q1, Smallest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Program Size, Q2</td>
<td>0.057</td>
<td><strong>0.193</strong>*</td>
<td>0.081</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.102)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Program Size, Q3</td>
<td><strong>0.096</strong>*</td>
<td><strong>0.213</strong>*</td>
<td><strong>0.137</strong>*</td>
</tr>
<tr>
<td>Program Size, Q4 (Largest)</td>
<td>0.220***</td>
<td>0.355***</td>
<td>0.193**</td>
</tr>
<tr>
<td>---------------------------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.095)</td>
<td>(0.086)</td>
</tr>
</tbody>
</table>

**University Traits**

<table>
<thead>
<tr>
<th>Public University (Binary)</th>
<th>-0.148***</th>
<th>-0.178***</th>
<th>-0.088</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.042)</td>
<td>(0.048)</td>
<td>(0.080)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>University Rank (Referent: Low)</th>
<th>University Rank: High</th>
<th>University Rank: Mid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.021</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td>(0.055)</td>
</tr>
<tr>
<td></td>
<td>0.004</td>
<td>-0.041</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.105)</td>
</tr>
<tr>
<td></td>
<td>-0.034</td>
<td>-0.065</td>
</tr>
<tr>
<td></td>
<td>(0.084)</td>
<td>(0.076)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>1,028</th>
<th>601</th>
<th>406</th>
</tr>
</thead>
<tbody>
<tr>
<td>Academic Field Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Region Controls Included</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Note: Marginal Effects presented; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Statistically significant results are bolded. Outcome: Binary indicator if any awards received; All standardized covariates are normalized by academic division

Due to perfect prediction, certain narrow fields were omitted from the estimations: For the full sample (1) computer science, mathematics, nutrition, and statistics & probability; for rank 1 programs (2) Computer Science, Nutrition, Statistics & Probability, Entomology, and Forestry & Forest Science; and for rank 2 & 3 programs (3) Mathematics, Entomology, Communication, Economics, Oceanography & Atmospheric Sciences, Operations Research & Systems Engineering, and Pharmacology & Toxicology

In the results for the full sample (column 1), the following regressors are statistically significant: standardized average number of publications per faculty; standardized percent of interdisciplinary faculty; standardized average GRE quantitative score; binary indicators for the number of student support programs, program size (Q3 and Q4, both with reference to Q1), and the binary indicator for public university. By normalizing the continuous regressors, we can more easily compare the marginal effects within each model. Notably, increasing the average number of publications per faculty by one standard deviation is associated with a 7.2 percentage point increase in the probability of the program having any GRFP award activity. The marginal effects for a standard deviation increase for the share of interdisciplinary faculty and the average GRE score are associated with a 3.0 and 6.7 percentage point increase, respectively, in the probability of the program having any GRFP award activity. In other words, programs with greater levels of faculty
publication activity, interdisciplinary faculty, and students with higher GRE scores are positively associated with GRFP award activity, holding constant the academic field of the program.

Turning to the set of binary regressors, the differential effect of having an above-field-average number of student support activities is associated with an 8.3 percentage point increase in having at least one student successfully obtain a GRFP award. In other words, programs with a higher proportion of student support activities such as travel funding, teacher training, or proposal support than the average program in their narrow academic field (e.g., economics) are more likely to have student applicants that achieve the GRFP award. Moreover, larger programs have a positive association compared to the smallest programs, categorized into quartiles by the NRC. Relative to Q1 programs (the reference group) Q4 programs have a 22.0 percentage point advantage in likelihood of GRFP award activity. Relative to Q1, Q3 programs also have a higher probability of award receipt, though the marginal effect is much smaller at 9.6 percentage points. Notably, when it comes to university traits, we estimate a large negative effect for public universities. The differential effect of the unique doctoral program belonging to a public – in contrast to a private – university, is associated with a 14.8 percentage point decrease in the probability of having any GRFP award activity by emerging student researchers.

When stratified by program ranking, results vary across rank 1 (column 2) and ranks 2 and 3 (column 3). The same set of significant regressors are robust and larger (in absolute value) for the rank 1 sample compared to the full sample, indicating that high doctoral program rank moderates the average effect. Additionally, all three size-related program dummies are positive and significant (again, results are in reference to Q1, the smallest program size). Standardized measures of average faculty publications and percent interdisciplinary faculty, along with binary measures of above-field-average student support activities and public university, are only robust for top-ranked programs. These regressors are no longer significant for lower ranked programs (ranks 2 & 3). For the sample
of programs with lower ranks, the measure for students with academic plans is significant, where a one standard deviation increase is associated with a 4.6 percentage point increase in the probability of having at least one applicant receive a GRFP award.

5.2 Step 2 Award Concentration for GRFP Active Sample

Step 2 includes a continuous outcome measure to account for the relative share of GRFP awards to eligible cohort size within a program. As with the set of continuous regressors, we standardized the outcome variable. We interpret the coefficients for the set of standardized regressors as follows: if \( x_1 \) increases by one standard deviation, then the share of GRFP awards to eligible cohort changes by \( \beta \) standard deviations, where \( \beta \) refers to the coefficient. The set of binary regressors are interpreted as follows: the differential effect of \( x_2 \) is associated with a \( \beta \) standard deviation change in the share of GRFP awards to eligible cohort, where once again \( \beta \) refers to the variable coefficient. Table 5 presents the coefficients from the OLS regressions for the full sample in column 1 and the stratified sample by program rank (rank 1 in column 2 and ranks 2 and 3 in column 3).

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Full Sample</th>
<th>(2) Rank 1</th>
<th>(3) Rank 2 &amp; 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Leadership Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized Average Publications per Faculty</td>
<td><strong>0.151</strong>*</td>
<td><strong>0.130</strong></td>
<td>0.149</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.066)</td>
<td>(0.115)</td>
</tr>
<tr>
<td>Standardized Percent of Faculty with Grants</td>
<td>0.012</td>
<td>0.077</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.048)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Standardized Percent Female Faculty</td>
<td>0.013</td>
<td>0.046</td>
<td>0.046</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.040)</td>
<td>(0.059)</td>
</tr>
<tr>
<td>Standardized Percent of Interdisciplinary Faculty</td>
<td>0.039</td>
<td><strong>0.053</strong></td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.031)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>Standardized Percent Non-Asian Minority</td>
<td>-0.023</td>
<td>-0.047</td>
<td>0.008</td>
</tr>
<tr>
<td>Category</td>
<td>Variable Description</td>
<td>Coefficient</td>
<td>Standard Error</td>
</tr>
<tr>
<td>----------------------------------------------</td>
<td>---------------------------------------------------------------------------</td>
<td>-------------</td>
<td>----------------</td>
</tr>
<tr>
<td><strong>Faculty</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Peer Quality &amp; Composition</strong></td>
<td>Standardized Average GRE Quantitative Score</td>
<td>0.159**</td>
<td>(0.075)</td>
</tr>
<tr>
<td></td>
<td>Standardized Percent Female Students</td>
<td>-0.043</td>
<td>(0.055)</td>
</tr>
<tr>
<td></td>
<td>Standardized Percent of Non-Asian Minority Students</td>
<td>0.047</td>
<td>(0.032)</td>
</tr>
<tr>
<td></td>
<td>Standardized Percent of Students with Academic Plans</td>
<td>0.059</td>
<td>(0.044)</td>
</tr>
<tr>
<td><strong>Program Support &amp; Traits</strong></td>
<td>Student Workspace Provided (Binary)</td>
<td>0.046</td>
<td>(0.058)</td>
</tr>
<tr>
<td></td>
<td>Student Proposal Support Provided (Binary)</td>
<td>0.059</td>
<td>(0.063)</td>
</tr>
<tr>
<td></td>
<td>Above Field Average in Student Support Programs (Binary)</td>
<td>0.050</td>
<td>(0.049)</td>
</tr>
<tr>
<td></td>
<td>Standardized Median Time to Degree</td>
<td>0.057</td>
<td>(0.043)</td>
</tr>
<tr>
<td></td>
<td>Program Size Quartiles (Referent: Q1, Smallest)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Program Size, Q2</td>
<td>-0.129</td>
<td>(0.149)</td>
</tr>
<tr>
<td></td>
<td>Program Size, Q3</td>
<td>-0.393***</td>
<td>(0.121)</td>
</tr>
<tr>
<td></td>
<td>Program Size, Q4 (Largest)</td>
<td>-0.342***</td>
<td>(0.107)</td>
</tr>
<tr>
<td><strong>University Traits</strong></td>
<td>Public University (Binary)</td>
<td>-0.186**</td>
<td>(0.079)</td>
</tr>
<tr>
<td></td>
<td>University Rank (Referent: Low)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>University Rank: High</td>
<td>0.203*</td>
<td>(0.114)</td>
</tr>
<tr>
<td></td>
<td>University Rank: Mid</td>
<td>0.037</td>
<td>(0.132)</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>0.560***</td>
<td>(0.189)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
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<td>611</td>
</tr>
<tr>
<td><strong>R-squared</strong></td>
<td></td>
<td>0.217</td>
<td>0.309</td>
</tr>
<tr>
<td><strong>Academic Field Fixed Effects</strong></td>
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<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Region Controls Included</strong></td>
<td></td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Note: OLS regression results, clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; statistically significant results are bolded; Outcome: Standardized ratio of awards to eligible student cohort; All standardized variables are normalized by academic division

We use the same vectors to estimate the effect of these institutional characteristics on the proportion of students receiving awards to capture variation across the sample on *award concentration* as opposed to *binary award recognition*. For the full sample, the following regressors are statistically significant: standardized average number of publications per faculty, standardized average GRE quantitative score, program size (Q3 and Q4, both in reference to Q1), the binary indicator for public university, and dummy for high-ranked university (in reference to low). The coefficients for measures of faculty publications, GRE activity, and high-ranked university are positive, while program size and the public indicator variable are negative. Increasing the average number of publications per faculty (average GRE quantitative score) by one standard deviation is associated with a 0.151 (0.159) standard deviation increase in GRFP award concentration. Moreover, the differential effect of high university rank in reference to low is associated with a 0.203 standard deviation increase in GRFP award concentration. Being a public university, meanwhile, as opposed to a private university is associated with a 0.186 standard deviation decrease in GRFP award concentration.

Lastly, the results for program-size are negative, which contrasts to our findings from Step 1. The differential effect of the largest program size, Q4, (second largest program size, Q3) in reference to the smallest program size is associated with a 0.342 (0.393) standard deviation decrease in the GRFP award concentration.

In considering the set of results for the stratified samples (columns 2 and 3), the positive effects of faculty publication activity, GRE scores, a university high rank are moderated by high ranked programs, while the negative results for the larger program sizes are moderated by the lower
ranked programs. The standardized measure for the percent of interdisciplinary activity is significant for the high ranked sample, though the beta coefficient is relatively small (0.053).

5.3 Step 3 Award Concentration for GRFP Award Sample

Step 3 restricts the sample to programs with at least one student award winner from 2005 to 2008 to estimate the GRFP award concentration on the same set of variables as reported in Steps 1 and 2. Given the functional form of the outcome variable, we interpret the beta coefficients in the same manner as Step 2, noting the added contingency of the subsample. Table 6 presents the coefficients from the OLS regressions for the full sample in column 1 and the stratified sample by program rank (rank 1 in column 2 and ranks 2 and 3 in column 3).

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Full Sample</th>
<th>(2) Rank 1</th>
<th>(3) Rank 2 &amp; 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Leadership Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized Average Publications per Faculty</td>
<td>0.085</td>
<td>0.052</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td>(0.079)</td>
<td>(0.192)</td>
</tr>
<tr>
<td>Standardized Percent of Faculty with Grants</td>
<td>0.041</td>
<td>0.090</td>
<td>-0.040</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.063)</td>
<td>(0.107)</td>
</tr>
<tr>
<td>Standardized Percent Female Faculty</td>
<td>0.014</td>
<td>0.047</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.057)</td>
<td>(0.080)</td>
</tr>
<tr>
<td>Standardized Percent of Interdisciplinary Faculty</td>
<td>0.026</td>
<td>0.035</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.036)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>Standardized Percent Non-Asian Minority Students</td>
<td>-0.013</td>
<td>-0.010</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.062)</td>
<td>(0.053)</td>
</tr>
<tr>
<td><strong>Peer Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized Average GRE Quantitative Score</td>
<td>0.107</td>
<td><strong>0.247</strong></td>
<td>-0.102</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.113)</td>
<td>(0.140)</td>
</tr>
<tr>
<td>Standardized Percent Female Students</td>
<td>-0.047</td>
<td>0.039</td>
<td>-0.039</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.107)</td>
<td>(0.134)</td>
</tr>
<tr>
<td>Standardized Percent of Non-Asian Minority Students</td>
<td>0.033</td>
<td>0.087</td>
<td>-0.012</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.077)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>Standardized Percent of Students with</td>
<td><strong>0.086</strong></td>
<td><strong>0.138</strong></td>
<td>0.044</td>
</tr>
</tbody>
</table>
For the full sample, the following regressors are significant: standardized percent of students with academic plans, standardized median time to degree, program size (in reference to Q1), and high university rank (in reference to low ranked). Notably, faculty publication activity, GRE scores,
and public university are no longer significant; however, when restricting the sample we find peer effects driven by those with academic plans and longer duration of programs increase the GRFP award concentration.

For high ranked programs, the peer effects are robust; in addition, GRE scores are also a positive and significant indicator of increased GRFP award activity. This latter result is consistent with Steps 1 and 2. Moreover, high-ranked programs are also moderating the effect of high university rank. Whereas, the lower ranked programs moderate the negative effects for larger program size.

6. Discussion

Academic programs, and universities more broadly, provide a useful context to examine the effect of institutional factors on innovative activity within graduate programs. We rely on competitive R&D funding variation between academic programs with GRFP honorable mention and award-winning students to investigate the importance of academic institutions on research funding success. Moreover, this study redirects attention from senior scholars to emerging researchers – an often-overlooked population at an earlier point in their professional careers with significant economic potential.

The results from Equation 1 (Table 4) examine the effect of a set of leadership, peer, programmatic, and university factors on having any GRFP award activity. The results are more pronounced for the subsample of high ranked programs, which suggests that these features are positively moderated by program rank. Even controlling for student applicant quality through program rank, we find that the program’s prestige influences funding decisions and consequently access to funding through highly productive faculty, exceptional students (measured by GRE score),
and programmatic support and size. Given the prestigious nature of NSF funding, this finding is not a surprise.

However, theoretically, if the merit-review solely focuses on the content of the proposal and not external information, we would expect to find no significant results. Our findings point to the importance of program characteristics, support, and reputation as recognizable quality signals to NSF reviewers and potentially as indirectly increasing proposal quality through giving student applicants more social and physical capital. For example, we find consistent positive effects of faculty publications on program award activity. We anticipate that increased faculty research activity sends a positive signal to the scholarly community, helping build or stabilize the reputation of a doctoral program, which indirectly influences the panel’s review of the emerging researcher’s proposal. Importantly, even controlling for student quality, we find that faculty productivity is positively associated with grant receipt. This activity may either spillover within the program, thus impacting the graduate student; or this research activity may spillover within the larger community, thus influencing the panel’s perception of the proposal’s potential. Given the nature of the data, we are unable to tease apart the specific mechanisms, direct or indirect; however, we suspect that both factor into the funding decision.

Additionally, the results indicate that larger program size positively influences whether a given program can expect student applicants to receive an award. While this measure directly counts student personnel within a program, it serves as a useful proxy for the number of resources and potential social connections within the program. Thus, we interpret this as evidence that programs with greater resources positively influence student grant receipt. Corroborating this finding, we find that being a public university, ceteris paribus, is associated with a decrease in the probability of award receipt for a graduate program. Public institutions, in contrast to private research universities,
on average tend to have less access to resources, which impacts research productivity (Aghion et al., 2010) and follow on funding (Lanahan et al. 2016).

In Steps 2 and 3, we adjust the outcome variable to examine the effect of the set of regressors on the share of award concentration. For Step 2 we draw upon the full sample of programs with any GRFP activity, while with Step 3 we restrict the sample to programs with any award activity only. The smaller sample allows us to control for an even higher baseline of student quality. For the former model on the full sample, the set of robust results closely mirror our findings from Step 1. However, by adjusting the outcome variable from binary to a continuous measure, we find evidence that program size in fact decreases the concentration of awards. This effect is moderated by lower ranked programs. Thus in contrast to the smallest sized programs (Q1), larger, lower-ranked programs are more likely to experience a lower share of award concentration. If we continue to view this measure as a signal of resources, this implies that larger programs may face coordination costs that are detrimental to the rate of graduate student success. While larger programs increase the likelihood of having any awards, the larger, lower-ranked programs appear to exhibit inefficiencies in scaling the activity. When we restrict the sample to programs with any award, the negative effect remains robust, where size is inversely related with the share of award concentration.

As with any research project, there are limitations to these analyses. It should be noted that we are looking at a limited timeframe due to the collection period of the NRC data. We utilize this period of GRFP activity from 2005 – 2008 to ensure that the programmatic characteristics overlap with the end of the collection for the NRC survey. While there is some annual variation in graduate programs, as an organization, they are quite static so we consider this to be a justified approach in assessing impacts. Moreover, by keeping the time period of analysis nearest to the NRC data collection timeframe, we can be even more confident that there is minimal noise created by annual changes.
Taken together, we have evidence that a series of leadership, peer, programmatic, and university characteristics are associated with grant funding success for emerging researchers. While we do lack sharp identification, we proxy for student quality in the program rank stratifications. Thus if the NSF merit-review is solely based on the contents of the proposal, then theoretically, we would expect to find no significant results. The significant results we do find indicate there are factors that work both directly and indirectly to improve an applicant’s chance at receiving an award given a baseline of quality. While we lack causal identification, the results suggest factors external to the grant application impact the funding outcome.

7. Conclusion

This study lays a foundation for research on emerging researcher activity through implementation of a strong research design. Notably, the design confronts the threat of endogeneity and draws upon a sample of US graduate programs to examine how factors external to the research proposal mediate funding success. Yet more work on this topic remains. We draw upon the full sample of GRFP honorable mentions and award winners from 2005 to 2008 and link students to programs in NRC data. Though without the entire sample of GRFP applicants, any effect we find theoretically has two parts: (i) the graduate program characteristics motivate students to apply for external research funding – whether from NSF or from other sources; and (ii) after prompting students to apply for external research funding, these unique characteristics work to ensure that applying students receive the resources necessary to ultimately secure grant funding and recognition. This could work in a variety of ways: providing necessary research proposal drafting support, ensuring emerging researchers have necessary skills to conduct research, or providing a collaborative atmosphere that allows them to learn how to develop research ideas from their peers and from faculty members. While NSF data on the full applicant pool is restricted, future research could
conducted follow-up surveys of members of the program – both faculty and emerging researchers – to illuminate these mechanisms. Bartolone and his colleagues (2014; 2015) have begun with these efforts.

The results from this paper support existing research on the value of human capital for innovation. While the GRFP is a competitive award for the student and is meritorious in its own right, the student’s continued success is closely tied to the program’s education and research support. Certain academic environments promote a culture that values success in obtaining these grants as they recognize the value of external funding to the student’s own financial stability, to the support of their lab, and for the prestige to their program. These graduate programs are providing a supportive environment to students that allow them to capitalize on their individual research ideas.

Anecdotal evidence suggests that the positive effects of GRFP receipt are felt strongest for winners located within laboratory environments, which are better accustomed to collaborative research projects, or in fields where mentorship is more prevalent. Put another way, the student may be at a research disadvantage if the external funding distanced her access to advising and mentorship during the graduate training. For example, an economics GRFP winner may become “silenced” within her program, which would isolate her away from faculty or other students and collaborative research opportunities. Contrary to the aims of the program, this could reduce the student’s research output. Though this paper does not address the impacts of GRFP receipt, these potential implications are important to consider. Further assessment is necessary to examine how the award affects the future success of both the emerging researchers and their programs. This could be measured in a number of ways including professional placement and productivity. As a baseline for this line of scholarship, however, this paper focuses on understanding the antecedent factors that lead to emerging researcher success in obtaining research funding.
References


Bartolone et al. (2014). Evaluation of the National Science Foundation’s Graduate Research Fellowship Program – Final Report. Chicago, IL: NORC at the University of Chicago.


Acknowledgements

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Appendix

Appendix A: Building the program-level dataset

We use data from two separate databases: the National Research Council’s data on Research Doctorate Programs and the National Science Foundation’s Graduate Research Fellowship Program (GRFP) grant database. The NRC database comprises a cross section of program observations, while the NSF GRFP database comprises annual proposal observations.

The NSF GRFP data is a time series dataset that is structured at the proposal-level and includes institutional affiliation and field of study for the population of awardees and honorable mentions, respectively. Data on NSF GRFP award and honorable mention activity was accessed publicly online. At the time of building this dataset, data on awardees was available from 1952 to 2014, and data on honorable mentions was available from 1994 to 2014. We built a database based on availability of data for the population of awardees and honorable mentions, therefore delimiting the timeframe from 1994 to 2014. This includes 58,218 unique observations. While this timeframe exceeds the four-year period used in this analysis, we built the database based on the full sample of data and then restricted the sample from 2005 to 2008 ex post for the empirical analysis. The NRC research doctorate study reports program-level data for 5,004 program at 212 universities. The survey reports program-level statistics for activity between 2000 and 2006; the results from the survey were made publicly available in 2010. The NRC sample defines the graduate programs examined for this analysis.

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20 NSF reports data on six fields: Name of applicant, Email Address, Baccalaureate Institution, Field of Study, Proposed Graduate Institution, and Current Institution, though not all fields appear for each year of awardee and honorable mention data available. Email Address and Current Institution fields are most complete after 2003.


22 This sample represents 99.22% of GRFP awardees and honorable mentions. Reporting for honorable mentions is 100 percent from 1994 – 2004. For more recent years (2005 – 2014), the average reporting ratio is 97.69 percent. The overall reporting ratio for honorable mentions is 98.90 percent. This was derived from the following source: https://www.fastlane.nsf.gov/grfp/AwardeeList.do?method=loadAwardeeList

457 observations were dropped due to missing data on one of the following fields: Field of Study, Proposed Graduate Institution, or Current Institution.
The academic program is the level of analysis for this paper, indexed by $i$ for the academic field and $n$ for the university. To merge the two datasets, we first needed to create a unique university-field crosswalk. We referred to the National Center for Education Statistics (NCES) Integrated Postsecondary Education Data System (IPEDS)\(^{23}\) and the NRC taxonomy of academic fields and subfields\(^{24}\) to assign a unique institutional identification and program identification, respectively. Although the former dataset provides extensive university-level information, for the purposes of this analysis we solely relied on this data source as an intermediate database to identify the unique numeric university IPEDS ID. We used these two identifications to uniquely define the university-field in each dataset before merging the two datasets together.

Below, we outline the three main steps to build this dataset. First, we identified the university IPEDS ID (Step 1) and academic field (Step 2) for the observations in each dataset respectively. For the former, we specify the parameters for identifying the graduate institution for the NSF GRFP database as well. Then, we merged the two datasets on the unique numeric university-field crosswalk (Step 3). We coded and documented the entire match procedure in STATA.

**Step 1: Assign University IPEDS ID**

*NSF GRFP Data*

Before assigning an IPEDS ID to the university, we relied on information from the fields ‘Current Institution’ and ‘Proposed Graduate Institution’ to define the university for the GRFP data. For the primary analysis, we included only those observations where the applicant’s Proposed Graduate Institution matched the Current Institution. With an emphasis on examining the effect of graduate programs on emerging researcher activity, we are interested in identifying the subset of individuals who applied for the GRFP program while enrolled in his/her graduate program. To

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\(^{23}\) Data on the population of US academic institutions is publicly available: https://nces.ed.gov/ipeds/datacenter/.

\(^{24}\) http://sites.nationalacademies.org/PGA/Resdoc/PGA_044522
reiterate, emerging researchers are eligible to apply for the GRFP prior to completing 12 academic months of graduate study. Thus, individuals completing their undergraduate degrees or master's degree en route to applying to a Ph.D. program are eligible. In these cases, the Current Institution and Proposed Graduate Institution may not match given that they may apply for the GRFP while they simultaneously apply to a graduate program at another institution. By limiting the population to those whose Proposed Graduate Institution match the Current Institution, we assume to identify those currently in a graduate program or at least exposed to the graduate program. Given the nature of the NRC data, which provides detailed data on research graduate programs, this enables us to estimate the effect of graduate organizations on scholastic promise.

As additional sensitivity checks, we also identified the university based on the Current Institution and Proposed Graduate Institution, respectively. In these two cases, we assume that the Current Institution or the Proposed Graduate Institution is the individual’s graduate institution. We recognize that these are weaker assumptions for two reasons: (i) the Current Institution may reflect the individual’s undergraduate or master’s institution – which may be different from his/her Ph.D. institution; or (ii) the individual may not end up enrolling at the listed Proposed Graduate Institution. The results were generally robust to the main models. This suggests that GRFP honorable mentions and awardees are typically acknowledged once enrolled their graduate program. As with rigorous peer-reviewed journals, it is common for proposals to undergo revisions before receiving an acknowledgement or an award. Thus, those successful – in terms of receiving a GRFP award or honorable mention – are likely not a first time applicant. We assume those that receive the

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25 In the event the individual’s Proposed Graduate Institution matches the Current Institution, yet the individual is not in a graduate program (but rather in the process of applying to the graduate program), we assume that the individual is in the same field of study completing his/her undergraduate or Master’s as the prospective graduate program. In this case, the individual will still be exposed to the graduate program characteristics. It is plausible, however, for the individual to be in a different undergraduate or Master’s program than his/her graduate program while at the same institution. Unfortunately, we are unable to vet this, yet we assume that this scenario is less prominent given that prior disciplinary training is often required to enroll in a research graduate program.

26 The results for these models are available upon request.
GRFP award or honorable mention are enrolled in a graduate program. For the primary analysis we report where the Current Institution matches the Proposed Graduate Institution as it more accurately captures the population of GRFP applicants enrolled in and exposed to the graduate program when they receive GRFP recognition.

In an effort to match the IPEDS ID with the GRFP university string variable, we wrote a code to define the unique core sequence of strings for each institution. Articles were dropped and common terms were recoded.\textsuperscript{27} This exercise defined 895 unique universities.\textsuperscript{28} We employed the same method for cleaning the population of universities listed in the IPEDS database. As a result, we defined 15,679 unique academic organizations in the IPEDS database. We merged the datasets based on the unique university string variable. Approximately 72\% NSF GRFP observations, directly matched.\textsuperscript{29} For the remaining observations, we hand-matched 8,258 observations (27\%) based on common sequences of strings. Among those that we were unable to assign an IPEDS ID 270 observations were foreign institutions\textsuperscript{30} and 45 observations listed institutions with no IPEDS id. In sum, we matched IPEDS ID for 97.9\% of the total NSF GRFP sample.

\textit{NRC Data}

We employed the same coding technique as noted above in terms of cleaning up the string variable to match universities in the NRC sample to IPEDS. For the first, automated round of matching, we directly matched 3,918 observations (78.3\% of the sample). We hand-matched an

\textsuperscript{27} The authors employed a number of procedures to match on string name including removing spaces, renaming common terms (e.g. “university” = “uni”; “college” = “coll”; “inst” = “institute”; “state” = “st”), and removing articles (e.g. “and”, “of”, “at”, “for”, etc.).

\textsuperscript{28} This reflects the number of Current Institutions based on a unique string sequence. There were 974 unique string sequences for the Proposed Graduate Institutions.

\textsuperscript{29} We would like to note that we merged the unique list of IPEDS IDs with the comprehensive list of GRFP proposals. Due to the nature of the GRFP data, this merge was based on a cleaned sequence of strings rather than a numeric id. String-based merges, however, introduce minor noise. We ran the model numerous times and compared the results of the analyses and found that the results are efficient and consistent across all specifications. Thus we attribute this minor variation as ignorable noise.

\textsuperscript{30} We suspect that those who listed a foreign institution were applying for the GRFP award while applying for a graduate program at a U.S. based institution. At the time of submitting the grant application; however, they were located at another institution. Given our emphasis on examining the effect of graduate programs on research promise, we removed this sample.
additional 985 observations (19.7%), which yielded a 98.0% match rate. It is worth noting that 31 of the NRC programs were affiliated with more than one university. We dropped these from the sample given their unique multi-university affiliation.

Step 2: Assign Field ID

NRC Data

We based the field ID classification directly on the NRC program listing, as specified by the broad field and narrow field classifications, corresponding to division and field, respectively, in the manuscript. This original dataset includes 62 narrow fields from five broad fields. Given the S&E scope of the NSF GRFP program, we removed 14 fields from the NRC dataset that comprise the Arts and Humanities broad field, and two fields with a health-related focus. This yielded a total of 46 S&E fields.

31 For example, the Public Health program in the Biological and Sciences field was listed at both San Diego State University and the University of California San Diego (http://publichealth.sdsu.edu); the Biomedical Engineering and Bioengineering program in the Engineering field was listed at both the Georgia Institute of Technology and Emory University http://www.bme.gatech.edu; and the Civil and Environmental Engineering program in the Engineering field was listed at the University of Alabama Birmingham and the University of Alabama in Huntsville (www.eng.uab.edu/cee).

32 http://sites.nationalacademies.org/pga/resdoc/

33 NRC 62 fields include: Aerospace Engineering; Agricultural and Research Economics; Animal Sciences; Anthropology; Applied Mathematics; Astrophysics and Astronomy; Biochemistry, Biophysics, and Structural Biology; Biology/Integrated Biology/Integrated Biomedical Sciences; Biomedical Engineering and Bioengineering; Cell and Developmental Biology; Chemical Engineering; Chemistry; Civil and Environmental Engineering; Communication; Computer Engineering; Computer Sciences; Earth Sciences; Ecology and Evolutionary Biology; Economics; Electrical and Computer Engineering; Engineering Science and Materials; Entomology; Food Science; Forestry and Forest Sciences; Genetics and Genomics; Geography; History; Immunology and Infectious Disease; Kinesiology; Linguistics; Materials Science and Engineering; Mathematics; Mechanical Engineering; Microbiology; Neuroscience and Neurobiology; Nursing; Nutrition; Oceanography, Atmospheric Sciences and Meteorology; Operations Research, Systems Engineering and Industrial Engineering; Pharmacology, Toxicology and Environmental Health; Physics; Physiology; Plant Sciences; Political Science; Psychology; Public Affairs, Public Policy and Public Administration; Public Health; Sociology; Statistics and Probability; American Studies; Classics; Comparative Literature; English Language and Literature; French and Francophone Language and Literature; German Language and Literature; History; History of Art, Architecture and Archaeology; Languages, Societies and Cultures; Music (except performance); Philosophy; Religion; Spanish and Portuguese Language and Literature; and Theatre and Performance Studies.

34 NRC 5 fields include: Engineering, Life Sciences, Physical and Mathematical Sciences, Social and Behavioral Sciences, and Arts and Humanities.

35 Arts and Humanities broad field includes: American Studies; Classics; Comparative Literature; English Language and Literature; French and Francophone Language and Literature; German Language and Literature; History; History of Art,
NSF GRFP Data

To match the GRFP graduate program with the list of 46 NRC fields, we defined a unique sequence of common strings based on the NRC’s taxonomy of fields and their subfields. For example, for the NRC field ‘aerospace engineering’ we identified a combination of the following strings as a common match: ‘aeronautical vehicles,’ ‘space vehicles,’ ‘systems engineering and multidisciplinary design optimization,’ ‘aerodynamics and fluid mechanics,’ ‘astrodynamics,’ ‘structures and materials,’ ‘propulsion and power,’ ‘navigation, guidance, control and dynamics,’ and ‘multi-vehicle systems and air traffic control.’ As another example, for the NRC field ‘genetics and genomics’ we identified a combination of the following strings as a common match: ‘computational biology,’ ‘genetics,’ ‘genomics,’ and ‘molecular genetics.’ As a result of this string-based approach, we matched NRC fields to GRFP graduate programs for 57,598 observations yielding a 98.9% match rate.

Step 3: Creating a university-field crosswalk

To merge the GRFP and NRC data, we created a university-field numeric identification based on the publicly available National Center for Education Statistics (NCES) Integrated Postsecondary Education Data System (IPEDS) and NRC S&E fields. We then collapsed the GRFP data to the program level to compute annual aggregate counts of awardees and honorable mentions. In preparation for the merge, we dropped all observations without both a university and field for each dataset respectively. This resulted in 3,951 S&E programs.

Architecture and Archaeology; Languages, Societies and Cultures; Music (except performance); Philosophy; Religion; Spanish and Portuguese Language and Literature; and Theatre and Performance Studies.

Health-related fields: Nursing, and Kinesiology.

Source: http://sites.nationalacademies.org/PGA/Resdoc/PGA_044478

538 observations reported ‘N/A’ for program.

Data on the population of US academic institutions is publicly available: https://nces.ed.gov/ipeds/datacenter/.

http://sites.nationalacademies.org/PGA/Resdoc/PGA_044522
When merging the NSF GRFP data to the NRC data, 49.2% of the NRC sample had some NSF GRFP activity over four-year timeframe, 2005 – 2008 leaving 50.8% with no NSF GRFP activity.\(^{41}\) As a side note, roughly 44% of the GRFP sample did not match to the NRC sample. We attribute this non-match based on the restrictions of the sample for the NRC dataset. Notably among those that did not match, they represent a large distribution of universities (310); this in fact exceeds the sample size of the NRC survey. In addition, these un-matched GRFP data overrepresented six narrow fields: Public Affairs, Public Policy and Public Administration; Operations Research, Systems Engineering and Industrial Engineering; Mathematics; Engineering Science and Materials (not elsewhere classified); Communication; Biochemistry, Biophysics, and Structural Biology. Taken together, this suggests that the true distributions of U.S. graduate programs for these six fields are larger than the distributions sampled by the NRC study. Importantly, the NRC study includes 5,004 programs, yet this distribution only represents 212 universities. On average then, 23 programs were surveyed from each institution, yet 62 programs in total were reviewed. Based on our assessment of the missing data, the GRFP data that did not merge to the NRC are programs that were not surveyed in the NRC study. We are unable to include this set in the analysis given that we do not have program-level data for the full population of U.S. graduate research programs. While the NRC study did not survey every program in the U.S., it is recognized as the most comprehensive and detailed survey of U.S. research graduate programs.

After the merge, we assessed the data and discovered a handful of NRC program duplicates.\(^{42}\) For those with more than one unique university-field, we computed an aggregate mean

\(^{41}\) When merging the NSF GRFP data to the NRC data, 62.1% of the NRC sample had some NSF GRFP activity over the 20-year timeframe; thus indicating that 37.9% of the programs surveyed by the NRC had no GRFP activity over the 20-year timeframe.

\(^{42}\) There were 612 duplicates. Based on the nature of the covariate, we either summed or took the average of the duplicate observations. As illustrative examples of the duplicates, Rice University had two narrow programs listed as “Civil and Environmental Engineering” to reflect the Civil Engineering and Environmental Engineering programs at the institution; the University of Southern California had four narrow programs listed as “Public Health” to reflect the Biometry, Epidemiology, Occupational Science, and Preventative Medicine (Health Behavior) programs at the
for the program observation and removed the duplicate values. As a result of this exercise, we deleted 612 additional duplicate program observations yielding a total of 3,339 unique programs. We removed an additional 81 that did not have complete information for the vector of covariates. This resulted in a total of 3,258 programs.
### Appendix Tables

Table A1: NRC Program Sample Frequency

<table>
<thead>
<tr>
<th>Program</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerospace Engineering</td>
<td>17</td>
<td>1.65</td>
</tr>
<tr>
<td>Animal Sciences</td>
<td>23</td>
<td>2.23</td>
</tr>
<tr>
<td>Anthropology</td>
<td>23</td>
<td>2.23</td>
</tr>
<tr>
<td>Applied Mathematics</td>
<td>2</td>
<td>0.19</td>
</tr>
<tr>
<td>Astrophysics and Astronomy</td>
<td>24</td>
<td>2.32</td>
</tr>
<tr>
<td>Biochemistry, Biophysics, and Structural Biology</td>
<td>38</td>
<td>3.68</td>
</tr>
<tr>
<td>Biology/Integrated Biology/Integrated Biomedical Sciences</td>
<td>31</td>
<td>3</td>
</tr>
<tr>
<td>Biomedical Engineering and Bioengineering</td>
<td>48</td>
<td>4.65</td>
</tr>
<tr>
<td>Cell and Developmental Biology</td>
<td>34</td>
<td>3.29</td>
</tr>
<tr>
<td>Chemical Engineering</td>
<td>32</td>
<td>3.1</td>
</tr>
<tr>
<td>Chemistry</td>
<td>54</td>
<td>5.23</td>
</tr>
<tr>
<td>Civil and Environmental Engineering</td>
<td>50</td>
<td>4.84</td>
</tr>
<tr>
<td>Communication</td>
<td>5</td>
<td>0.48</td>
</tr>
<tr>
<td>Computer Sciences</td>
<td>1</td>
<td>0.1</td>
</tr>
<tr>
<td>Earth Sciences</td>
<td>52</td>
<td>5.03</td>
</tr>
<tr>
<td>Ecology and Evolutionary Biology</td>
<td>50</td>
<td>4.84</td>
</tr>
<tr>
<td>Economics</td>
<td>18</td>
<td>1.74</td>
</tr>
<tr>
<td>Electrical and Computer Engineering</td>
<td>63</td>
<td>6.1</td>
</tr>
<tr>
<td>Entomology</td>
<td>8</td>
<td>0.77</td>
</tr>
<tr>
<td>Forestry and Forest Sciences</td>
<td>5</td>
<td>0.48</td>
</tr>
<tr>
<td>Genetics and Genomics</td>
<td>24</td>
<td>2.32</td>
</tr>
<tr>
<td>Geography</td>
<td>15</td>
<td>1.45</td>
</tr>
<tr>
<td>Immunology and Infectious Disease</td>
<td>16</td>
<td>1.55</td>
</tr>
<tr>
<td>Linguistics</td>
<td>22</td>
<td>2.13</td>
</tr>
<tr>
<td>Materials Science and Engineering</td>
<td>36</td>
<td>3.48</td>
</tr>
<tr>
<td>Mathematics</td>
<td>1</td>
<td>0.1</td>
</tr>
<tr>
<td>Mechanical Engineering</td>
<td>60</td>
<td>5.81</td>
</tr>
<tr>
<td>Microbiology</td>
<td>26</td>
<td>2.52</td>
</tr>
<tr>
<td>Neuroscience and Neurobiology</td>
<td>35</td>
<td>3.39</td>
</tr>
<tr>
<td>Nutrition</td>
<td>2</td>
<td>0.19</td>
</tr>
<tr>
<td>Oceanography, Atmospheric Sciences, and Meteorology</td>
<td>8</td>
<td>0.77</td>
</tr>
<tr>
<td>Operations Research, Systems Engineering, and Industrial Engineering</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Engineering</td>
<td>12</td>
<td>1.16</td>
</tr>
<tr>
<td>Pharmacology, Toxicology and Environment Health</td>
<td>15</td>
<td>1.45</td>
</tr>
<tr>
<td>Physics</td>
<td>15</td>
<td>1.45</td>
</tr>
<tr>
<td>Physiology</td>
<td>12</td>
<td>1.16</td>
</tr>
<tr>
<td>Plant Sciences</td>
<td>14</td>
<td>1.36</td>
</tr>
<tr>
<td>#</td>
<td>Subject</td>
<td>Count</td>
</tr>
<tr>
<td>-----</td>
<td>----------------------------------------------</td>
<td>-------</td>
</tr>
<tr>
<td>37</td>
<td>Political Science</td>
<td>44</td>
</tr>
<tr>
<td>38</td>
<td>Psychology</td>
<td>67</td>
</tr>
<tr>
<td>39</td>
<td>Public Affairs, Public Policy and Public Administration</td>
<td>3</td>
</tr>
<tr>
<td>40</td>
<td>Sociology</td>
<td>27</td>
</tr>
<tr>
<td>41</td>
<td>Statistics and Probability</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>1,033</td>
</tr>
</tbody>
</table>
### Table A2: Description of Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outcome Variables</strong></td>
<td></td>
</tr>
<tr>
<td>Any Award Activity in 2005-2008 (Step 1)</td>
<td>Binary variable equal to 1 if the program has any doctoral students receive a GRFP award between 2005 and 2008.</td>
</tr>
<tr>
<td>Share of Awards to Eligible Students in 2005-2008 (Steps 2 &amp; 3)</td>
<td>Ratio of the following: average number of annual GRFP awards received per year by doctoral students within the program between 2005 and 2008 (numerator) over double the size of the average first-year cohort as measured from 2002-2006 (denominator).</td>
</tr>
<tr>
<td><strong>Leadership Quality</strong></td>
<td></td>
</tr>
<tr>
<td>Average Number of Publications (2000-2006) per Allocated Faculty, 2006</td>
<td>Average number of publications published by allocated faculty members in a program between 2000 and 2006 as of data collection in 2006 by Thomson Reuters. See page 241 in Ostriker et al. (2011) for more information.</td>
</tr>
<tr>
<td>Percent of Faculty with Grants, 2006</td>
<td>Number of faculty with extramural grant or contract support divided by the total number of faculty in the program in 2006.</td>
</tr>
<tr>
<td><strong>Leadership Composition</strong></td>
<td></td>
</tr>
<tr>
<td>Percent Female Faculty, 2006</td>
<td>Number of female core and new faculty members as of 2006 as a percent of total core and new faculty members in the program (not including allocated faculty).</td>
</tr>
<tr>
<td>Percent of Interdisciplinary Faculty, 2006</td>
<td>Number of faculty &quot;associated&quot; with the program and at least one other program divided by the total number of faculty comprising that program including associated, core, and new faculty members in 2006.</td>
</tr>
<tr>
<td>Percent Non-Asian Minority Faculty, 2006</td>
<td>Number of non-Hispanic Blacks, Hispanics, and American Indians or Alaskan Natives as of 2006 as a percent of total core and new faculty members including non-Hispanic Whites and Asians or Pacific Islanders in the program (not including allocated faculty). Does not include faculty with unknown race/ethnicities, non-US citizens, and non-permanent residents.</td>
</tr>
<tr>
<td><strong>Peer Quality</strong></td>
<td></td>
</tr>
<tr>
<td>Average GRE Quantitative Scores, 2004-2006</td>
<td>Weighted average quantitative GRE score for the program, calculated by multiplying the number of individuals reporting scores each year (2004, 2005, and 2006, separately) by the reported average GRE score for that year, summing these 3 quantities together, and dividing by the total sum of individuals reporting scores between 2004 and 2006 in that program.</td>
</tr>
</tbody>
</table>
### Peer Composition

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Female Students, 2005</td>
<td>Number of female students enrolled in the program as of Fall 2005 as a percent of the total number of graduate students in the program. Number of non-Hispanic Blacks, Hispanics, and American Indians or Alaskan Natives students enrolled in the program as of Fall 2005 as a percent of the total number of domestic graduate students in the program with known race/ethnicities. Does not include faculty with unknown race/ethnicities, non-US citizens, and non-permanent residents.</td>
</tr>
<tr>
<td>Percent of Non-Asian Minority Students, 2005</td>
<td>Percent of doctoral students with definite plans for an academic position, calculated via a crosswalk with the NSF Doctorate Records File using data between 2001-2005. The percentage represents the number of individuals who signed or were negotiating a contract for a position at an educational institution in that field divided by the total number of survey respondents in that field between 2001 and 2005. See page 245 in Ostriker et al. (2011) for more information.</td>
</tr>
<tr>
<td>Percent of Students with Academic Plans, 2001-2005</td>
<td></td>
</tr>
</tbody>
</table>

### Program Support

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student Workspace Provided</td>
<td>Binary variable equal to 1 if the program provides students with workspace.</td>
</tr>
<tr>
<td>Proposal Support Available</td>
<td>Binary variable equal to 1 if the program or university provides students with proposal writing assistance or training.</td>
</tr>
<tr>
<td>Ratio of Student Support Programs to Field Average Indicator</td>
<td>Binary variable equal to 1 if the ratio of number of student activities offered compared to average number offered within academic field is above average, or greater than 1. This is based off of the 18 potential student activities listed in the NRC, which includes: student orientation, international student orientation, language support, writing support, statistics support, prizes for teaching or research, proposal support, on-campus graduate research conference, academic integrity training, graduate student association, staff and graduate student association, financial support of graduate student association, academic grievance support, dispute resolution, regular graduate program meeting, annual review, teacher training, travel support</td>
</tr>
<tr>
<td>Median Time to Degree, 2004-2006</td>
<td>Median time to degree for full-time and part-time students in the program measured in years and averaged over the years 2004-2006.</td>
</tr>
<tr>
<td>Program Size Quartile Ranking, Fall 2005</td>
<td>Categorical variable equal to the quartile ranking of the program based on the number of students enrolled as of Fall 2005; 1 is smallest while 4 is largest.</td>
</tr>
</tbody>
</table>

### University Traits
Region

Public University
Binary variable equal to 1 if the university is a public institution rather than privately controlled.

University Rank
Categorical variable of the Barron's university rankings grouped into three tiers of: Most & Highly Competitive, Very Competitive, or Competitive & Less Competitive.

**Note:** All variable definitions and descriptions are based off information published in the National Research Council's (NRC) Data-Based Assessment of Research-Doctorate Programs in the United States database and Methodology Guide, released in 2010-11. "Allocated" faculty are those who supervise dissertations across multiple programs. Their position assignment (=1) is therefore split proportionally across the programs they are affiliated with so that the sum of their allocated positions was equal to 1 to any faculty member supervising dissertation. “Core” faculty are those whose primary appointment is in the doctoral program while "new" faculty are those with tenure track appointments who were appointed in 2003-2006.
Table A3: Binary Model Comparison of Marginal Effects for Step 1 Estimations

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Logit</th>
<th>(2) Probit</th>
<th>(3) OLS LPM</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Leadership Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized Average Publications per Faculty</td>
<td>0.072***</td>
<td>0.071***</td>
<td>0.065***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Standardized Percent of Faculty with Grants</td>
<td>-0.002</td>
<td>0.000</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Standardized Percent Female Faculty</td>
<td>-0.011</td>
<td>-0.011</td>
<td>-0.013</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.016)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Standardized Percent of Interdisciplinary Faculty</td>
<td>0.030**</td>
<td>0.031**</td>
<td>0.030**</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Standardized Percent Non-Asian Minority Faculty</td>
<td>0.000</td>
<td>-0.000</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.017)</td>
</tr>
<tr>
<td><strong>Peer Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized Average GRE Quantitative Score</td>
<td>0.067***</td>
<td>0.067***</td>
<td>0.069***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Standardized Percent Female Students</td>
<td>-0.005</td>
<td>-0.008</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.018)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Standardized Percent of Non-Asian Minority Students</td>
<td>0.013</td>
<td>0.014</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Standardized Percent of Students with Academic Plans</td>
<td>0.008</td>
<td>0.008</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.022)</td>
</tr>
<tr>
<td><strong>Program Support &amp; Traits</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student Workspace Provided (Binary)</td>
<td>0.022</td>
<td>0.023</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.038)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Student Proposal Support Provided (Binary)</td>
<td>0.012</td>
<td>0.015</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.032)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Above Field Average in Student Support Programs (Binary)</td>
<td>0.083***</td>
<td>0.084***</td>
<td>0.094**</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.031)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Standardized Median Time to Degree</td>
<td>-0.008</td>
<td>-0.007</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Program Size Quartiles (Referent: Q1, Smallest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Program Size, Q2</td>
<td>0.057</td>
<td>0.058</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.052)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>Program Size, Q3</td>
<td>0.096*</td>
<td>0.098*</td>
<td>0.117*</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.052)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Program Size, Q4 (Largest)</td>
<td>0.220***</td>
<td>0.223***</td>
<td>0.239***</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.053)</td>
<td>(0.063)</td>
</tr>
<tr>
<td><strong>University Traits</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public University (Binary)</td>
<td>-0.148***</td>
<td>-0.149***</td>
<td>-0.152***</td>
</tr>
</tbody>
</table>
University Rank (Referent: Low)  | (0.042) | (0.042) | (0.043)  
University Rank: High  | 0.021 | 0.020 | 0.018  
                     | (0.057) | (0.057) | (0.060)  
University Rank: Mid  | -0.003 | -0.001 | -0.004  
                     | (0.055) | (0.055) | (0.072)  
Observations  | 1,028 | 1,028 | 1,033  
Academic Field Fixed Effects  | Yes | Yes | Yes  
Region Controls Included  | Yes | Yes | Yes  

Note: Clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Average Marginal Effects presented for (1) and (2), OLS coefficients (marginal effects) presented for (3)  
Outcome: Binary indicator if any awards received; All standardized covariates are normalized by academic division  
Narrow fields of computer science, mathematics, nutrition, and statistics & probability were omitted from the estimation of (1) and (2) due to perfect prediction  

Table A4: Coefficients of Logistic Estimation of Equation 1, Step 1  

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Full Sample</th>
<th>(2) Rank 1</th>
<th>(3) Rank 2 &amp; 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Leadership Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized Average Publications per Faculty</td>
<td>0.391***</td>
<td>0.536***</td>
<td>0.365</td>
</tr>
<tr>
<td></td>
<td>(0.123)</td>
<td>(0.193)</td>
<td>(0.258)</td>
</tr>
<tr>
<td>Standardized Percent of Faculty with Grants</td>
<td>-0.009</td>
<td>0.180</td>
<td>-0.085</td>
</tr>
<tr>
<td></td>
<td>(0.088)</td>
<td>(0.167)</td>
<td>(0.117)</td>
</tr>
<tr>
<td>Standardized Percent Female Faculty</td>
<td>-0.060</td>
<td>0.058</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.137)</td>
<td>(0.123)</td>
</tr>
<tr>
<td>Standardized Percent of Interdisciplinary Faculty</td>
<td>0.163**</td>
<td>0.209*</td>
<td>0.087</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.122)</td>
<td>(0.123)</td>
</tr>
<tr>
<td>Standardized Percent Non-Asian Minority Faculty</td>
<td>0.002</td>
<td>0.053</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>(0.078)</td>
<td>(0.144)</td>
<td>(0.105)</td>
</tr>
<tr>
<td><strong>Peer Quality &amp; Composition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized Average GRE Quantitative Score</td>
<td>0.363***</td>
<td>0.580***</td>
<td>0.338**</td>
</tr>
<tr>
<td></td>
<td>(0.105)</td>
<td>(0.204)</td>
<td>(0.149)</td>
</tr>
<tr>
<td>Standardized Percent Female Students</td>
<td>-0.026</td>
<td>-0.147</td>
<td>0.100</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.186)</td>
<td>(0.137)</td>
</tr>
<tr>
<td>Standardized Percent of Non-Asian Minority Students</td>
<td>0.072</td>
<td>0.164</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td>(0.161)</td>
<td>(0.104)</td>
</tr>
<tr>
<td>Standardized Percent of Students with Academic Plans</td>
<td>0.042</td>
<td>-0.092</td>
<td>0.224*</td>
</tr>
<tr>
<td></td>
<td>(0.084)</td>
<td>(0.150)</td>
<td>(0.119)</td>
</tr>
<tr>
<td><strong>Program Support &amp; Traits</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student Workspace Provided (Binary)</td>
<td>0.118</td>
<td>-0.057</td>
<td>0.319</td>
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<tr>
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<td>Coefficient 1</td>
<td>Coefficient 2</td>
<td>Coefficient 3</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>---------------</td>
<td>---------------</td>
<td>---------------</td>
</tr>
<tr>
<td>Student Proposal Support Provided (Binary)</td>
<td>0.067</td>
<td>0.283</td>
<td>-0.139</td>
</tr>
<tr>
<td></td>
<td>(0.175)</td>
<td>(0.279)</td>
<td>(0.256)</td>
</tr>
<tr>
<td>Above Field Average in Student Support Programs (Binary)</td>
<td>0.453***</td>
<td>0.754***</td>
<td>0.359</td>
</tr>
<tr>
<td></td>
<td>(0.169)</td>
<td>(0.270)</td>
<td>(0.254)</td>
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<tr>
<td>Standardized Median Time to Degree</td>
<td>-0.042</td>
<td>-0.086</td>
<td>-0.076</td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.157)</td>
<td>(0.115)</td>
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<tr>
<td>Program Size Quartiles (Referent: Q1, Smallest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Program Size, Q2</td>
<td>0.308</td>
<td>1.321*</td>
<td>0.393</td>
</tr>
<tr>
<td></td>
<td>(0.284)</td>
<td>(0.704)</td>
<td>(0.345)</td>
</tr>
<tr>
<td>Program Size, Q3</td>
<td>0.524*</td>
<td>1.454**</td>
<td>0.662*</td>
</tr>
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<td></td>
<td>(0.285)</td>
<td>(0.665)</td>
<td>(0.370)</td>
</tr>
<tr>
<td>Program Size, Q4 (Largest)</td>
<td>1.197***</td>
<td>2.423***</td>
<td>0.934**</td>
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<tr>
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<td>(0.297)</td>
<td>(0.670)</td>
<td>(0.424)</td>
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<tr>
<td><strong>University Traits</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public University (Binary)</td>
<td>-0.805***</td>
<td>-1.214***</td>
<td>-0.426</td>
</tr>
<tr>
<td></td>
<td>(0.232)</td>
<td>(0.342)</td>
<td>(0.390)</td>
</tr>
<tr>
<td>University Rank (Referent: Low)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>University Rank: High</td>
<td>0.115</td>
<td>0.028</td>
<td>-0.163</td>
</tr>
<tr>
<td></td>
<td>(0.308)</td>
<td>(0.712)</td>
<td>(0.409)</td>
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<td>University Rank: Mid</td>
<td>-0.015</td>
<td>-0.280</td>
<td>-0.314</td>
</tr>
<tr>
<td></td>
<td>(0.297)</td>
<td>(0.716)</td>
<td>(0.368)</td>
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<tr>
<td>Observations</td>
<td>1,028</td>
<td>601</td>
<td>406</td>
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<tr>
<td>Academic Field Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Region Controls Included</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Note: Coefficients presented; Clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Outcome: Binary indicator if any awards received; All standardized covariates are normalized by academic division
Due to perfect prediction, certain narrow fields were omitted from the estimations: For the full sample (1) computer science, mathematics, nutrition, and statistics & probability; for rank 1 programs (2) Computer Science, Nutrition, Statistics & Probability, Entomology, and Forestry & Forest Science; and for rank 2 & 3 programs (3) Mathematics, Entomology, Communication, Economics, Oceanography & Atmospheric Sciences, Operations Research & Systems Engineering, and Pharmacology & Toxicology