The Class Gap in Career Progression: Evidence from US academia

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Unlike gender or race, class is rarely a focus of research or DEI efforts in elite US occupations. Should it be? In this paper, we document a large class gap in career progression in one labor market: US tenure-track academia. Using parental education to proxy for socioeconomic background, we compare career outcomes of people who got their PhDs in the same institution and field (excluding those with PhD parents). First-generation college graduates are 13% less likely to end up tenured at an R1, and are on average tenured at institutions ranked 9% lower, than their PhD classmates with a parent with a (non-PhD) graduate degree. We explore three sets of mechanisms: (1) research productivity, (2) networks, and (3) preferences. Research productivity can explain less than a third of the class gap, and preferences explain almost none. Our analyses of coauthor characteristics suggest networks likely play a role. Finally, examining PhDs who work in industry we find a class gap in pay and in managerial responsibilities which widens over the career. This means a class gap in career progression exists in other US occupations beyond academia.

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1 Introduction

Race and gender disparities in elite career progression – including hiring, pay, and promotions – are the focus of a voluminous body of academic research, as well as major organizational and legislative efforts to tackle them. Socioeconomic background or class origin, in contrast, is rarely considered in this context. This absence of research in part reflects a lack of data. Socioeconomic background is rarely measured by large-scale government surveys, or by organizations' DEI efforts. For example, in 2020 "not one of the companies on DiversityInc's 'Top 50 Companies for Diversity' mentioned social class in their diversity, inclusion, and equity goals and programs" (Ingram, 2021). This absence of data collection, though, itself suggests that many researchers and practitioners assume class is unimportant for elite career progression – that, while socioeconomic background may matter for getting into a good college, any lingering impacts of class are washed out beyond that point. This assumption is incorrect.

In this paper, we show that socioeconomic background is an important determinant of elite career progression – using US tenure-track academia as a case study. This is an interesting setting in itself, as professors' background may impact their research and teaching. More importantly, though, tenure-track academia is a setting which is uniquely suited for detailed, quantitative study of the role of socioeconomic background in elite career progression more generally: (i) there is a relatively standardized hiring and promotion process across organizations (tenure-track job market and tenure), (ii) productivity is quantifiable (through data on research output), and (iii) the relative quality of jobs at different organizations is to some extent quantifiable (e.g. research-intensiveness or rank of academic institutions). By examining the class gap in career progression in tenure-track academia, we can shed light on mechanisms by which analogous class gaps may emerge in other elite occupations.

Indeed if anything tenure-track academia likely represents a lower bound: in other elite occupations where productivity is less objectively measurable, promotion is less ostensibly meritocratic, and networking with elite clients or colleagues is more openly relevant for productivity, we would expect class to matter even more.

Our main data set is the NSF Survey of Doctorate Recipients, a large representative survey of US PhD recipients. We use parental education to proxy for socioeconomic background, primarily focusing on the "class gap" in outcomes between first-generation college graduates vs. people with a parent with a *non-PhD* graduate degree (since we want to focus on the effects of generalized socioeconomic advantage, and not academia-specific advantages conferred by PhD parents).[1]

Our core finding is that PhD graduates from less advantaged backgrounds are less likely to end up tenured at a research-intensive or highly-ranked school – as compared to their more-advantaged PhD program classmates. Specifically, conditional on fixed effects for PhD institution and field, first-generation college graduates are 13% less likely to end up tenured at an R1 than people with a parent with a non-PhD graduate degree. Among those tenured at ranked institutions, first-gen college grads are tenured at institutions ranked 9% lower – again, conditional on fixed effects for PhD institution and field.[2] Note that by conditioning on fixed effects for PhD field and PhD institution, we effectively compare people *within* rough PhD program cohorts. All our analyses also condition on fixed effects for gender, race/ethnicity, and birth region, isolating the effect of socioeconomic background from other correlated demographic characteristics.

[1] We refer to class and socioeconomic background interchangeably, and abbreviate socioeconomic background to "SEB", using "lower-SEB" for less advantaged backgrounds, and vice versa.

[2] The coefficient for those with a parent with a college degree but no graduate degree is between the other two groups, consistent with monotonic class advantage. Those with a PhD parent are even more likely to end up tenured at an R1 or highly-ranked institution than those with a parent with a non-PhD graduate degree – suggestive of academia-specific advantages.

We examine the junctures at which this class gap emerges. First, note that the class gap is not a result of lower-SEB PhD recipients disproportionately choosing to leave academia for industry: there is no gap by socioeconomic background in whether someone leaves academia, conditional on our baseline fixed effects. That is, socioeconomic background does not affect *whether* someone stays in academia, but does affect *where* they end up. A large class gap in outcomes exists at both crucial junctures in the PhD to tenure pipeline: there is a class gap in placement in tenure-track jobs at R1s or highly-ranked schools, conditional on PhD institution and field, *and* also a class gap in whether or not someone who is already on the tenure track gets tenure – even when compared to their peers who were on the tenure track at the same institution.[3] And the class gap does not just manifest in institution rank or research-intensiveness: we also find a class gap in earnings among tenured and tenure-track academics (of 2.7%), and a meaningful class gap in job satisfaction.

Strikingly, the class gap in the likelihood of ending up tenured at an R1 is as large as or larger than the analogous race or gender gaps. This emphasizes that – just as race and gender gaps require serious scrutiny – the class gap is also worthy of research and policy attention. Note, though, that the mechanisms by which the class gap is generated may differ from the mechanisms by which gender and racial gaps are generated, in large part because class is less directly observable than race or gender.

What explains the class gap? In section 4, we explore three possible channels: research, networks, and preferences.

We start with research. Lower-SEB academics might produce less or lower quality research than their PhD classmates if, for example, they have less time to dedicate to

[3]Conditional on tenure-track institution, first-gen college grads are 6.3 percentage points less likely to get tenure than people with a parent with a non-PhD graduate degree. Sample limited to those at ranked institutions, and following Sarsons et al. (2021) in defining "getting tenure" as ending up with tenure at their tenure-track institution, or a similarly-ranked or higher-ranked institution.

research and/or less access to the mentorship required to develop their skills. Using a new linkage between the 2015 SDR, Web of Science, and NSF award data, we estimate class gaps in tenure outcomes with detailed field-specific controls for research quantity and quality, including publications, citations, journal impact factor, authorship position and contribution, and NSF awards. Controlling for research explains only one third of the class gap in tenure institution rank, and less than one-tenth of the class gap in the rate of getting tenure. Thus, differential research productivity cannot explain most of the class gap: first-gen college grads are "underplaced", tenured at lower-ranked institutions than would be predicted by their research output.

Next, we examine networks. It is possible that lower-SEB academics have smaller professional networks – perhaps if lacking relevant social or cultural capital – and that this impedes their career progression. We find evidence consistent with this. First, coauthorship homophily: the coauthors of lower-SEB academics are more likely to also be lower-SEB than their other characteristics would predict. This suggests frictions to forming professional networks across socioeconomic background, which matters because most academics at elite institutions come from elite backgrounds. Second, lower-SEB academics' coauthors are less well-published, suggesting a less professionally valuable coauthorship network. Third, lower-SEB academics receive fewer NSF awards than would be predicted by their institution, seniority, and prior publication, citation, and NSF award receipt history. While funding awards are a function both of the quality of the research and of the networks of the individual, the fact that this gap in NSF award receipt exists even conditional on detailed research controls suggests factors other than research quality are at play.

Finally, preferences: it is possible that lower-SEB academics choose tenured jobs at lower-ranked or less research intensive institutions because of different preferences or constraints than their higher-SEB peers – perhaps trading off employer prestige in order to be closer to family or community, to prioritize higher paying jobs as a result of financial constraints, to prioritize family care needs, or to work at an institution with a stronger social mission. We explore each of these to the extent possible in our data and find no evidence consistent with preferences playing a major role.

Is the class gap unique to tenure-track academia? In section 5, we examine PhDs who work in industry. We find substantial evidence of a class gap in career progression: (i) a class pay gap, conditional on our baseline fixed effects, which widens substantially with years of experience; (ii) a class gap in job satisfaction, with particular dissatisfaction with the level of responsibility and opportunities for advancement; and (iii) class gaps in the likelihood of being a manager, and in the number of supervisees, emerging as individuals progress in their careers. This means that tenure-track academia is not unique. A class gap in career progression also exists for PhDs in private industry – and thus likely in other elite US occupations as well.

Overall, our analyses show that even conditional on PhD program, there are large class gaps in career outcomes in US tenure-track academia, and that most of this class gap cannot be explained by differential research output. We find little evidence consistent with the class gap emerging because of differential preferences, but substantial evidence consistent with differential ability to form professional networks. And, in our analysis of PhDs in industry, we find strong evidence that the class gap exists not just in tenure-track academia but in other occupations as well.

Socioeconomic background is rarely considered in DEI efforts in either academia or other elite US occupations. This paper, along with other recent work (cited below), builds a strong case for researchers to consider socioeconomic background as an additional, crucial, axis of advantage in elite career progression, and to embark on the data collection and research efforts needed to document and understand the class gap in career progression in more detail.

2 Background and Empirical Setting

2.1 Related literature

There is vanishingly little work in economics on the role of class in career outcomes like hiring, pay, or promotion - in contrast to a large and growing literature on gender and race.[4] Our paper builds on a small recent sociology literature on the role of socioeconomic background in career progression in elite occupations. This includes influential recent qualitative work on the "class ceiling" in elite UK occupations (Friedman and Laurison, 2020; Friedman, 2023), as well as research finding large within-occupation pay gaps by class origin in the US and other countries, conditional on education level (Laurison and Friedman, 2024; Witteveen and Attewell, 2017; Torche, 2011).[5] We also build on work in sociology and economics on the role of socioeconomic background in *access* to good jobs, including Rivera (2012), Rivera and Tilcsik (2016), Shukla (2022), and Galos (2024) on hiring discrimination by socioeconomic background (via cultural capital); and Engzell and Wilmers (2021), Staiger (2023), and Michelman et al. (2022) on the importance of family and social ties.

We see our contribution as threefold. First, we provide detailed, large-scale, quantitative evidence of a large class gap in career progression in an elite occupation. To our knowledge, we are the first paper to do this.[6] Second, we can quantify multiple aspects of career progression, including not just pay but also promotion and the quality

[4] A large literature documents how socioeconomic background affects whether and where someone goes to college (e.g. Chetty et al., 2020), but there is little work on the role of class beyond that point – whether and how class background affects people's career outcomes once they've graduated.

[5] See also Friedman and Laurison (2020) for the UK, Falcon and Bataille (2018) for France, Hällsten (2013) for Sweden, and Núñez and Gutiérrez (2004) for Chile.

[6] Specifically, we estimate class gaps *conditional on* very fine-grained measures of the point of entry into the occupation (specific PhD program or tenure-track job). This is crucial: data limitations mean prior studies, such as those estimating class pay gaps, have not been able to condition on fine-grained measures of educational attainment and/or first job. This means that estimated class pay gaps in earlier work may be explained by people from less advantaged backgrounds having started on a worse footing (e.g. less prestigious college, lower grades, or a worse initial employer).

of the employer institution. Third, we can shed light in detail on the mechanisms – in particular, the role of productivity, as proxied by highly granular measures of research quantity and quality, and the role of networks, by studying coauthor characteristics.

In focusing specifically on academia, we build on Morgan et al. (2022), who show that US tenure-track faculty are highly socioeconomically elite, and that those with more advantaged backgrounds place at more prestigious institutions; Stansbury and Schultz (2023), who study the socioeconomic background of US PhD recipients; and contemporaneous work by Airoldi and Moser (2024), who find class gaps in who became a "star" in early 20th century US academia.[7]

More broadly, our work speaks to the large literature on demographic disparities in elite career progression, which is primarily focused on gender and race (e.g. among a large literature, Cullen and Perez-Truglia, 2023; Benson et al., 2024; Biasi and Sarsons, 2022; Linos et al., 2023). In academia specifically, research has found gender differences in reference letters (Eberhardt et al., 2023), recognition or evaluation of work (Sarsons et al., 2021; Card et al., 2020; Hengel, 2022), coauthorship (Ross et al., 2022; Davies, 2022), and citations (Koffi, 2021); and racial differences in funding awards (Ginther et al., 2018; 2011) and citation patterns (Koffi et al., 2024). Our work emphasizes that class should also be considered an important axis of (potential) disadvantage in elite occupations.

2.2 Data

Our main dataset is the National Science Foundation's Survey of Doctorate Recipients ("SDR"). The SDR is a biennial survey of a representative sample of people who received a PhD from a US institution in a science, social science, engineering, or health field. The SDR is matched with the NSF's Survey of Earned Doctorates

[7] Our work also emphasizes that, even beyond disparities in the opportunity to become a scientist at all (Bell et al., 2019), socioeconomic background affects career success once in academic science.

("SED"), an annual census of all individuals who receive a research doctorate from a US institution in a given year. We use the SDR to obtain information on individuals' employment, including sector, salary, and – if in academia – employer institution and the type of position, and the SED to obtain information on parental education, other demographics, and PhD field and institution. To study research output, we use new linkages between the 2015 SDR and (1) the Web of Science bibliometric database, as well as (2) data from the NSF on all NSF awards.[8]

For most of our analyses, we use the 1993-2021 SDR surveys. This represents 14 survey waves, with about 30,000 individuals per wave for 1993-2013 and 80,000 for 2015-2021. The median respondent appears in 4 survey waves. Since our analyses typically pool over multiple survey waves, we cluster standard errors at the individual level. In all our main analyses, we weight our results using the survey weights provided by the NSF.[9] We restrict the sample for all our analyses to those living in the US.

2.3 Measuring socioeconomic background

To measure socioeconomic background, we use the highest level of education attained by either parent or guardian, creating four categories: (i) less than a four-year college degree ("first-gen"), (ii) four-year college degree, (iii) non-PhD graduate degree, and (iv) PhD. While we compare all four parental education groups, our main focus is on differences in outcomes between first-generation college graduates and people with a parent with a non-PhD graduate degree (considering these two groups to be the least and most socioeconomically advantaged groups we observe).[10] We do not

[8]See Chang et al. (2022) for details on the SDR 2015 - Web of Science link.

[9]These weights adjust for differential sampling and nonresponse rates in order to be representative of the SDR population – US PHD recipients in science, social science, engineering, and health fields – with respect to gender, race/ethnicity, location, PhD year, and PhD field. SDR response rates are around two thirds. Unweighted regressions for all core analyses provide similar results.

[10]The four parental education groups can proxy for average household income: for example, in the 1992 Current Population Survey (when many in our sample would have been children), the average household income of households with children, by the highest level of education of either parent,

focus on people with a parent with a PhD because we want to evaluate the effects of generalized socioeconomic advantage on career outcomes, and having a parent with a PhD may confer academia-specific preferences, knowledge, or resources.[11] Ideally, we would have access to the two other common indicators of socioeconomic background - family incomes and parental occupations (e.g. Hauser, 1994; Sirin, 2005). These are not available in our data. But we believe parental education is an effective proxy for socioeconomic background, both because it is a strong predictor of family income (Sirin, 2005), and because parental education itself can provide students with a better understanding of elite professional opportunities, and the strategies needed to access and succeed in them.

2.4 Descriptive statistics

The bulk of our analyses focus on PhD recipients who are 10-30 years post-PhD and working in the US. Among this group in the 2021 SDR (aka people who got their PhD between 1991-2011), 32% were first-gen college grads; 25% had a parent with at most a four-year college degree; 29% had a parent with at most a non-PhD graduate degree; and 14% had a parent with a PhD.

The tenure outcomes among these four groups differ starkly: among both first-gen college grads, and those with a parent with a four-year college degree only, 22% were in tenured positions. This compares to 25% among people with a parent with a non-PhD graduate degree, and 29% among people with a parent with a PhD. Tenure rates at R1 institutions differ even more: 7.6% of the first-gen college grads in our

was: $29,300 for less than a four year college degree; $52,600 for a four-year college degree; $66,200 for a non-PhD graduate degree; and $76,600 for a PhD. Note that our SDR data does not tell us what kind of non-PhD graduate degree a person's parent received; the most common non-PhD graduate degrees are professional degrees like MBAs, JDs, MDs, and masters degrees in education, psychology, or social work, as well as masters degrees in STEM fields (Altonji et al., 2016).

[11] A large literature shows occupational inheritance even within socioeconomic groups (e.g. Weeden and Grusky, 2005; Dal Bó et al., 2009), including in academia (Morgan et al., 2022).

sample were tenured at R1s, as compared to 10% of people with a parent with a non-PhD graduate degree. Thus, a randomly selected PhD recipient with a parent with a non-PhD graduate degree was about 14% more likely to be a tenured professor *somewhere*, and about 32% more likely to be a tenured professor at an R1, than a randomly selected first-gen college grad from the same group.[12]

Thus, tenured professors - particularly at elite institutions - are much more socioeconomically elite than the population of PhD recipients from which they draw (as also shown by Morgan et al., 2022). This drop-off in socioeconomic diversity motivates our analysis: it could reflect a class gap in career *starting point*, since lower-SEB individuals are more likely to do their PhDs at lower-ranked programs which send fewer graduates to elite tenure-track jobs; or it could reflect a class gap in career *progression* even conditional on PhD program. Our paper examines the latter.

3 Empirical Analysis

Our core analyses document whether tenure outcomes differ by socioeconomic background conditional on PhD program. Specifically, for all SDR respondents who are employed in the US and 10-30 years post-PhD,[13] we estimate, for three different dependent variables $TenureVar_i$:

$$TenureVar_i = \alpha + \beta_1 ParentalEducation_i + X_i\gamma + \epsilon_i,$$

Our three dependent variables are (i) *Tenure anywhere*, a binary dependent variable taking value 1 if someone is in a tenured academic job and 0 otherwise, (ii) *Tenure*

[12]Statistics calculated as, respectively: 24.9/21.8=1.14, 10.0/7.6=1.32. People with a PhD parent are even more likely to be tenured, and tenured at R1s. See Appendix Table A1. We show parental education shares of tenured professors over time in Appendix Figure A1.

[13]Starting at 10 years so that most individuals have faced their (first) tenure decision, and ending at 30 years to exclude any differential retirement patterns by SEB.

at an R1, a binary dependent variable taking value 1 if someone is tenured at an R1 and 0 otherwise, and (iii) *(log) Tenure institution rank*, measured as the most recent *US News and World Report* ("USNWR") graduate program ranking for the tenure institution (in the field in which the person got their PhD).[14] For the first two dependent variables, we can use the full sample of working individuals, including those in non-tenure-track academic positions, industry, or government. For the third, however, our sample is by definition limited to those tenured at ranked institutions.

All regressions include fixed effects for PhD field, PhD institution, survey year, years since PhD, year of PhD receipt (in 5-year buckets), birth region, gender, and race/ethnicity (X_i).[15] We refer to this set of fixed effects as our *baseline fixed effects* and use them in all analyses unless noted otherwise. Note that PhD field and institution fixed effects hold constant any differences in socioeconomic background and tenure rates by PhD institution or field, roughly comparing individuals who got their PhD in the same PhD program (and in a robustness check we explicitly control for PhD program fixed effects).

3.1 Main results

Table 1 (and Figure 1) illustrate our main results. Our core comparison of interest is between first-gen college grads (labeled "Less than college") and people with a parent with a non-PhD graduate degree (the omitted category).

Conditional on our baseline fixed effects, there is no statistically significant difference in the likelihood of ending up a tenured academic between first-gen college grads and people with a parent with a non-PhD graduate degree (column 1). The point estimate is very close to zero (-0.003) and the 95% confidence interval rules out more than a one percentage point difference in either direction – a small margin when

[14] "R1" denotes the institutions deemed the most research-intensive by the Carnegie Classifications.

[15] See Appendix C for more details on these variables.

compared to the 26% of our sample who are tenured.

In contrast, we find a large class gap in the likelihood of tenure at an R1. Conditional on our baseline fixed effects, a first-gen college grad is 1.3 percentage points less likely to be tenured at an R1, as compared to someone with a parent with a non-PhD graduate degree (column 2). Since only 10% of our full sample are tenured at R1s, this means first-gen college grads are about 13% less likely to end up tenured at an R1 than their classmates from the same PhD program who had a parent with a non-PhD graduate degree. The coefficient estimates for those with a parent with a college degree only are between the two groups, suggestive of a monotonic class advantage across parental education groups.

We also find a large class gap among those tenured at ranked institutions: first-gen college grads are at institutions ranked 9.2 log points lower than their PhD classmates with a parent with a non-PhD graduate degree (column 3). Again, the estimates for those with a parent with a college degree only are between the two groups.

Our results show that, conditioning on PhD field and institution, there is a large "class gap" in career progression in US academia. Defining the extensive margin as selection into or out of tenured academia, and the intensive margin as institution type conditional on being a tenured academic, we see that *this class gap exists entirely on the intensive margin, with no class gap on the extensive margin.*[16]

While not our main focus, it is interesting to also examine the results for those with PhD parents. Compared to those with a parent with a *non-PhD* graduate degree, they are more likely to end up in a tenured position at all (by 1.2pp), more likely to be tenured at an R1 (by 1.7pp), and are tenured on average at institutions ranked 15 log points higher. This is suggestive of academia-specific advantages which matter

[16] Our tenure at an R1 regression implicitly combines the intensive and extensive margins by including non-tenured academics in the "0" group. We show this same regression, limiting our sample to tenured academics only, in Appendix Table A2 column 9.

even beyond generalized socioeconomic advantage.

Robustness. Using alternative measures for tenure institution research-intensiveness or rank, we also find large, statistically significant class gaps, suggesting that our main results are not artefacts of specific definitions of tenure institution type.[17] We also show that our coefficients are robust to alternate regression specifications: (i) including fixed effects for field-specific PhD program rank instead of PhD institution; (ii) including fixed effects for PhD field by institution by decade (directly comparing individuals in the same PhD program); (iii) including saturated fixed effects for age and time periods, specifically age at survey (5-year group), years since PhD receipt, survey year, and year of PhD receipt (5-year group); (iv) including fixed effects for narrow PhD field instead of our baseline PhD field definition; (v) including fixed effects for birth country instead of broader birth region; and (vi) not using survey weights (Appendix Figure A2). We also run our baseline regressions separately for each SDR survey year, showing that the class gap remains relatively consistent across time (Appendix Figure A3).

3.2 The pipeline: PhD, tenure-track hiring, and tenure decision

At what stage of the PhD to tenure pipeline does the class gap in tenure institution type emerge? We do not see all stages of each individual's career in our SDR sample, so we use subsamples of our full data set to examine two junctures: from PhD to tenure-track job, and from tenure-track job to tenure.

To examine the PhD to tenure-track juncture, we limit our sample to those observed 1-9 years after their PhD, giving us our best guess of their first tenure-track job post PhD.[18] We then run a directly analogous set of regressions to those for Ta-

[17] These include whether an institution is research-intensive at all, rather than just an R1; whether an institution is ranked in the top 50 or top 20; and using undergraduate institution rank instead of graduate program rank. See Appendix Table A2.

[18] Using up to 9 years to incorporate time for a postdoc. This population is made up, on average, of

ble 1, but using tenure-track positions instead of tenured positions. The results are shown in Table 2, columns 1-3. In this sample we once again find no class gap in the likelihood of being on the tenure track anywhere, but large class gaps on the other two outcomes: first-gen college grads are 1 percentage point less likely to be tenure-track at an R1 as compared to those a parent with a non-PhD graduate degree (representing 12% of the baseline mean), and among those on the tenure track at ranked institutions, they are at institutions ranked 7.7 log points lower. That is, there is no class gap on the extensive margin from PhD to tenure-track job, but there is a large class gap on the intensive margin.

To examine the tenure-track to tenure juncture, we limit our sample only to those who we observe in the SDR on the tenure track without tenure, and then again after their inferred tenure decision year. (This reduces our sample very substantially). Our core outcome is whether someone "got tenure", which we define following Sarsons et al. (2021) as having tenure at an institution with a rank which is higher or at most 5 rank points lower than their tenure-track institution.[19] We include our baseline fixed effects with one alteration: instead of PhD institution fixed effects, we use fixed effects for tenure-track institution to implicitly compare individuals who are coming from the same department. We find a large class gap: first-gen college grads are 6.3 percentage points less likely to "get tenure" (9% of the baseline mean), compared to someone with a parent with a non-PhD graduate degree who was on the tenure track at the same institution (Table 2, column 4).[20]

later PhD cohorts relative to our main estimates in Table 1.

[19]This limits our sample to those on the tenure track at ranked institutions. We also limit to institutions for which we observe at least 5 individuals from that institution at the tenure juncture. See Appendix C for how we infer the tenure decision year.

[20]The first-gen college grads who do not get tenure seem to mostly move to non-tenure-track academic jobs or industry, or to another tenure-track but not tenured academic job (Appendix Table A3). For academics on the tenure track at non-ranked institutions, we are not able to construct an equivalent "got tenure" outcome; there are no statistically detectable class gaps in getting tenure anywhere, but standard errors are large (Appendix Table A4).

3.3 Socioeconomic Background, Race, and Gender

To isolate the relationship between SEB and career outcomes, all our analyses condition on fixed effects for gender, race/ethnicity, and birth region. This is particularly important for race and birth region, which are both correlated with SEB and can themselves affect career progression. Thus, the class gap in career progression we identify is a gap based on differences in parental education, and *not* arising from correlated differences in race/ethnicity or country of origin.[21]

Strikingly, the class gap in the likelihood of ending up tenured at an R1 is as large as or larger than the analogous gender and racial/ethnic gaps (estimated controlling for parental education). But these gaps do not arise in the same way. While the class gap arises entirely at the intensive margin, the gender gap arises mostly at the extensive margin (the "leaky pipeline").[22] And racial and ethnic disparities in tenure outcomes arise both at the extensive and intensive margin.[23] Since gender and race/ethnicity are not our focus, we do not explore these dynamics further here, but present coefficients for gender and race/ethnicity for our main tables in Appendix B.

This comparison emphasizes that, just as race and gender gaps are important to study, class gaps are large enough to be worthy of serious scrutiny. Moreover, it emphasizes that class needs a distinct approach: it does not necessarily operate in the same way as gender or as race.

[21] In addition, we re-run our baseline regressions limiting the sample only to White non-Hispanic US-born individuals, finding similar-sized class gaps in tenure institution type.

[22] Among the women who do stay in tenured academia, there is little detectable gender gap in the rank of their tenured jobs – or, indeed in the rate of "getting tenure" conditional on tenure track institution fixed effects (consistent with findings in Ginther and Kahn, 2014; Ceci et al., 2014; 2023).

[23] Black and Hispanic academics are more likely to go into tenured academia, conditional on our fixed effects; but among those who are tenured, they are tenured at lower-ranked institutions (though the result for Black academics is not statistically significant). Black academics are also less likely to get tenure, conditional on tenure-track institution. Note that these estimated race/ethnicity gaps control for parental education; since Black and Hispanic academics are also more likely to be first-gen college grads, they will be disproportionately affected by class gaps too. Intersectionality between class, gender, and race/ethnicity is beyond our scope but worthy of further study

4 Mechanisms

Our findings show a class gap in career progression in tenure track academia, conditional on PhD program attended, on the *intensive margin*: first-gen college grads are no less likely to end up tenured than their PhD classmates with a parent with a non-PhD graduate degree, but end up tenured at less research-intensive and lower-ranked institutions. Why might this class gap emerge between PhD program and tenure? We propose five channels:

1. **Differential endowments** of research ability at the point of PhD entry.
2. **Differential development** of research ability during PhD and tenure track.
3. **Differential signaling** of research ability at point of hiring or tenure decision.
4. **Differential treatment**, by SEB, at point of hiring or tenure decision.
5. **Differential choice** over jobs, driven by preferences and/or constraints.

Channel 1: Endowments. Lower-SEB PhD recipients may enter their PhD program with less research ability on average than their higher-SEB PhD classmates (if, e.g., they had fewer opportunities to build relevant skills during undergrad). If so, this would lead to lower-SEB academics producing less or lower quality research, leading to tenured jobs at lower-ranked institutions.[24]

Channel 2: Development. Lower-SEB individuals may be less able to develop their research ability during their PhDs or tenure-track jobs. This may be a result of having less time for research (e.g. if they need to do other paid work or attend to family responsibilities (Lee, 2017; Waterfield et al., 2019)). Or, lower-SEB individuals may have more difficulties forming valuable professional relationships, whether

[24] Since our analyses condition on fixed effects for PhD institution and field, this channel requires differential endowments of research ability *within PhD program cohorts.* Note that affirmative action by socioeconomic background in PhD admissions is rare (Posselt, 2016), making it highly unlikely that lower-SEB individuals enter PhD programs with large differences in prior research ability which are *observable* to admissions committees. See Appendix D for further discussion.

because of limited social capital, with fewer family or community ties in academia (Haney, 2015), or limited cultural capital of the kind valued in academia.[25] In qualitative studies, lower-SEB academics in the US and Canada report feeling excluded as a result of lacking cultural capital: feeling "isolated", "ill at ease", and as if they are "cultural outsiders" (Lee, 2017; Waterfield et al., 2019).[26] This could affect development as a researcher by affecting mentorship or advice received, the potential pool of coauthors, and other opportunities for learning (e.g. presenting research).

Channel 3: Signaling. Since judgments on the merits of research can differ widely (Lamont, 2009), tenure-track hiring and tenure decisions inherently feature much subjectivity (Rivera, 2017; Posselt et al., 2020), with decisions based both on (somewhat) objective, quantifiable measures of research output, and on more subjective evaluations of researcher quality by letter writers or committee members. If lower-SEB individuals are less able to signal their research ability than their higher-SEB peers, a class gap in career progression may emerge even conditional on research output. Networks could also play a role here, for example if lower-SEB academics are less able to build ties to high-profile letter writers.[27] Limited networks may also reduce lower-SEB academics' ability to generate other signals of research ability, like citations or awards. We explore the role of networks in section 4.2.

Channel 4: Differential treatment. In the US, socioeconomic background is rarely

[25]We define social capital, following Bourdieu (1986), as the availability of and quality of networks and relationships which can provide useful resources (in the academic context, principally advice and opportunities). Also following Bourdieu, we define cultural capital as the acquired tastes, ideas, habits, and behaviors which confer status or recognition in the specific (academic) context.

[26]Examples from Waterfield et al. (2019) include not feeling "put together", bringing the "wrong things" to departmental potlucks, feeling unable to share personal stories, and pressure to speak in a particular way. "Almost all" participants singled out conferences as places where they felt particularly ill at ease. Lee (2017) cites an individual "chastised for my dress, my speaking, ... my hobbies", and others having difficulties fitting in because of implicit class-normed rules. A low-SEB academic in Haney (2015)'s survey wrote "I did not have experiences such as family vacations, attendance at cultural events such as opera, theatre... which showed in my interactions with others."

[27]Weaker networks might affect who writes letters, since reputations can be weighed heavily (Rivera, 2017); and/or letter content, if a weaker relationship affects the quality of the letter.

as directly observable as gender or race/ethnicity. Yet hiring decisions in elite occupations are often influenced by notions of "fit" with the existing culture and with idealized expectations of how a professional looks and behaves (Rivera, 2012; Rivera and Tilcsik, 2016; Friedman and Laurison, 2020). As a decision on a potential lifetime colleague, "fit" is central to tenure-track hiring and tenure decisions (Rivera, 2017). Since academia, particularly at elite institutions, is made up predominantly of elite-origin individuals, there may be differential treatment of lower-SEB academics based on perceived "fit".[28] Indeed, lower-SEB academics report concerns about discrimination in qualitative studies.[29]

Channel 5: Choice. Finally, it may be that lower-SEB academics on average *choose* lower-ranked or less research-intensive tenured jobs than their otherwise equivalent higher-SEB peers.[30] One possibility is geographic constraints: lower-SEB academics may choose to be closer to family or community at the expense of institution rank (Gardner, 2013). Another possibility is financial constraints, if there is a trade-off between pay or financial security and institution quality. A third possibility is family constraints, if care responsibilities induce lower-SEB academics to choose less time-intensive jobs. A fourth possibility is pro-social preferences, if lower-SEB academics would prefer to work at a lower-ranked institution which served a less advantaged student body. We explore each of these in section 4.3.

The role of discrimination. Some of these channels reflect discrimination against lower-SEB individuals in academia. Channel 4 is direct discrimination: differential

[28] Judgments of ability may also be subconsciously influenced by class: Lamont (2009)'s research on grant-making found that judgments of "excellence" were often made on the basis of displaying cultural capital, and by fitting with subjective notions of "intuition, flair, elegance, and spark".

[29] One US academic in Lee (2017) said "I don't think it's a wise idea... to reveal my class background"; another that he was worried his background would adversely shape colleagues' opinion. Several low-SEB academics report trying, and finding it difficult, to hide their class origins because of their mode of dress, manners of speech, or even their teeth (Haney, 2015; Lee, 2017; Waterfield et al., 2019).

[30] Note that it does not appear to be the case that lower-SEB PhDs are less likely to want to get a tenured job at all: there is no class gap at the "extensive margin" (Table 1 column 1).

treatment based solely on socioeconomic background. Channels 2 and 3 might reflect systemic discrimination against lower-SEB academics (in the framework of Bohren et al. (2023)), if the structure of academia itself means that lower-SEB individuals have less chance to develop their research ability (channel 2), or to send good signals of their research ability (channel 3), and this in turn means they are treated differently at the point of tenure-track hiring or the tenure decision.[31]

4.1 Research Output

To evaluate whether differential research output explains the class gap in academia, we use our linked 2015 SDR - Web of Science - NSF award sample. This gives us a close-to-exhaustive set of the observable measures of research *quantity*, in terms of number of publications; *quality* in terms of journal impact factor and citations (using CNCI, citations normalized for publication age and field); individual *contribution* in terms of authorship position and number of coauthors; and *funding success* using NSF award receipt. (See Appendix C for more details on these data).

Is there a class gap in research output? We first examine whether there actually is a class gap in research output, conditional on PhD program attended. Using all tenured academics in our linked SDR sample, we regress various research output measures on parental education alongside our baseline fixed effects X_i.[32] Our de-

[31] For example, if lower-SEB academics are less able to attend conferences because of financial constraints, and this reduces their ability to get good feedback on their research, which reduces their research quality at the point of tenure-track hiring, this would reflect systemic discrimination. Direct discrimination at an earlier stage can also generate systemic discrimination at a later stage. For example, if a high-profile PhD advisor chooses to mentor a high-SEB student more intensively than a low-SEB student because of a perception that the higher-SEB student is more "polished", this direct discrimination during the PhD may translate into systemic discrimination later in the individual's career both in terms of lower quality research, or e.g. less enthusiastic letters of recommendation.

[32] We take all individuals who were tenured in 2015 and match them to their cumulative publication record as of 2015. To maximize our sample, we also incorporate all individuals who were untenured in 2015 but tenured in a later SDR year, and match them to their cumulative publication record as of 2017 (the last year we have Web of Science data). Of our final sample, 77% are first observed tenured in 2015, 9% in 2017, 8% in 2019, and 6% in 2021.

pendent variables are: (1) total number of publications, (2) number of first-author publications, (3) number of last-author publications, (4) average CNCI, (5) average journal impact factor, (6) number of NSF awards (bucketed), (7) share of publications which were in the top 10 percent by CNCI in their publication year, and (8) share of publications in a high impact journal.[33] We see a statistically significant class gap in research output across all research measures: first-gen college grads are on average 4 percentiles lower in the distribution of the number of publications, 3 percentiles lower in citations per paper, and 2 percentiles lower in average journal impact factor, than their PhD classmates with a parent with a non-PhD graduate degree.

Predicting tenure institution type using research output: are lower-SEB tenured academics "underplaced"? The fact that lower-SEB academics produce fewer publications and have fewer citations than their higher-SEB former PhD classmates suggests that research productivity may help explain the class gap in tenure institution type. But, the causality can run both ways: if lower-SEB academics get tenure-track jobs at institutions with less time or resources for research, they will also end up producing less research. Thus, we re-examine our two baseline outcomes which are least vulnerable to this reverse causality concern. First, we re-run our baseline regression for (log) tenure institution rank, controlling for detailed measures of research output. This asks "are low-SEB academics tenured at lower-ranked institutions than you would predict, based on their PhD institution and field, other demographics, *and* research output?"[34] Next, we re-run our "got tenure" regressions, controlling

[33] For all except (6), (7), and (8), we use the PhD-field specific percentile rank of the variable, calculated within each of 10 broad PhD fields (see Appendix C for details). We use the percentile rank rather than a raw number because these variables are heavily skewed, but using a log transformation would not enable us to include zeroes. All of our results with percentile rank also hold in terms of statistical significance and sign when instead using logs or raw numbers. NSF awards are bucketed into a variable taking value 0 if 0 awards, 1 if 1 award, 2 if 2-3 awards, or 3 if 4+ awards. High impact journals are defined by Clarivate as the top 10% by impact factor. Results are shown in Appendix Table A5.

[34] Although note that this likely still somewhat over-estimates the explanatory power of research for the

again for detailed measures of research output. This asks "are lower-SEB academics less likely to get tenure than their peers at the same tenure track institution, even controlling for their other demographics, field, *and* research output?". Both of these analyses limit our sample to those at ranked institutions, where (i) research is the main determinant of hiring and tenure decisions (Schimanski and Alperin, 2018) and (ii) professors have substantial time and resources to dedicate to research.

We show results for the tenure institution rank regression in Table 3, Panel A, and for the "got tenure" regression in Panel B (and visualize the results in Figure 2). Column 1 presents the baseline results without research controls (for this more limited sample). Column 2 incorporates our baseline research controls, which are second order polynomials in the number of publications, average CNCI, average impact factor, and average number of authors per paper, all interacted with PhD field group. Column 3 incorporates additional research controls: second order polynomials in first-author publications and in last-author publications, the number of NSF awards (bucketed), the share of publications that were in the top 10 percent CNCI in the year published, and the share of publications which were in high impact journals, all also interacted with PhD field group.[35]

If socioeconomic background *only* affects tenure outcomes through its relationship with research productivity, we should see no significant relationship between tenure institution type and parental education when controlling for research output ($\beta_1 = 0$). This is not the case: controlling for even our most detailed measures of research quantity and quality explains only around a third of the class gap. Specifically, in

class gap: a lower-SEB academic who is on the tenure track at a lower-ranked institution may have less opportunity to do good research and publish well, meaning that they have less or lower-quality research by the time we observe them.

[35] We have three PhD field groups: biological sciences, physical sciences, and social sciences. For the number of publications, first-author pubs, last-author pubs, CNCI, impact factor, and authors per paper, we again use the field-specific percentile rank. In Appendix Table A6 we show results using raw numbers instead of field-specific percentile rank; results are very similar.

this sample there is a 15 log point class gap in tenure institution rank with our baseline fixed effects but without research controls. The class gap falls to 10 log points with the full suite of research controls, and remains statistically significant at the 1% level (Panel A).[36] Lower-SEB academics are "underplaced", tenured at substantially lower ranked institutions than you would predict by their educational history and research output, relative to their more socioeconomically advantaged peers.

Controlling for research has even less effect on the class gap in the rate of "getting tenure", conditional on tenure track institution. With our baseline fixed effects, the class gap in "getting tenure" in this sample is 6.3pp; with our full suite of research controls, it reduces by less than one-tenth, to 6.0pp, and remains statistically significant at the 1% level (Panel B). Thus, even conditional on a high-dimensional measure of research output, there remains a large class gap in the likelihood of getting tenure for two people who are on the tenure track at the same institution.

At which kinds of institutions is this "underplacement" of lower-SEB academics particularly pronounced? We re-run our log rank regression, but without parental education, and show kernel density plots of the residuals by parental education in Figure 3. A negative residual tells us that a person is tenured at an institution that has a better rank than you would predict given their PhD program history and research output, and vice versa. The missing mass for first-gen individuals is predominantly in the left tail: higher-SEB individuals are more likely to be tenured at places that are *better-ranked than you would expect* given their research output. In contrast the distributions in the right tail of the graph are much more consistent across parental education groups, meaning there is less difference by SEB in the likelihood of being

[36] The above regressions tell us that lower-SEB tenured academics are "underplaced" relative to their contemporaneous research record. But it is possible that at the time of the tenure decision, their outcome was a fair reflection of their research record. This does not appear to be the case: we find a similar-sized class gap in tenure institution type when controlling for cumulative research output at the (inferred) time of the tenure decision.

tenured at a place that is *worse-ranked than you would expect* given research output.

Unobservable aspects of research quality. Our research measures cover almost all possible observable measures of research quality and quantity, and are widely agreed to be central to tenure decisions (Schimanski and Alperin, 2018). But some aspects of research are unobservable to us. For unobservable research quality to explain the class gap, it would need to be the case that higher-SEB academics have much better unobservable research quality than low-SEB academics, even conditional on all our detailed observable measures of research quantity and quality. Coefficient stability when adding research controls suggests to us that unobservable research quality is likely of limited importance: incorporating our baseline research controls brings the class gap down from 14.9 to 10.3 log points, and increases the R-squared from 24% to 36%. Adding a vast suite of additional research controls only reduces the class gap a little, from 10.3 to 10.1 log points, and increases the R-squared to 37%.

4.2 Networks

Next, we explore whether lower-SEB academics have more limited professional networks. First, we find suggestive evidence of this: lower-SEB academics have fewer coauthors per paper, conditional on our baseline fixed effects (Table A5 column 9). Next, we use the linked 2015 SDR-Web of Science data to explore coauthor characteristics, examining the subset of each individual's coauthors who also happened to be in the 2015 SDR. We can observe at least one coauthor for over 23,000 individuals.

Coauthorship homophily. We use this partial coauthorship network to ask: are people more likely to coauthor with people of the same socioeconomic background - is there homophily in coauthoring? We find strong evidence of homophily in coauthorship by SEB. First-gen college grads have coauthors who are 0.7 percentage points more likely on average to also be first-gen college grads than you would predict, given these coauthors' other demographics and PhD characteristics (Table 4, column 1). When considering only coauthors employed at academic institutions, we find even stronger homophily: the coauthors of a first-gen college grad are 1.5 percentage points more likely to also be first-gen college grads than you would predict based on their other demographics, PhD characteristics, and academic employer institution (column 2).[37] Our findings would be consistent with lower-SEB academics finding it easier to collaborate with other lower-SEB academics which, since the majority of academics at elite institutions are higher-SEB, would make the formation of valuable professional networks more difficult for lower-SEB academics.

Coauthors' research output. We follow an analogous procedure for coauthors' publication records.[38] We find that first-gen college grads have coauthors who have fewer publications and citations, and publish in lower impact journals, than you would predict based on these coauthors' demographics, PhD field and institution, and seniority (Table 4 columns 1, 3, and 5). We even find similar results when controlling for coauthors' current academic employer, although these results are noisier (columns 2, 4, and 6). This suggests that lower-SEB academics may face greater frictions in forming relationships with more productive or successful academics.

NSF awards. Coauthorship networks give us direct measures of professional net-

[37] Specifically, we take every individual in the 2015 SDR and residualize a dummy for whether they are a first-gen college grad on fixed effects for their gender, race/ethnicity, birth region, PhD year, PhD field, and PhD institution. We then calculate the average of this residual across each individual's coauthors, weighting by their authorship share on each publication. We then regress this average coauthor residual on a dummy for the first-gen status of the original author. This gives the regression coefficients in Table 4, column 1. In column 2 we residualize on the same set of fixed effects as well as fixed effects for current academic employer institution. Columns 3 and 4 perform the analogous calculation for gender, and columns 5 and 6 for race/ethnicity, showing homophily by gender and race (echoing e.g. Boschini and Sjögren, 2007; Freeman and Huang, 2015). Notably, the degree of homophily by SEB is not much smaller than by gender or race.

[38] Specifically, we residualize each research measure on parental education and our baseline fixed effects, calculating the weighted average residual across coauthors, and regressing this on parental education. We use research at the time of the co-authored publication, and use the field-specific percentile rank.

works. We also examine a potential indirect signal of networks: NSF award receipt.[39] Without controlling for research output, we find that first-gen college grads were 3.3 percentage points less likely to receive an NSF award over 2016-20, as compared to their peers *at the same institution* with a parent with a non-PhD graduate degree (Table 5, column 1). Adding full research controls for pre-2016 research record, the gap falls only a little, to 2.8 percentage points (column 3). Even adding a control for pre-2016 NSF award receipt, we still see a class gap of around 2 percentage points in NSF award receipt, which is statistically significant at the 10% level. Since 18% of this sample receive at least one NSF award over 2016-20, this reflects a class gap of 11% (=0.02/0.18) in NSF award receipt probability relative to baseline. While it is possible that this class gap reflects unobservable research quality differences (even conditional on very detailed measures of research output), it seems plausible that it reflects a class gap in the kinds of networks needed to win a prestigious research award – a decision which is based not just on academic record but also subjective judgments of potential and excellence, which in turn may be affected by evaluations from high-profile researchers and broader professional reputation (Lamont, 2009).[40]

4.3 Preferences and Other Explorations

In this section we explore reasons lower-SEB academics may *choose* lower-ranked or less-research-intensive tenured jobs, as well as other dimensions of heterogeneity.

Distance from home. Lower-SEB academics may prefer (or need) to be employed

[39] Specifically, we regress a dummy for NSF award receipt 2016-20 on parental education and fixed effects for gender, race/ethnicity, birth region, years since PhD, PhD year, PhD field, current institution, and tenure status, for all tenure-track or tenured individuals in the 2015 SDR.

[40] We also find that publications where the author is a first-gen collge grad are less well cited than you would predict from the publication's field, year, type, and journal impact factor, and the author's other demographics, seniority, and institution of employment (Appendix Table A7.) This gap would be consistent either with lower-SEB academics writing lower-quality papers conditional on journal impact factor or with lower-SEB academics having more difficulty generating citations (e.g. if limited networks lead to fewer seminar invites).

at institutions closer to their home and family – perhaps because of family commitments or financial constraints – even at the cost of job quality. We find no evidence that this is driving our results, though: the class gap is essentially unchanged when controlling for a third-order polynomial in the distance between city of current institution and high school state (limiting the sample to those who went to high school in the US - see Appendix Figure A4). We also find a class gap in tenure institution type among foreign-born academics – again consistent with distance from home not being a key driving factor. Moreover, using a question in the SDR asking individuals to rate the perceived importance of 10 different components of a job, we find no class gap in the perceived importance of job location, conditional on our baseline fixed effects (Appendix Figure A5).

Financial constraints. Lower-SEB academics likely face greater financial constraints, so they may trade off tenure institution rank or research intensiveness for higher pay. On average, though, there is no such tradeoff: higher-ranked and more research-intensive institutions pay more.[41] Moreover, we find the class gap essentially unchanged when controlling for a third-order polynomial in the amount of student debt – one proxy for the degree of financial constraint (Appendix Figure A4).

Family constraints. Lower-SEB academics may make different trade-offs between career and family. We re-run our baseline regressions, separately for those in our sample who ever had children vs. those who never had children, and find that the class gaps are similarly large for both groups, suggesting different career-family tradeoffs

[41] A regression of log earnings for tenure-track and tenured academics on a dummy for R1 status, as well as fixed effects for survey year, 5-year PhD group, years since PhD, and PhD field, finds that R1 jobs pay on average 24 log points more; the analogous regression for institution rank finds that each 10-rank-point increment pays 1.8 log points more. Note that financial constraints may drive selection on the extensive margin (out of tenure-track academia into private industry), but that we do not see any class gap on the extensive margin overall, so the story would need to be one of a differential selection gradient by ability by SEB. One piece of evidence for this would be if the fields with larger industry-academia earnings differentials are also the fields with greater selection out of academia by lower-SEB individuals. We do not find this.

do not explain the class gap in tenure institution type (Appendix Figure A4).

Institution type preferences. Lower-SEB academics may prefer to work at an institution which serves less advantaged students. Since private institutions tend to have higher-SEB student bodies (Chetty et al., 2020), we examine whether lower-SEB academics are more likely to be tenured at public institutions (vs. private), conditional on tenure institution rank group and our baseline fixed effects, but find no evidence of this.[42] Moreover, using the SDR question on perceived importance of job components, we find no class gap in the perceived importance of a job's contribution to society, conditional on our baseline fixed effects (Appendix Figure A5).

Other explorations. We estimate our baseline regressions separately for the three major field groups (biological sciences, physical sciences, and social sciences), finding similar-sized class gaps in each field group. This would suggest that factors common across academic fields are the key drivers of the class gap. We also estimate class gaps separately for people who did their PhD at programs ranked 1-30 or 30+, finding class gaps within both groups (Appendix Figure A4).

5 Beyond Academia: Class gaps in other sectors

Only about 30% of our SDR sample are tenured or tenure-track. The rest work in industry, government, or non-tenure-track academia. We have much less information on the SDR recipients working in these sectors than we do on those in academia. Nonetheless, we can examine earnings, job satisfaction, and managerial responsibilities to see if there is evidence of a class gap in these other sectors. This will help us understand if our results on the class gap in career progression can generalize to other sectors of the US economy.

[42] We also re-run our main regression separately for public and private institutions, finding class gaps in institution rank *within* public institutions and *within* private institutions.

Earnings. We regress log annual earnings on parental education and our baseline fixed effects separately for those employed in each sector. We find a class earnings gap of 2.7 log points for those in tenure-track academia and of 1.6 log points in industry (between first-gen college grads and people with a parent with a non-PhD graduate degree) – but no gap in government or non-tenure-track education (Table 6).[43]

Job satisfaction. We regress dummy variables for job satisfaction overall, as well as for nine sub-components, on parental education and our baseline fixed effects.[44] In tenure-track academia and industry – the two sectors where we found class earnings gaps – we also find class gaps in job satisfaction. First-gen college grads in tenure-track academia are 2.8pp less likely to report being "very satisfied" overall relative to people with a parent with a non-PhD graduate degree; the analogous gap in industry is 1.1pp (Figure 4). For both sectors, the class gaps in job satisfaction are particularly large in three categories which closely reflect concepts of career progression: opportunities for advancement, intellectual challenge, and level of responsibility. And, just as we found no class earnings gaps in these sectors, we find no overall class gap in job satisfaction for PhDs working in government or non-tenure-track education.

Career progression in industry. Our findings on pay and job satisfaction suggest that there is a class gap in post-PhD career success for PhDs who go into industry, but not in government or non-tenure track education. We thus examine industry further. We re-run our earnings gap regressions interacting SEB and 5-year-buckets since PhD (and incorporating our baseline fixed effects). We find large increases in the class earnings gap over the course of a career (Figure 5, top left panel). In fact, in the first 5 years after PhD graduation, the class earnings gap is slightly

[43] Torche (2018) finds only a small association between parental education and adult children earnings in the SDR, but does not control for PhD field or PhD institution, or choice of industry post-PhD.

[44] The sub-components are salary, benefits, job security, location, opportunities for advancement, intellectual challenge, level of responsibility, degree of independence, and contribution to society.

positive, but the gap soon becomes negative, growing to an 8.1 log point gap by 20-25 years after the PhD. This may reflect slower progression for lower-SEB individuals to senior positions. In the other panels of Figure 5 we run analogous regressions with dependent variables reflecting managerial responsibilities – the log of 1 + the number of supervisees, and dummies reflecting whether someone reports being in any managerial occupation or a top managerial occupation. We see growing class gaps over the course of a career in all three metrics, suggesting slower progression to managerial roles for lower-SEB individuals.[45] Together, these findings on pay, job satisfaction, and managerial responsibilities suggest that the class gap in career progression is not a phenomenon unique to tenure-track academia: it exists in private industry as well.

6 Conclusion

Disparities in career outcomes by gender and race, across a range of elite occupations, have rightly attracted substantial attention from research and policy. Class background, in contrast, is rarely the focus of data collection, research, or DEI efforts in elite occupations (Ingram, 2021).

This paper documents large, persistent disparities in career outcomes by socioeconomic background in tenure-track academia. Specifically, we show that when comparing two PhD recipients from the *same institution and same field*, socioeconomic background as proxied by parental education is a strong predictor of whether someone ends up tenured at a research-intensive or highly-ranked institution. Disparities in research production explain some of the gap (which could result from differential endowments of research ability pre-PhD or differential ability to develop research

[45] We do not see growing class gaps in earnings or these measures of managerial responsibilities over the course of the career in either government or non-tenure-track academia.

ability and produce research during PhD and tenure track). But large class gaps in tenure institution type persist even conditional on very detailed controls for research quantity and quality, suggesting that lower SEB academics are "underplaced" relative to their research record. Analyzing coauthor networks, we find strongly suggestive evidence that it is more difficult for lower-SEB academics to form valuable professional networks. In contrast, we find no evidence consistent with the hypothesis that the class gap in tenure institution type is explained by lower-SEB academics choosing to trade off job prestige or quality for other factors, like location or pay. Finally, we find class gaps in pay, job satisfaction, and progression to managerial responsibilities among PhDs in industry.

We see our results as as a proof of concept for elite occupations outside academia – that class matters not just for *access* to elite occupations but also for career *progression* within them. While tenure-track academia is a setting uniquely suited to examine the role of class in career progression – with detailed data on productivity, promotions, and firm quality – if anything class likely matters even more in occupations where productivity is less measurable, promotion decisions are less ostensibly meritocratic, and elite networking is more important. Identifying to what extent and at what stage class gaps in career progression exist in other elite occupations, and what drives them, is worthy of further study.

References

Anna Airoldi and Petra Moser. Inequality in science: Who becomes a star? *Working Paper*, 2024.

Joseph G Altonji, Peter Arcidiacono, and Arnaud Maurel. The analysis of field choice in college and graduate school: Determinants and wage effects. In *Handbook of the Economics of Education*, volume 5, pages 305–396. Elsevier, 2016.

Alex Bell, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen. Who becomes an inventor in america? the importance of exposure to innovation. *The Quarterly Journal of Economics*, 134(2):647–713, 2019.

Alan Benson, Danielle Li, and Kelly Shue. Potential and the gender promotions gap. *Available at SSRN*, 2024.

Barbara Biasi and Heather Sarsons. Flexible wages, bargaining, and the gender gap. *The Quarterly Journal of Economics*, 137(1):215–266, 2022.

J. Aislinn Bohren, Peter Hull, and Alex Imas. Systemic discrimination: Theory and measurement. *preprint*, 2023.

Anne Boschini and Anna Sjögren. Is team formation gender neutral? evidence from coauthorship patterns. *Journal of Labor Economics*, 25(2):325–365, 2007.

Pierre Bourdieu. The forms of capital. *Handbook of Theory and Research for the Sociology of Education.*, 1(81-93):949, 1986.

David Card, Stefano DellaVigna, Patricia Funk, and Nagore Iriberri. Are referees and editors in economics gender neutral? *The Quarterly Journal of Economics*, 135(1):269–327, 2020.

Stephen J Ceci, Donna K Ginther, Shulamit Kahn, and Wendy M Williams. Women in academic science: A changing landscape. *Psychological science in the public interest*, 15(3):75–141, 2014.

Stephen J Ceci, Shulamit Kahn, and Wendy M Williams. Exploring gender bias in six key domains of academic science: An adversarial collaboration. *Psychological Science in the Public Interest*, 24(1):15–73, 2023.

Wan-Ying Chang, Maryah Garner, Jodi Basner, Bruce Weinberg, and Jason Owen-Smith. A linked data mosaic for policy-relevant research on science and innovation: Value, transparency, rigor, and community. *Harvard data science review*, 4(2), 2022.

Raj Chetty, John N Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. Income segregation and intergenerational mobility across colleges in the united states. *The Quarterly Journal of Economics*, 135(3):1567–1633, 2020.

Zoe Cullen and Ricardo Perez-Truglia. The old boys' club: Schmoozing and the gender gap. *American Economic Review*, 113(7):1703–1740, 2023.

Ernesto Dal Bó, Pedro Dal Bó, and Jason Snyder. Political dynasties. *The Review of Economic Studies*, 76(1):115–142, 2009.

Benjamin Davies. Gender sorting among economists: Evidence from the nber. *Economics Letters*, 217:110640, 2022.

Markus Eberhardt, Giovanni Facchini, and Valeria Rueda. Gender differences in reference letters: Evidence from the economics job market. *The Economic Journal*, 133(655):2676–2708, 2023.

Per Engzell and Nathan Wilmers. Firms and the intergenerational transmission of labor market advantage. *SocArXiv. December*, 27, 2021.

Julie Falcon and Pierre Bataille. Equalization or reproduction? long-term trends in the intergenerational transmission of advantages in higher education in france. *European Sociological Review*, 34(4):335–347, 2018.

Richard B Freeman and Wei Huang. Collaborating with people like me: Ethnic coauthorship within the united states. *Journal of Labor Economics*, 33(S1):S289–S318, 2015.

Sam Friedman. Climbing the velvet drainpipe: class background and career progression within the uk civil service. *Journal of Public Administration Research and Theory*, 33(4):563–577, 2023.

Sam Friedman and Daniel Laurison. The class ceiling: Why it pays to be privileged, 2020.

Diana Roxana Galos. Social media and hiring: a survey experiment on discrimination based on online social class cues. *European Sociological Review*, 40(1):116–128, 2024.

Susan K Gardner. The challenges of first-generation doctoral students. *New Directions for Higher Education*, 2013(163):43–54, 2013.

Donna K Ginther and Shulamit Kahn. Women's careers in academic social science: Progress, pitfalls, and plateaus. *The economics of economists*, pages 285–315, 2014.

Donna K Ginther, Walter T Schaffer, Joshua Schnell, Beth Masimore, Faye Liu, Laurel L Haak, and Raynard Kington. Race, ethnicity, and nih research awards. *Science*, 333(6045):1015–1019, 2011.

Donna K Ginther, Jodi Basner, Unni Jensen, Joshua Schnell, Raynard Kington, and Walter T Schaffer. Publications as predictors of racial and ethnic differences in nih research awards. *PloS one*, 13(11):e0205929, 2018.

Donna K Ginther, Carlos Zambrana, Patricia Oslund, and Wan-Ying Chang. Do two wrongs make a right? measuring the effect of publications on science careers. *National Bureau of Economic Research Working Paper*, (31844), 2023.

Martin Hällsten. The class-origin wage gap: heterogeneity in education and variations across market segments. *The British Journal of Sociology*, 64(4):662–690, 2013.

Timothy J Haney. Factory to faculty: Socioeconomic difference and the educational experiences of university professors. *Canadian Review of Sociology/Revue canadienne de sociologie*, 52(2):160–186, 2015.

Robert M Hauser. Measuring socioeconomic status in studies of child development. *Child development*, 65(6):1541–1545, 1994.

Erin Hengel. Publishing while female: Are women held to higher standards? evidence from peer review. *The Economic Journal*, 132(648):2951–2991, 2022.

Paul Ingram. The forgotten dimension of diversity. *Harvard Business Review*, 99(1): 58–67, 2021.

Marlène Koffi. Innovative ideas and gender inequality. Technical report, Working Paper, 2021.

Marlène Koffi, Roland Pongou, and Leonard Wantchekon. Racial inequality and inclusion in economics research. Technical report, Working Paper, 2024.

Michèle Lamont. *How professors think: Inside the curious world of academic judgment*. Harvard University Press, 2009.

Daniel Laurison and Sam Friedman. The class ceiling in the united states: Class-origin pay penalties in higher professional and managerial occupations. *Social Forces*, page soae025, 2024.

Elizabeth M Lee. "where people like me don't belong": faculty members from low-socioeconomic-status backgrounds. *Sociology of Education*, 90(3):197–212, 2017.

Elizabeth Linos, Sanaz Mobasseri, and Nina Roussille. Asymmetric peer effects at work: The effect of white coworkers on black women's careers. 2023.

Valerie Michelman, Joseph Price, and Seth D Zimmerman. Old boys' clubs and upward mobility among the educational elite. *The Quarterly Journal of Economics*, 137(2):845–909, 2022.

Allison C Morgan, Nicholas LaBerge, Daniel B Larremore, Mirta Galesic, Jennie E Brand, and Aaron Clauset. Socioeconomic roots of academic faculty. *Nature human behaviour*, 6(12):1625–1633, 2022.

Javier Núñez and Roberto Gutiérrez. Class discrimination and meritocracy in the labor market: evidence from chile. *Estudios de Economía*, 31(2):113–132, 2004.

Julie Posselt, Theresa E Hernandez, Cynthia D Villarreal, Aireale J Rodgers, and Lauren N Irwin. Evaluation and decision making in higher education: Toward equitable repertoires of faculty practice. *Higher Education: Handbook of Theory and Research: Volume 35*, pages 1–63, 2020.

Julie R Posselt. *Inside graduate admissions: Merit, diversity, and faculty gatekeeping*. Harvard University Press, 2016.

Lauren A Rivera. Hiring as cultural matching: The case of elite professional service firms. *American sociological review*, 77(6):999–1022, 2012.

Lauren A Rivera. When two bodies are (not) a problem: Gender and relationship status discrimination in academic hiring. *American Sociological Review*, 82(6): 1111–1138, 2017.

Lauren A Rivera and András Tilcsik. Class advantage, commitment penalty: The gendered effect of social class signals in an elite labor market. *American Sociological Review*, 81(6):1097–1131, 2016.

Matthew B Ross, Britta M Glennon, Raviv Murciano-Goroff, Enrico G Berkes, Bruce A Weinberg, and Julia I Lane. Women are credited less in science than men. *Nature*, 608(7921):135–145, 2022.

Heather Sarsons, Klarita Gërxhani, Ernesto Reuben, and Arthur Schram. Gender differences in recognition for group work. *Journal of Political economy*, 129(1): 101–147, 2021.

Lesley A Schimanski and Juan Pablo Alperin. The evaluation of scholarship in academic promotion and tenure processes: Past, present, and future. *F1000Research*, 7, 2018.

Soumitra Shukla. Making the elite: Top jobs, disparities, and solutions. *arXiv preprint arXiv:2208.14972*, 2022.

Selcuk R Sirin. Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of educational research*, 75(3):417–453, 2005.

Matthew Staiger. The intergenerational transmission of employers and the earnings of young workers. *Working paper*, 2023.

Anna Stansbury and Robert Schultz. The economics profession's socioeconomic diversity problem. *Journal of Economic Perspectives*, 2023.

Florencia Torche. Is a college degree still the great equalizer? intergenerational mobility across levels of schooling in the united states. *American journal of sociology*, 117(3):763–807, 2011.

Florencia Torche. Intergenerational mobility at the top of the educational distribution. *Sociology of Education*, 91(4):266–289, 2018.

Bea Waterfield, Brenda L Beagan, and Tameera Mohamed. "you always remain slightly an outsider": Workplace experiences of academics from working-class or impoverished backgrounds. *Canadian Review of Sociology/Revue canadienne de sociologie*, 56(3):368–388, 2019.

Kim A Weeden and David B Grusky. The case for a new class map. *American Journal of Sociology*, 111(1):141–212, 2005.

Dirk Witteveen and Paul Attewell. Family background and earnings inequality among college graduates. *Social Forces*, 95(4):1539–1576, 2017.

Tables and Figures

Table 1: Baseline regression – Tenure outcomes, conditional on PhD institution and field

Dep. var.	(1) Tenure anywhere	(2) Tenure at R1	(3) Tenure institution rank (log)
Parental education (omitted category: non-PhD graduate degree)			
Less than college	-0.00285	-0.0127***	0.0916***
	(0.0055)	(0.0039)	(0.033)
College	-0.00440	-0.00567	0.0279
	(0.0060)	(0.0043)	(0.037)
PhD	0.0124*	0.0168***	-0.153***
	(0.0072)	(0.0056)	(0.045)
Demographics FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
PhD Field FE	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes
Dep Var Mean	0.26	0.10	3.93
Observations	239,065	239,065	31,596
Unique Individuals	76,841	76,841	10,960
Absorbed DF	489	489	394
Sample:	*All employed individuals 10-30 yrs since PhD*		*Tenured at ranked institutions only*

Source: SDR 1993-2021. *Notes:* Standard errors clustered at individual level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variables for cols 1 and 2 are binary variables taking value 1 if individual is tenured anywhere (col 1), or tenured at an R1 (col 2) and 0 if in any other job. Dependent variable for column 3 is the log rank of the tenure institution (field-specific graduate program rank from *USNWR*). Sample for all columns is restricted to people 10-30 years since PhD receipt, currently working in the US. Columns 1-2 cover SDR years 1993-2021 and column 3 years 1997-2021. Sample in column 3 is restricted only to those tenured at ranked institutions (by definition of the dependent variable). Regressions weighted by NSF-provided survey weights. Demographics FE are fixed effects for gender, race/ethnicity, and birth region. Time FE are fixed effects for survey year, years since PhD, and PhD year (5-year group). "Absorbed DF" shows degrees of freedom absorbed by fixed effects.

Table 2: Where in the pipeline does the class gap appear?

Juncture	PhD to tenure track			Tenure track to tenure
	(1)	(2)	(3)	(4)
Dep. var.	TT anywhere	TT at R1	TT institution rank (log)	Got Tenure
Parental education (omitted category: non-PhD graduate degree)				
Less than college	-0.00355	-0.00954***	0.0774**	-0.0625***
	(0.0045)	(0.0029)	(0.035)	(0.023)
College	-0.00482	-0.00741**	0.0146	-0.0373
	(0.0046)	(0.0030)	(0.040)	(0.025)
PhD	0.00623	0.0171***	-0.117	0.0168
	(0.0059)	(0.0043)	(0.048)	(0.025)
Demographics FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
PhD Field FE	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	
TT Institution FE				Yes
Dep Var Mean	0.22	0.077	3.84	0.72
Observations	177,852	177,852	16,087	3,670
Unique Individuals	82,420	82,420	8,834	3,670
Absorbed DF	509	509	378	308
Sample:	*All employed individuals 1-9 yrs since PhD*		*TT at ranked institutions only*	*TT at ranked institutions only*

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows regressions for the PhD to tenure-track juncture (columns 1-3) and tenure-track to tenure juncture (column 4). *PhD to tenure-track juncture:* Dependent variables for cols 1 and 2 are binary variables taking value 1 if individual is on the tenure track anywhere (col 1), or on the tenure track at an R1 (col 2), and 0 if in any other job. Dependent variable for column 3 is the log rank of the tenure-track institution (field-specific graduate program rank from *USNWR*). Sample for columns 1-3 is restricted to people 1-9 years since PhD receipt, currently working in the US. Columns 1-2 cover SDR years 1993-2021 and column 3 years 1997-2021. Sample in column 3 is restricted only to those on the tenure track at ranked institutions (by definition of the dependent variable). *Tenure track to tenure juncture:* Dependent variable is a binary variable taking value 1 if individual has tenure at the original tenure-track institution, or an institution ranked higher or at most 5 rank points lower, and 0 if doing anything else. Sample restricted to those on the tenure track without tenure at ranked US institutions in the last survey observation before their inferred tenure decision year (and for which we observe at least 5 individuals at that institution). *All:* Regressions weighted by NSF-provided survey weights. Demographics FE are fixed effects for gender, race/ethnicity, and birth region. Time FE are fixed effects for survey year, years since PhD, and PhD year (5-year group). "Absorbed DF" shows degrees of freedom absorbed by fixed effects. Standard errors are clustered at individual level in columns 1-3 and are robust in column 4.

Table 3: Tenure outcomes with research controls

	No research controls	With research controls	
	(1)	(2)	(3)
Panel A: Tenure institution rank (log)			
Less than college	0.149***	0.103**	0.101**
	(0.046)	(0.043)	(0.042)
College	0.0455	0.0563	0.0674
	(0.049)	(0.045)	(0.044)
PhD	-0.104*	-0.0672	-0.0542
	(0.055)	(0.049)	(0.049)
Observations	6,969	6,920	6,920
R-Squared	0.24	0.36	0.37
Adjusted R-Squared	0.20	0.32	0.34
PhD Institution FE	Yes	Yes	Yes
Panel B: Got tenure, conditional on tenure-track institution			
Less than college	-0.0635***	-0.0594**	-0.0596***
	(0.022)	(0.023)	(0.023)
College	0.00959	-0.0141	-0.0140
	(0.023)	(0.024)	(0.023)
PhD	0.00859	-0.0108	-0.0210
	(0.022)	(0.023)	(0.023)
Observations	1,907	1,894	1,894
R-Squared	0.61	0.65	0.67
Adjusted R-Squared	0.54	0.58	0.60
TT Institution FE	Yes	Yes	Yes
Demographics FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
PhD Field FE	Yes	Yes	Yes
Baseline Research Controls		Yes	Yes
Add'l Research Controls			Yes

Source: SDR 2015-2021, matched with Web of Science and NSF Awards. *Notes:* Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel A replicates our baseline tenure institution rank regression in Table 1, column 3, but with controls for research output. Panel B replicates our baseline "got tenure" regression in Table 2, column 4, but with controls for research output. Sample restricted to 2015 SDR respondents who were tenured at a US institution in 2015, or in the first SDR year we observe them with tenure after 2015. Demographics FE are fixed effects for gender, race/ethnicity, and birth region. Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group). Panel A includes fixed effects for PhD institution, and Panel B for tenure-track institution. Columns 2 and 3 add controls for research output, all interacted with broad PhD field group. Baseline Research Controls are second order polynomials in: number of publications (field-specific percentile rank "fspr"), average CNCI per paper (fspr), average number of authors per publication (fspr), average impact factor per publication (fspr). Additional ('Add'l') Research Controls are second order polynomials in first author publications (fspr) and in last author publications (fspr), as well as NSF Award buckets (categorical var for 0, 1, 2, 3, or 4+), share of publications in top 10% CNCI, and share of publications in high impact journals. Regressions weighted by NSF-provided survey weight.

Table 4: Coauthor characteristics

Panel A: Coauthor homophily

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var	First-gen	First-gen	Female	Female	URM	URM
Parental education (omitted category: at least a college degree)						
First-gen college grad	0.00717***	0.0153***				
	(0.0025)	(0.0043)				
Gender (omitted category: male)						
Female			0.0325***	0.0392***		
			(0.0023)	(0.0040)		
Race/ethnicity (omitted category: neither Black nor Hispanic)						
Under-Represented Minority (Black or Hispanic)					0.0490***	0.0319***
					(0.0028)	(0.0045)
Observations	23,171	8,708	23,171	8,708	23,171	8,708

Panel B: Coauthor research output

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var	Publications	Publications	Citations	Citations	Impact Factor	Impact Factor
Parental education (omitted category: non-PhD graduate degree)						
Less than college	-0.00459***	-0.00386	-0.00668***	-0.00596**	-0.0100***	-0.00441
	(0.0017)	(0.0026)	(0.0017)	(0.0026)	(0.0018)	(0.0028)
College	-0.000602	-0.00325	-0.00299	-0.00550*	-0.00386*	-0.00248
	(0.0018)	(0.0027)	(0.0019)	(0.0028)	(0.0020)	(0.0031)
PhD	-0.00320	-0.00129	-0.00177	-0.000341	-0.000516	0.00147
	(0.0021)	(0.0031)	(0.0022)	(0.0031)	(0.0023)	(0.0035)
Observations	23,160	8,662	23,160	8,662	23,160	8,662

Source: Web of Science matched with 2015 SDR. *Notes:* Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions are at author level. Dependent variables in each column are the average residual of an individual's coauthors. In Panel A, the residual is based on demographics, estimated from a regression of a dummy for first-gen status (cols 1/2), female (cols 3/4), or URM (cols 5/6) on fixed effects for all other demographics (parental education, gender, race/ethnicity, birth region), PhD year, PhD institution, and PhD field (cols 1/3/5) as well as fixed effects for current academic institution (cols 2/4/6). In Panel B, the residual is based on research output, estimated from a regression of cumulative publications (cols 1/2), cumulative CNCI (cols 3/4), or average journal impact factor (cols 5/6) (at time of publication of coauthored paper) on fixed effects for the coauthor's demographics (parental education, gender, race/ethnicity, birth region), PhD year, PhD institution, and PhD field (cols 1/3/5) as well as fixed effects for current academic institution (cols 2/4/6). Field-specific percentile rank is used for publications, CNCI, and journal impact factor.

Table 5: NSF Award Receipt (2016-20), conditional on research output

	(1)	(2)	(3)	(4)
Dep var:	Receipt of NSF award 2016-2020 (Binary: 1 if yes)			
Parental education (omitted category: non-PhD graduate degree)				
Less than college	-0.0331***	-0.0288**	-0.0279**	-0.0203*
	(0.012)	(0.012)	(0.012)	(0.011)
College	0.00234	0.00396	0.00407	0.000451
	(0.014)	(0.014)	(0.013)	(0.012)
PhD	0.00203	0.00315	0.00349	0.00342
	(0.016)	(0.016)	(0.016)	(0.015)
Demographics FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
PhD Field FE	Yes	Yes	Yes	Yes
Current Institution FE	Yes	Yes	Yes	Yes
Tenure Status FE	Yes	Yes	Yes	Yes
Baseline Research Controls		Yes	Yes	Yes
Add'l Research Controls			Yes	Yes
Prior NSF Awards				Yes
Dep Var Mean	0.18	0.18	0.18	0.18
Observations	10,654	10,485	10,485	10,485
R-Squared	0.29	0.32	0.32	0.42
Adjusted R-Squared	0.21	0.24	0.24	0.35

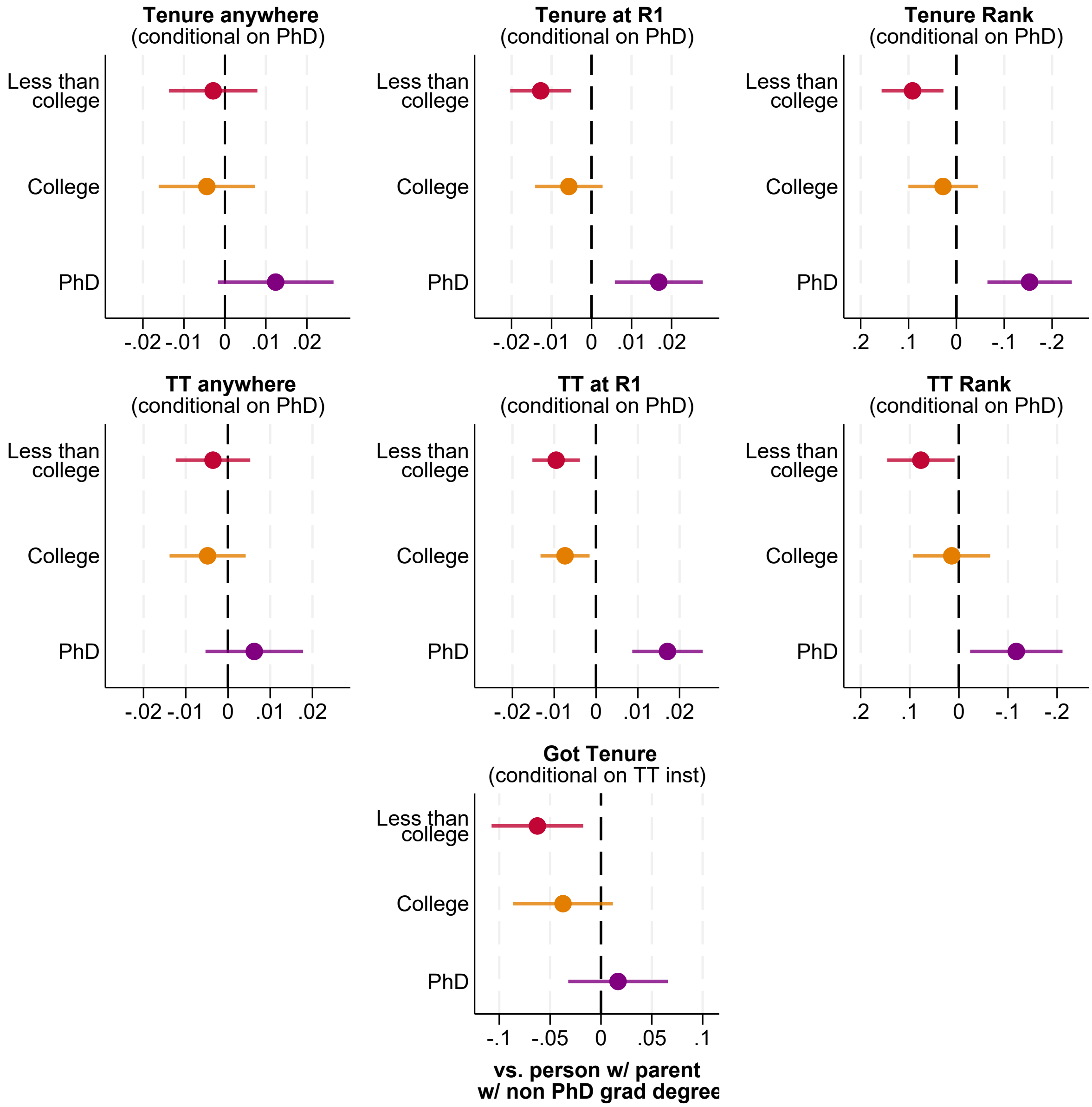
Source: 2015 SDR matched with Web of Science and NSF awards. *Notes:* Unit of analysis is the individual level. Sample limited to those with tenure or on the tenure track at an identifiable US academic institution in 2015. Sample excludes those with PhDs in Economics or Health related disciplines, since NSF awards are rare in these disciplines. Dep var is dummy taking value 1 if an individual receives an NSF award in any year 2016-2020 and 0 otherwise. Regressions weighted by NSF-provided survey weight. Demographics FE are fixed effects for gender, race/ethnicity, and birth region. Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group). Research controls defined as in Table 3, with the exception that "Add'l Research Controls" does *not* include prior NSF awards in column 3; column 4 then adds controls for prior NSF award receipt.

Table 6: Class gap in earnings for PhD recipients, by sector of employment

Dep. var: Log earnings	(1)	(2)	(3)	(4)	(5)
Sector	Tenure-track academia	Industry	Government	Non-tenure-track education	Tenure track, w/ institution FEs
Parental education (omitted category: non-PhD graduate degree)					
Less than college	-0.0273***	-0.0162*	-0.000631	-0.00759	-0.0141**
	(0.0077)	(0.0096)	(0.011)	(0.011)	(0.0067)
College	-0.0144*	-0.00862	-0.00327	-0.0406***	-0.00926
	(0.0083)	(0.0098)	(0.012)	(0.012)	(0.0071)
PhD	0.0159	-0.000952	0.0125	-0.0220	-0.00300
	(0.0099)	(0.013)	(0.014)	(0.015)	(0.0084)
Demographics FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
PhD Field FE	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	
Current Institution FE					Yes
Faculty Rank FE					Yes
Dep Var Mean	11.1	11.3	11.1	10.7	11.1
Observations	93,433	142,764	35,333	69,725	90,152
Unique Individuals	32,538	55,082	15,189	35,037	31,179
Absorbed DF	475	506	458	494	2,821

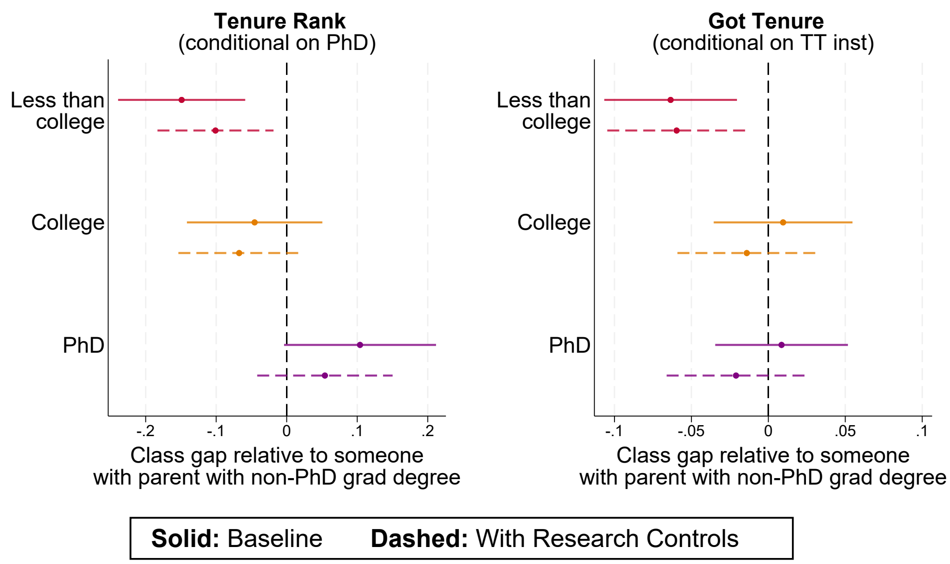
Source: SDR 1993-2021. *Notes:* Standard errors, clustered at individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample restricted to people up to 30 years since PhD receipt, currently working in the US; each column restricts sample to sector in title. Column 5 replicates column 1 but with fixed effects for institution and for faculty rank (assistant, associate, full professor). Regressions weighted by NSF-provided survey weight. Demographics FE are fixed effects for gender, race/ethnicity, and birth region. Time FE are fixed effects for survey year, years since PhD, and PhD year (5-year group). "Absorbed DF" shows degrees of freedom absorbed by fixed effects.

Figure 1: Baseline regression – Tenure outcomes



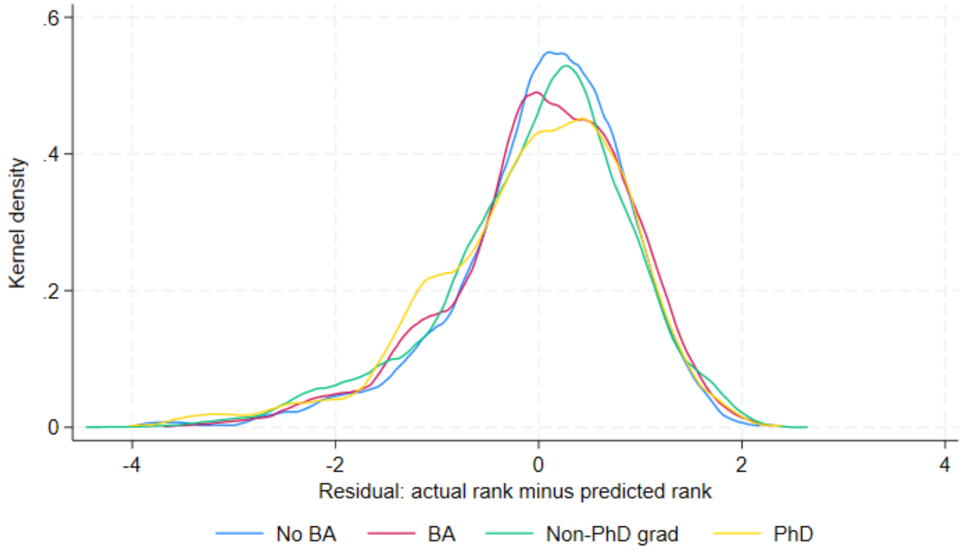
Source: SDR 1993-2021. *Notes:* Point estimates and 95% confidence intervals, from our baseline regressions: "Tenure" plots in the first row show coefficients from Table 1, "TT" plots in the second row show coefficients from Table 2 Columns 1-3, and "Got Tenure" plot in the third row shows coefficients from Table 2 Column 4. Dependent variable for each subplot is shown in the subplot title. All dependent variables are binary vars (1/0) except Tenure Rank and TT Rank which are the log of the tenure or tenure-track institution rank respectively. Coefficients are relative to the omitted category: people with a parent with a non-PhD graduate degree. Estimates for tenure and TT regressions are conditional on our baseline fixed effects: gender, race/ethnicity, birth region, time, PhD institution, PhD field. Estimates for "got tenure" are for those at ranked TT institutions only, and are conditional on tenure track institution fixed effects as well as demographic, time, and PhD field fixed effects. Regressions weighted by NSF-provided survey weight. Rank x-axes are inverted for ease of comparison with other outcomes.

Figure 2: Tenure outcomes with research controls



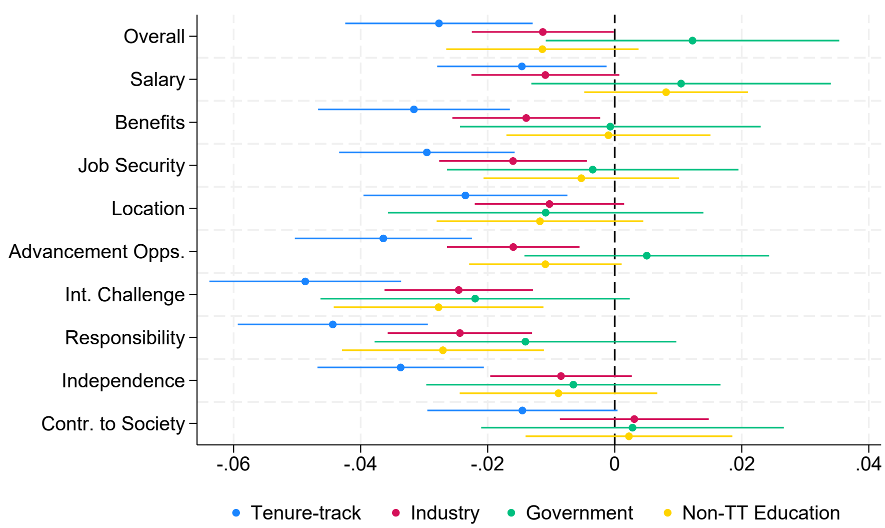
Source: SDR 1993-2021. *Notes:* Point estimates and 95% confidence intervals, from our regressions with research controls in Table 3. Tenure Rank subplot shows coefficients from Panel A, Columns 1 and 3. Got Tenure subplot shows coefficients from Panel B, Columns 1 and 3. Dependent variable for each subplot is shown in the subplot title. Coefficients are relative to the omitted category: people with a parent with a non-PhD graduate degree. Estimates for tenure rank regressions are conditional on our baseline fixed effects: gender, race/ethnicity, birth region, time, PhD institution, PhD field. Estimates for "got tenure" are for those at ranked TT institutions only, and are conditional on tenure track institution fixed effects as well as demographic, time, and PhD field fixed effects. Regressions weighted by NSF-provided survey weight. Research controls described in notes to Table 3.

Figure 3: Are individuals "underplaced" or "overplaced" relative to their research output?



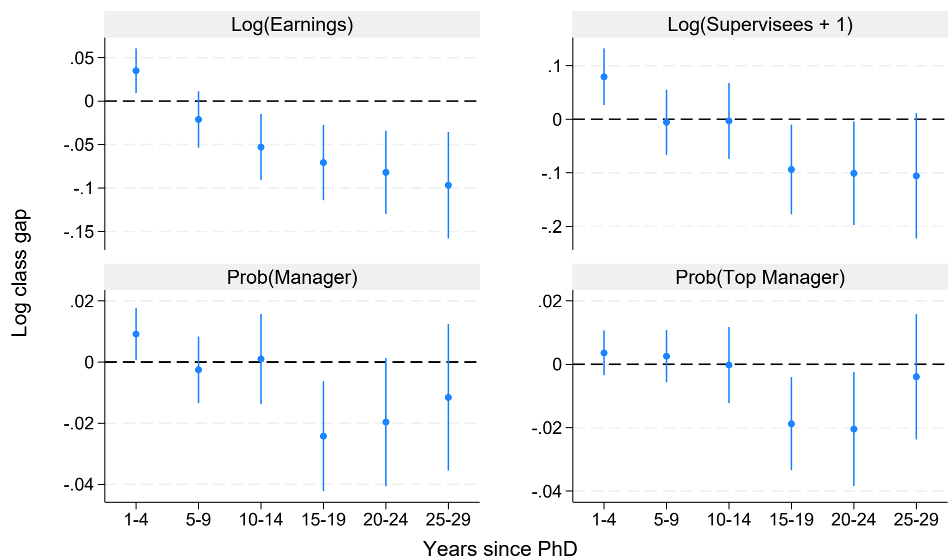
Source: SDR 2015-2021, matched with Web of Science, and NSF Awards. *Notes:* This figure shows kernel density plots of the residuals, by parental education group, from a regression of log tenure institution rank on our baseline fixed effects and full research controls. (replicating the regression in Table 3, Panel A, column 3, but excluding parental education). Regressions weighted by NSF-provided survey weight. Negative residuals represent people who are "overplaced" relative to what their research output and educational history would predict, and vice versa.

Figure 4: Class gap in job satisfaction, by sector of employment



Source: SDR 1993-2021. *Notes:* Coefficient estimates and 95% confidence intervals from regressions of self-reported job satisfaction on parental education and our baseline fixed effects; only coefficients on first-gen college grads are plotted (relative to people with a parent with a non-PhD graduate degree). Regressions are run separately by sector; standard errors clustered at individual level; sample limited to people working in the US, less than 30 years since PhD receipt. Dep vars, listed on y-axis, are dummies taking value 1 if the individual is "very satisfied" with that aspect of their job, and 0 otherwise. (Int. challenge = intellectual challenge; Contr. to society = contribution to society).

Figure 5: Class gap in career progression in industry



Source: SDR 1993-2021. *Notes:* Coefficient estimates and 95% confidence intervals from regressions of dependent variables listed in subplot titles on parental education interacted with 5-year-group since PhD, and on our baseline fixed effects. Only coefficients on first-gen college grads are plotted (relative to people with a parent with a non-PhD graduate degree). Standard errors clustered at individual level; sample limited to people working in Industry in the US, less than 30 years since PhD receipt. Regressions weighted by NSF-provided survey weight. "Supervisees" = number of direct and indirect supervisees. "Prob(Manager)" and "Prob(Top Manager)" = dummies taking value 1 if occupation is any, or a top, managerial occupation respectively.

Online Appendix

A Appendix Tables and Figures

Table A1: Tenure outcomes of US SEH PhD recipients, by parental education group (Sample: 2021 SDR, PhD recipients 1991-2011)

Parental education	Share tenured anywhere	Share tenured at R1	Share tenured at top 50
Less than college	21.8%	7.6%	3.9%
College	21.8%	8.6%	4.5%
Non-PhD grad degree	24.9%	10.0%	6.2%
PhD	28.7%	14.1%	10.0%

Source: SDR 2021, matched with SED 2021. *Notes:* Sample restricted to those in the 2021 SDR, who are 10-30 years since PhD receipt and working in the US. Table shows shares among each parental education group who are tenured, tenured at an R1 institution, and tenured at a top 50 ranked institution (per *USNWR* grad program rank), respectively. Weighted by NSF-provided survey weights.

Table A2: Tenure Outcomes - Robustness - Alternate dependent variables

	(1) Tenure at Research Institution	(2) Tenure at R1 or R2	(3) Tenure at Top 50 (Grad rank)	(4) Tenure at Top 50 (Grad or BA)	(5) Tenure at Top 20 (Grad rank)	(6) Tenure Institution Log BA rank	(7) Tenure Institution Rank	(8) Tenure Institution BA Rank	(9) Tenure at R1 (tenured sample only)
Parental education (omitted category: non-PhD graduate degree)									
Less than college	-0.00813*	-0.0109**	-0.00883***	-0.00916***	-0.00513***	0.138***	4.296**	10.94***	-0.0423***
	(0.0045)	(0.0044)	(0.0031)	(0.0032)	(0.0020)	(0.031)	(1.87)	(2.55)	(0.011)
College	-0.00405	-0.00469	-0.00417	-0.00439	-0.00426*	0.0670*	1.151	4.474	-0.0151
	(0.0050)	(0.0049)	(0.0034)	(0.0035)	(0.0022)	(0.035)	(2.02)	(2.77)	(0.013)
PhD	0.0140**	0.0157***	0.0194***	0.0218***	0.0155***	-0.135***	-5.227**	-7.860***	0.0387***
	(0.0062)	(0.0061)	(0.0072)	(0.0049)	(0.0034)	(0.043)	(2.10)	(2.99)	(0.015)
Demographics FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PhD Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.15	0.14	0.059	0.065	0.025	4.33	77.6	112.9	0.40
Observations	239,065	239,065	216,475	216,475	216,475	33,548	31,596	33,548	64,429
Unique Individuals	76,841	76,841	74,144	74,144	74,144	11,649	10,960	11,649	20,698
Absorbed DF	473	473	486	470	470	392	378	376	431

Source: SDR 1993-2021. *Notes:* Standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dep vars for cols 1-5 are binary variables taking value 1 if individual is tenured at a research institution (col 1), tenured at an R1 or R2 (col 2), tenured at a top-50 ranked institution by field-specific graduate program rank (col 3) tenured at a top-50 ranked institution by either graduate or undergraduate rank (col 4), and tenured at a top-20 ranked institution by graduate program rank (col 5), and 0 if in any other kind of job. All these include all working individuals, including those in non-tenured jobs in academia as well as jobs outside academia. Dep var for col 6 is the log undergraduate institution rank of the tenure institution. Dep vars for cols 7 and 8 are the field-specific graduate program rank or undergraduate institution rank of the tenure institution, respectively. (Ranks from *USNWR*). Dep var for col 9 is a binary variable taking value 1 if individual is tenured at an R1 and 0 if not tenured at an R1, but with the sample limited to tenured academics only (aka equivalent to Table 1, column 2, but with a more limited sample). Sample for all cols is restricted to people 10-30 years since PhD receipt, currently working in the US. Cols 1, 2 and 9 cover SDR years 1993-2021 and cols 3-8 years 1997-2021 inclusive. Sample in cols 6-8 is restricted only to those tenured at ranked institutions. Demographics FE are fixed effects for gender, race/ethnicity, and birth region. Regressions weighted by NSF-provided survey weight. Time FE are fixed effects for survey year, years since PhD, and PhD year (5-year group). "Absorbed DF" shows degrees of freedom absorbed by fixed effects.

Table A3: Getting tenure, conditional on tenure-track institution
(Sample: those on tenure track at ranked institutions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: *(binary 1/0)*	Tenure anywhere	"Got tenure" (similar or higher ranked)	Tenure at lower ranked	Tenure track elsewhere	Industry	Government	Non-TT education	Not working
Parental education (omitted category: non-PhD graduate degree)								
Less than college	-0.0706***	-0.0625***	-0.00803	0.0139	0.0161	0.00779	0.0243	0.00842
	(0.022)	(0.023)	(0.011)	(0.011)	(0.012)	(0.0072)	(0.016)	(0.0084)
College	-0.0405*	-0.0373	-0.00321	0.00935	0.0155	0.00507	0.0157	-0.00513
	(0.023)	(0.025)	(0.011)	(0.012)	(0.012)	(0.0062)	(0.018)	(0.0076)
PhD	0.00756	0.0168	-0.00929	-0.0148	0.0178	-0.00761	-0.0171	0.0141
	(0.023)	(0.025)	(0.013)	(0.010)	(0.013)	(0.0048)	(0.017)	(0.0091)
Demographics FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PhD Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tenure-Track Inst. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.76	0.72	0.045	0.044	0.055	0.014	0.10	0.023
Observations	3,670	3,670	3,670	3,670	3,670	3,670	3,670	3,670
Absorbed DF	308	308	308	308	308	308	308	308

Source: SDR 1993-2021. *Notes:* Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dep vars are binary variables taking value 1 if the individual is working in that job type / industry in the next survey observation after the inferred tenure decision year. Outcomes in cols 2-8 are mutually exclusive and collectively exhaustive. (Col 2 refers to having tenure at the original tenure-track institution or an institution ranked higher or at most 5 rank points lower; this outcome is also shown in Table 2 column 4 in the main paper. Col 3 refers to having tenure at any other institution (ranked 5+ points lower or unranked). Col 4 refers to being on the tenure track without tenure at a new institution.) Sample restricted to those on the tenure track without tenure at ranked US institutions in the last survey observation before their inferred tenure decision year (and for which we observe at least 5 individuals at that institution). Regressions weighted by NSF-provided survey weights. Fixed effects are included for the tenure track institution. Demographics FE are fixed effects for gender, race/ethnicity, and birth region. Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group). "Absorbed DF" shows degrees of freedom absorbed by fixed effects. Analogous outcomes for those on tenure track at non-ranked institution shown in Appendix Table A4.

Table A4: Getting tenure, conditional on tenure-track institution
(Sample: those on tenure track at non-ranked institutions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Tenure anywhere	Tenure at same institution	Tenure at R1	Tenure track elsewhere	Industry	Government	Non-TT education	Not working
Parental education (omitted category: non-PhD graduate degree)								
Less than college	-0.0378	-0.0422	-0.00476	-0.0141	-0.00709	-0.00446	0.0354*	0.0281**
	(0.030)	(0.031)	(0.0078)	(0.017)	(0.014)	(0.0085)	(0.019)	(0.012)
College	-0.0165	-0.0544	0.00790	-0.0146	0.00537	-0.00516	0.0120	0.0189*
	(0.032)	(0.034)	(0.0096)	(0.019)	(0.016)	(0.0090)	(0.020)	(0.010)
PhD	-0.0691*	-0.108***	0.0121	-0.00818	0.0204	0.0153	0.0299	0.0117
	(0.037)	(0.039)	(0.014)	(0.017)	(0.019)	(0.017)	(0.023)	(0.012)
Demographics FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PhD Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tenure-Track Inst. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.83	0.78	0.027	0.047	0.034	0.014	0.060	0.016
Observations	1,559	1,559	1,559	1,559	1,559	1,559	1,559	1,559
Absorbed Degrees of Freedom	373	373	373	373	373	373	373	373

Source: SDR 1993-2021. *Notes:* Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dep vars are binary variables taking value 1 if the individual is working in that job type / industry in the next survey observation after the inferred tenure decision year. Outcomes in columns 1 and 4-8 are mutually exclusive and collectively exhaustive. Sample restricted to those on the tenure track without tenure at non-ranked US institutions in the last survey observation before their inferred tenure decision year (and for which we observe at least 5 individuals at that institution). Regressions weighted by NSF-provided survey weights. Demographics FE are fixed effects for gender, race/ethnicity, and birth region. Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group). "Absorbed DF" shows degrees of freedom absorbed by fixed effects. Analogous outcomes for those on tenure track at ranked institution shown in Appendix Table A3.

Table A5: Research output of tenured professors, conditional on PhD institution and field

	(1) Publications (fspr)	(2) First Author Pubs (fspr)	(3) Last Author Pubs (fspr)	(4) Average CNCI (fspr)	(5) Average Impact Factor (fspr)	(6) NSF Awards (buckets)	(7) Top 10% CNCI Share	(8) High Impact Journal Share	(9) Average Authors Per Pub (fspr)
Parental education (omitted category: non-PhD graduate degree)									
Less than college	-0.0419***	-0.0240***	-0.0428***	-0.0339***	-0.0232***	-0.0913***	-0.0148***	-0.0123**	-0.0192**
	(0.0087)	(0.0090)	(0.0083)	(0.0091)	(0.0085)	(0.032)	(0.0050)	(0.0056)	(0.0089)
College	-0.0181*	-0.0144	-0.0213**	-0.0130	0.0121	0.0133	-0.00644	0.00738	-0.00138
	(0.0094)	(0.0096)	(0.0089)	(0.0095)	(0.0090)	(0.035)	(0.0055)	(0.0063)	(0.0096)
PhD	0.0105	0.000339	0.0132	0.0104	0.0231**	0.0322	-0.00309	0.0130*	0.00710
	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.040)	(0.0062)	(0.0071)	(0.011)
Demographics FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PhD Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,296	12,296	12,296	12,296	12,077	12,296	12,296	12,296	12,296
R-Squared	0.21	0.15	0.25	0.16	0.25	0.27	0.14	0.26	0.15
Adjusted R-Squared	0.18	0.13	0.22	0.14	0.22	0.24	0.11	0.24	0.12
Absorbed DF	371	371	371	371	371	371	371	371	371

Source: SDR 2015-2021, matched with Web of Science and NSF Awards. *Notes:* Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample restricted to 2015 SDR respondents who were tenured at a US institution in 2015, or in the first SDR year we observe them with tenure after this year (2017, 2019, or 2021), matched to their publication record as of 2015 (for 2015 observations) or 2017 (for 2017, 2019, or 2021 observations). Cols 1-3 reflect the field-specific percentile rank ('fspr') for the number of total publications, first author publications, and last author publications respectively. Col 4 is the field-specific percentile rank of the average CNCI across all publications, where CNCI is the category normalized citation count taking into account field and publication type. Col 5 is the field-specific percentile rank of the average journal impact factor across all publications. Col 6 is a categorical variable that separates number of NSF awards in to 0, 1, 2 or 3, and greater than 4. Cols 7 & 8 are the share of publications that were in the top 10% CNCI for the field and year of publication, or in a high impact journal, respectively. Col 9 is the field-specific percentile rank 9 of the average authors per publication. Regressions weighted by NSF-provided survey weight. Demographics FE are fixed effects for gender, race/ethnicity, and birth region. Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group). "Absorbed DF" shows degrees of freedom absorbed by fixed effects.

Table A6: Tenure outcomes with research controls - robustness

	No research controls	With research controls	
	(1)	(2)	(3)
Panel A: Tenure institution rank (log)			
Less than college	0.149***	0.111***	0.112***
	(0.046)	(0.043)	(0.042)
College	0.0455	0.0583	0.0664
	(0.049)	(0.045)	(0.044)
PhD	-0.104*	-0.0841*	-0.0703
	(0.055)	(0.050)	(0.049)
Observations	6,969	6,920	6,920
R-Squared	0.24	0.35	0.37
Adjusted R-Squared	0.20	0.32	0.33
PhD Institution FE	Yes	Yes	Yes
Panel B: Got tenure, conditional on tenure-track institution			
Less than college	-0.0635***	-0.0582**	-0.0536**
	(0.022)	(0.024)	(0.023)
College	0.00959	-0.0106	-0.00523
	(0.023)	(0.025)	(0.024)
PhD	0.00859	-0.00888	-0.0181
	(0.022)	(0.024)	(0.024)
Observations	1,907	1,894	1,894
R-Squared	0.61	0.64	0.67
Adjusted R-Squared	0.54	0.58	0.60
TT Institution FE	Yes	Yes	Yes
Demographics FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
PhD Field FE	Yes	Yes	Yes
Baseline Research Controls		Yes	Yes
Add'l Research Controls			Yes

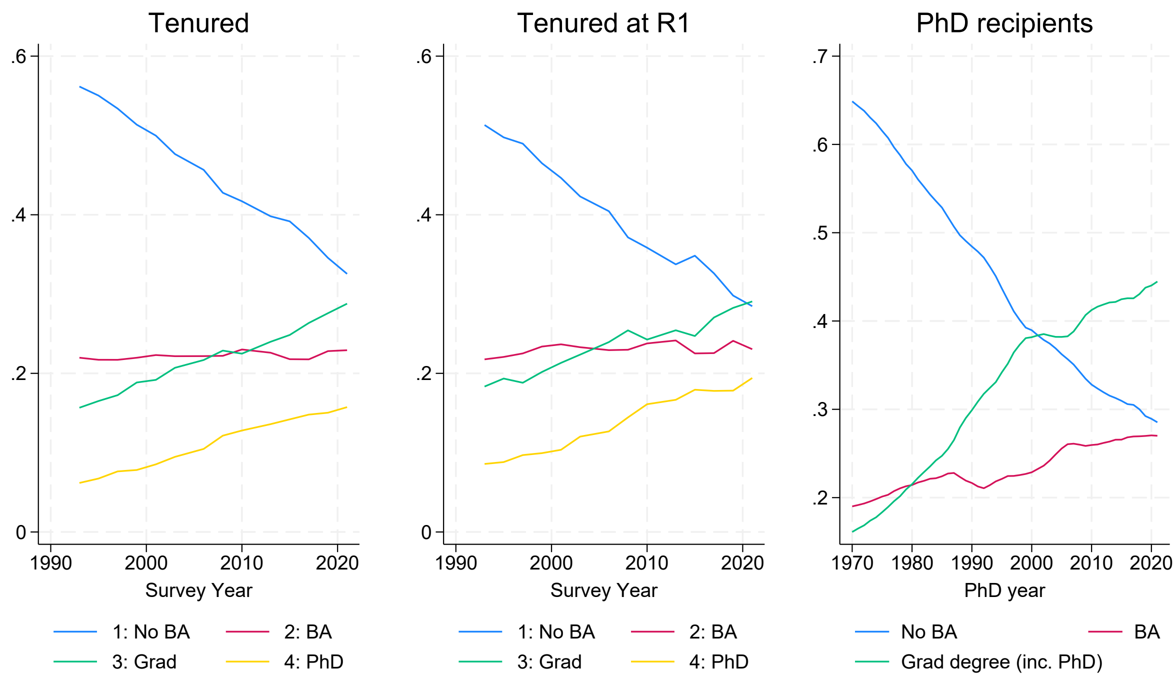
Source: SDR 2015-2021, matched with Web of Science and NSF Awards. *Notes:* Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Replicates Table 3, but using the raw numbers rather than field-specific percentile rank for research control variables in Columns 2 and 3.

Table A7: Citations per publication

Dep. var	(1) Any Cites	(2) Log(Cites(5y))	(3) Log(1+Cites(5y))	(4) Log(CNCI)	(5) Log(1+CNCI)
Panel A: Controlling for third-order polynomial in journal impact factor					
Less than college	-0.00518***	-0.0373**	-0.0417**	-0.0386**	-0.0480**
	(0.0020)	(0.017)	(0.016)	(0.019)	(0.020)
College	-0.00556**	-0.0186	-0.0274*	-0.0369**	-0.0476**
	(0.0022)	(0.016)	(0.016)	(0.019)	(0.021)
PhD	-0.00138	0.00583	0.00209	-0.0125	-0.0145
	(0.0022)	(0.019)	(0.018)	(0.021)	(0.023)
Panel B: Controlling for decile of journal impact factor interacted with broad PhD field					
Less than college	-0.00430**	-0.0296*	-0.0333**	-0.0334*	-0.0408**
	(0.0018)	(0.017)	(0.016)	(0.019)	(0.020)
College	-0.00485**	-0.0147	-0.0223	-0.0356**	-0.0447**
	(0.0021)	(0.016)	(0.015)	(0.018)	(0.020)
PhD	-0.00150	0.00817	0.00419	-0.0112	-0.0143
	(0.0021)	(0.018)	(0.017)	(0.021)	(0.022)
Dep Var Mean	0.95	2.50	2.51	-0.20	4.28
Observations	261,443	248,515	261,443	252,760	261,443
Unique individuals	11,428	11,060	11,428	11,187	11,428
Demographic FE	Yes	Yes	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes	Yes	Yes
Pub. Year FE	Yes	Yes	Yes	Yes	Yes
Pub. Field FE	Yes	Yes	Yes	Yes	Yes
Pub. Type FE	Yes	Yes	Yes	Yes	Yes
Num. Authors FE	Yes	Yes	Yes	Yes	Yes

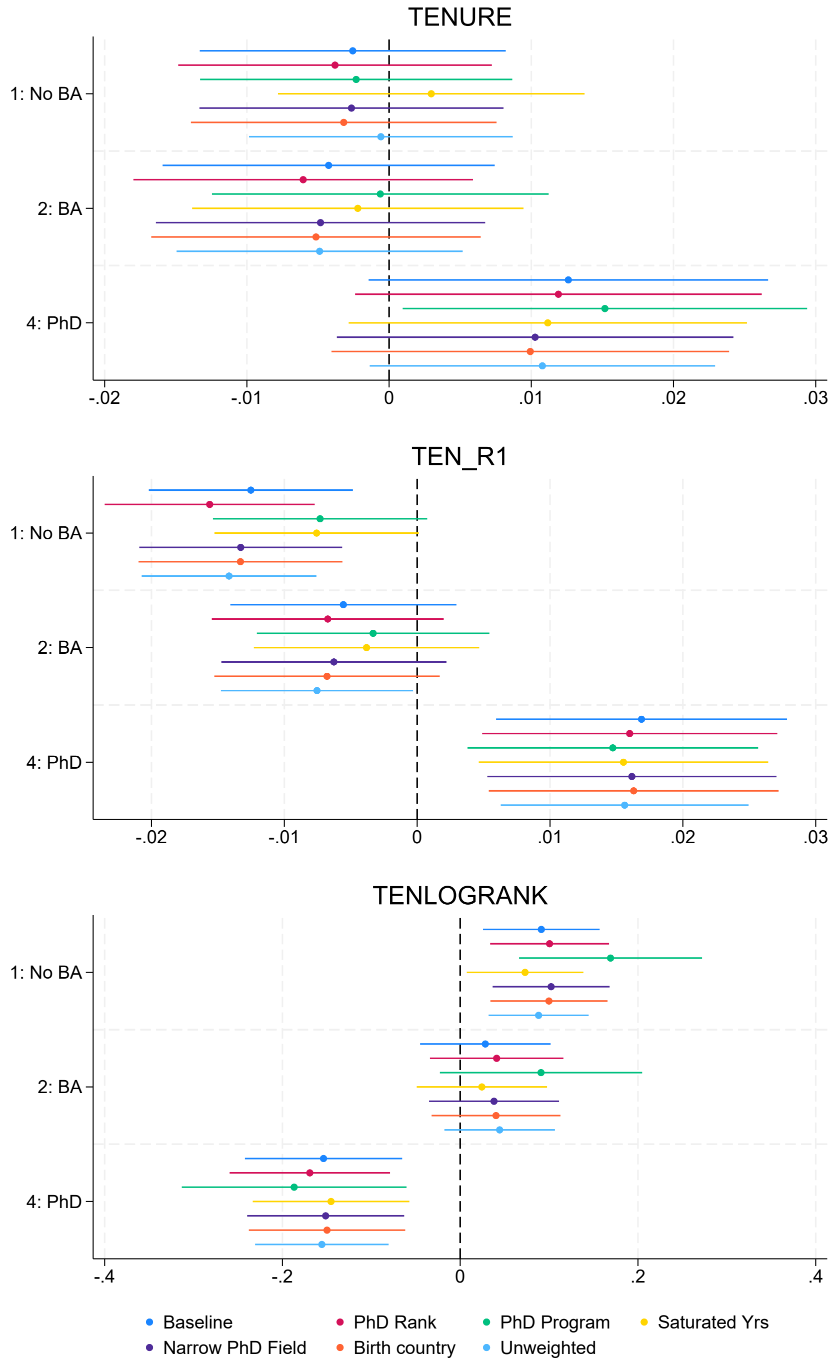
Source: Web of Science bibliometric data, matched with 2015 SDR. *Notes:* Standard errors clustered at individual level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This Table shows the coefficients on parental education in regressions of citations per publication on the parental education level of the author, alongside various controls. The regressions are run at the publication-author level. The dependent variables are, respectively: (1) Any Cites = a binary variable taking the value 1 if the publication has any citations in the first 5 years, and 0 otherwise; (2) Log Cites(5y) = the log of the number of citations in the first 5 years; (3) Log(1+Cites(5y)) = the log of 1 + the number of citations in the first 5 years; (4) Log(CNCI) = the log of the CNCI for the publication; (5) Log(1+CNCI) = log of 1 + CNCI. Sample is restricted to academics that were on the tenure track at a US institution in the 2015 SDR, and to publications which were Articles or Reviews, from 1997 onward (which is the first year we have access to impact factor information). Demographics FE are birth region, gender, and race/ethnicity, alongside seniority (5-year bucket between publication year and PhD receipt). Institution FE are fixed effects for the author's academic institution of employment as of 2015 SDR. Pub Type FE are fixed effects for publication type (article or review), and indicators for whether the publication was in a high impact or a low impact journal (or neither). Pub Field reflects a narrow categorization of the publication's primary field, per Clarivate. Num. Authors FE is a fixed effect for the number of authors (separated into buckets of : 1, 2, 3, 4, 5-9, 10-19, 20-49, and 50+). Panel A also has controls for a third order polynomial in the impact factor of the publication. Panel B instead has fixed effects for the decile of the publication impact factor interacted with the broad PhD field. Weighted by NSF provided survey weights.

Figure A1: Parental education shares of tenured professors, tenured professors at R1s, and PhD recipients (sample limited to those with US PhDs in SEH fields)



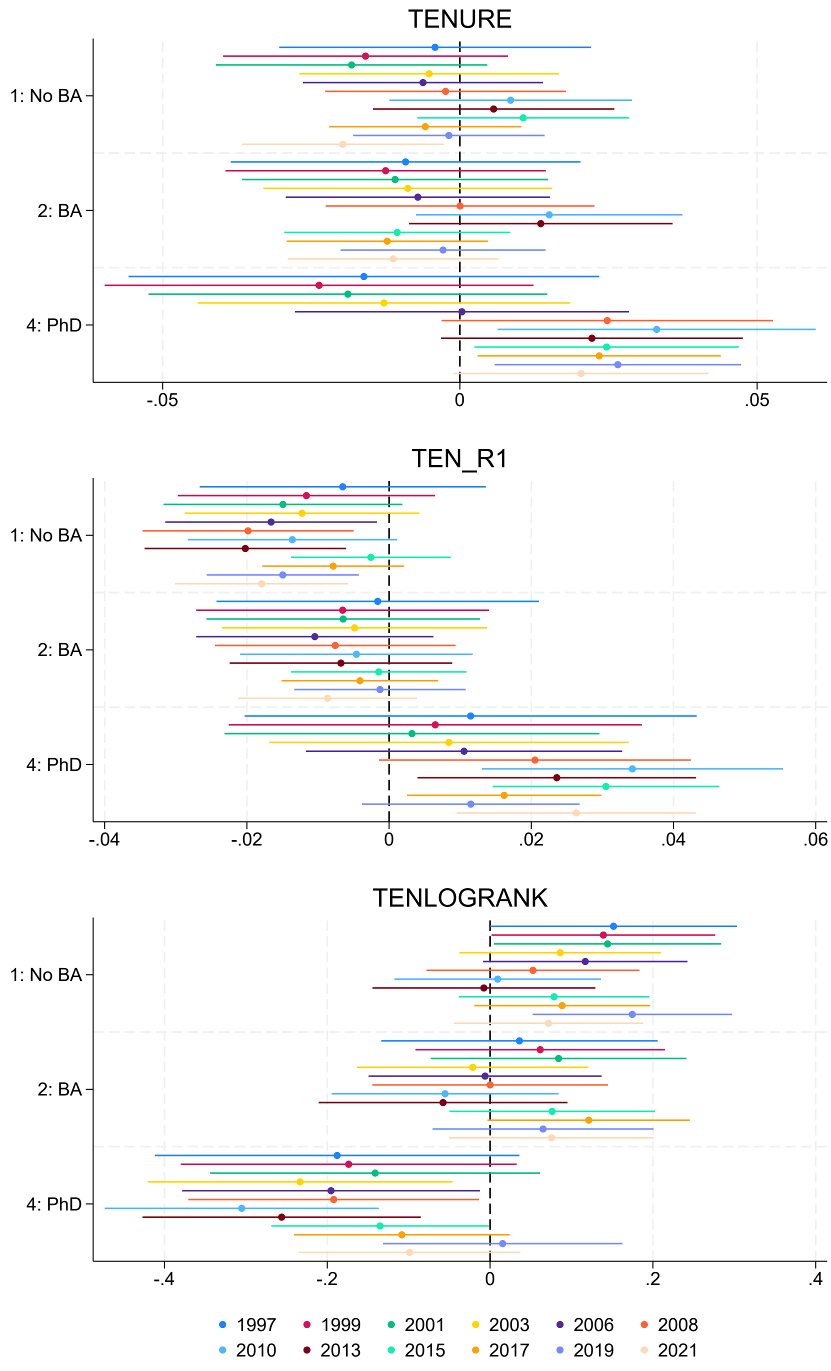
Source: Tenured professors: SDR 1993-2021, matched with SED 2021. PhD recipients: SED 2021. *Notes:* Figures show the share of each group (tenured profs, tenured at R1s, and PhD recipients) who have each level of parental education. Tenured professor sample limited to those tenured at US institutions and weighted by NSF-provided survey weights. Figures only show people with a US PhD in a Science, Engineering, or Health field (including social sciences), because of SDR and SED sample restrictions. PhD recipients figure combines people with a parent with a non-PhD graduate degree and with a PhD into one category.

Figure A2: Tenure outcomes - Robustness - Alternate fixed effects or weights



Source: SDR 1993-2021. *Notes:* Each sub-plot is a coefficient plot showing coefficients and 95% confidence intervals from regressions of the dependent variable indicated in the sub-plot titles on parental education, as well as our baseline fixed effects as in Table 1. Dependent variables are: TENURE = tenure anywhere, TEN_R1 = tenure at R1 institution, TENLOGRANK = log rank of tenure institution. Dependent variables and sample restrictions are as in Table 1. Each color represents a different regression specification, which modifies our baseline specification in some way. All controls and fixed effects are as in Table 1 except the modifications, listed in order: Dark blue: Baseline. Pink: PhD Rank FEs instead of PhD institution FEs. Green: PhD Program FE (institution X field X decade) instead of PhD institution and PhD field FEs. Yellow: Saturated survey year, age, PhD year, and years since PhD FEs. Purple: Narrowest PhD field category FE instead of baseline PhD field category. Orange: Birth country FE instead of birth region FE. Light blue: Unweighted regressions.

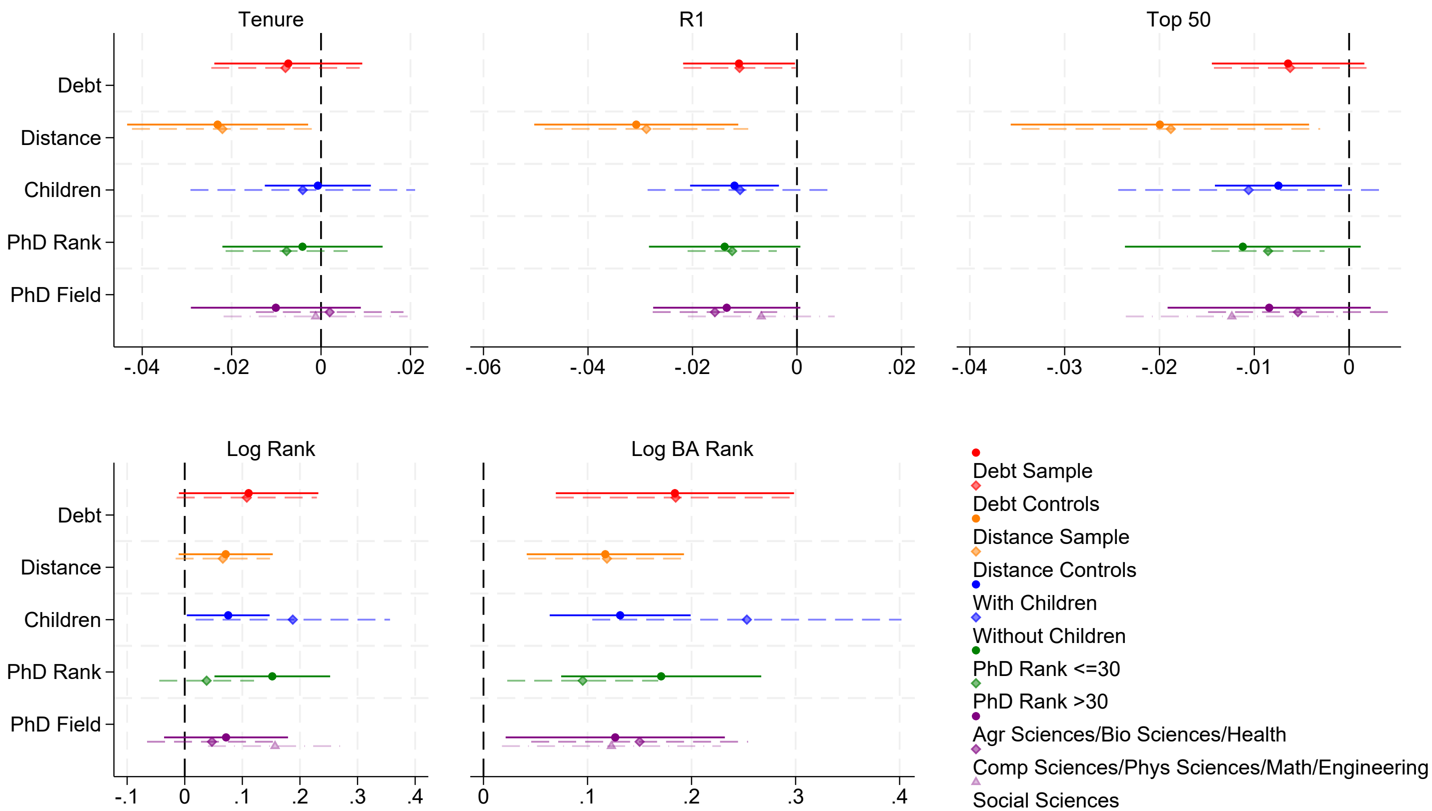
Figure A3: Tenure outcomes - Robustness - Year-by-year regressions



Source: SDR 1997-2021. *Notes:* Each sub-plot is a coefficient plot show coefficients and 95% confidence intervals from regressions of the dependent variable in the sub-plot title on parental education, as well as our baseline fixed effects as in Table 1. Dependent variables are: TENURE = tenure anywhere, TEN_R1 = tenure at R1 institution, TENLOGRANK = log rank of tenure institution. Each color represents a regression run on one specific survey year, as denoted in the legend. Results are also similar for 1993 and 1995 for our first two dependent variables - tenure anywhere, and tenure at an R1. We do not have results for 1993 and 1995 for our dependent variables that rely on rank data due to a change in the institution coding in the SDR between the 1995 and 1997 surveys.

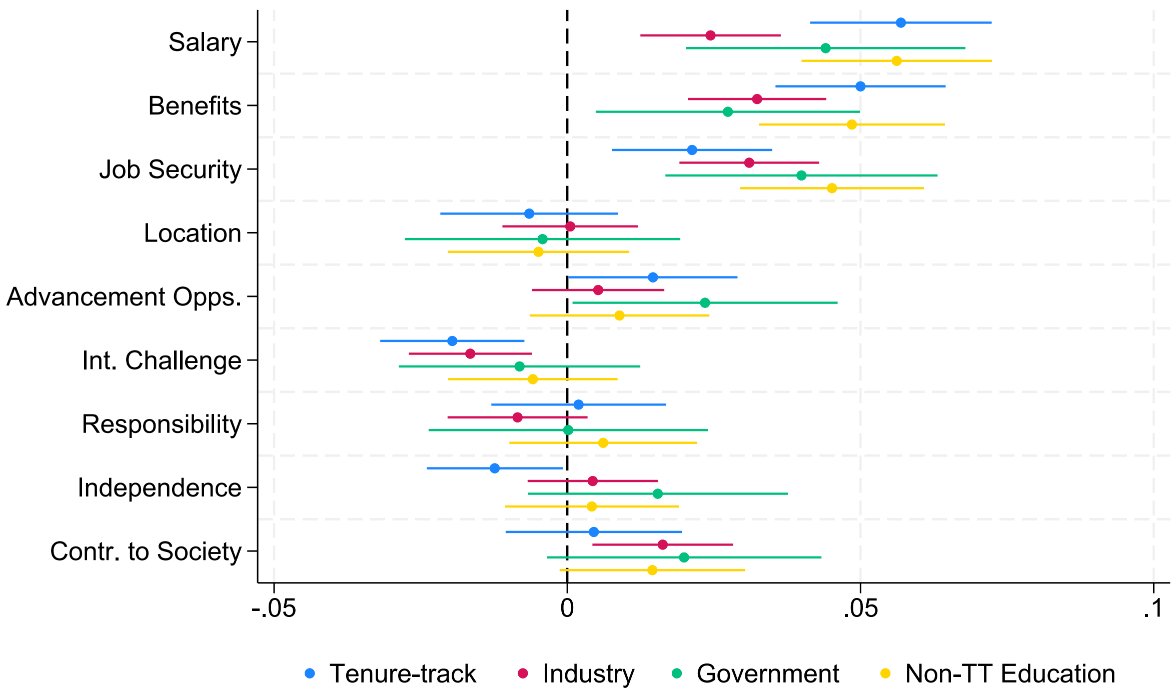
Figure A4: Class gap in tenure outcomes - Heterogeneity

Difference in outcomes between first-gen college graduates and people with a parent with a non-PhD graduate degree



Source: SDR 1993-2021. *Notes:* Each sub-plot is a coefficient plot showing coefficients and 95% confidence intervals from regressions of the dependent variable (sub-plot title) on parental education and our baseline fixed effects, with regressions weighted by survey weights and standard errors clustered at individual level. Only the coefficient on first-generation college graduates is shown, with the omitted category being people with no parent with a graduate degree. Dependent variables are our three baseline (Tenure anywhere, Tenure at R1, and Log Tenure Institution Rank) plus two additional robustness checks (Tenure at a top-50 ranked institution, and Log Tenure Institution Undergraduate (BA) Rank). The five categories on the y-axis show five different axes of heterogeneity: *Debt*: baseline regressions, with sample limited to those with information on student debt levels ("debt sample") and adding controls for a third order polynomial in total student debt level ("debt controls"). *Distance*: baseline regressions, with sample limited to those with information on high school state ("distance sample") and adding controls for a third order polynomial in distance between current employer city and high school state using population-weighted centroids ("distance controls"). *Children*: baseline regressions run separately for those who ever have, or never have, children in our linked SED-SDR dataset. *PhD Rank*: baseline regressions run separately for those who did their PhD at a program ranked 1-30, or greater than 30, on the most recent US News and Report graduate program rankings. *PhD Field*: baseline regressions run separately for three PhD field groups. See Appendix C for field group definitions.

Figure A5: Class gap in perceived importance of job components: Difference between first-generation college graduates and people with a parent with a non-PhD graduate degree, conditional on our baseline controls



Source: Survey of Doctorate Recipients 1993-2021 inclusive, matched with Survey of Earned Doctorates.
Notes: The coefficient plot shows results of regressions of a series of dependent variables for perceived importance of each component of a job on parental education, alongside our baseline fixed effects. Only the coefficients on first-generation college graduates are plotted, with the omitted category being people with a parent with a non-PhD graduate degree. Each coefficient plotted shows the point estimate and 95% confidence interval. Regressions are weighted by the NSF provided survey weight, and have standard errors clustered at the individual level. Sample is limited only to people working the US, less than 30 years since PhD receipt. The dependent variables, listed on the y-axis, are binary variables taking the value 1 if the individual reports that each aspect of a job is "very important" to them, and 0 otherwise. (Int. challenge = intellectual challenge; Contr. to society = contribution to society). These regressions are run separately for each of the four sectors of employment – tenure-track academia, industry, government, and non-tenure track education – indicated by the coefficient colors as detailed in the legend.

B Appendix: Gender and Race/Ethnicity Coefficients

Table B1: Gender and race/ethnicity coefficients from Table 1

Dep. var.	(1) Tenure anywhere	(2) Tenure at R1	(3) Tenure institution rank (log)
Gender (omitted category: male)			
Female	-0.0248***	-0.0133***	-0.0112
	(0.0046)	(0.0032)	(0.029)
Race/ethnicity (omitted category: White Non-Hispanic)			
Asian, Non-Hispanic	-0.0452***	-0.0125*	-0.0767
	(0.010)	(0.0071)	(0.071)
Black, Non-Hispanic	0.0436***	0.0104	0.0613
	(0.011)	(0.0074)	(0.066)
Hispanic, All Races	0.0311***	-0.00140	0.193***
	(0.0100)	(0.0073)	(0.056)
Other, Non-Hispanic	-0.0295**	-0.0133	0.0493
	(0.015)	(0.0095)	(0.098)

Source: SDR 1993-2021. *Notes:* Standard errors clustered at individual level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Shows gender and race coefficients from Table 1.

Table B2: Gender and race/ethnicity coefficients from Table 2

Juncture	PhD to tenure track			Tenure track to tenure
	(1)	(2)	(3)	(4)
Dep. var.	TT anywhere	TT at R1	TT inst. Rank (log)	Got Tenure
Gender (omitted category: male)				
Female	-0.0134***	-0.0105***	0.0437	-0.0211
	(0.0037)	(0.0024)	(0.030)	(0.019)
Race/ethnicity (omitted category: White Non-Hispanic)				
Asian, Non-Hispanic	-0.0448***	-0.0134***	-0.0253	0.0473
	(0.0072)	(0.0051)	(0.073)	(0.046)
Black, Non-Hispanic	0.0294***	0.0268***	-0.205***	-0.141***
	(0.0085)	(0.0055)	(0.066)	(0.041)
Hispanic, All Races	0.0370***	0.00802	-0.0211	-0.0102
	(0.0076)	(0.0051)	(0.061)	(0.038)
Other, Non-Hispanic	-0.0174*	-0.00712	0.0265	0.0307
	(0.0100)	(0.0063)	(0.086)	(0.054)

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Shows gender and race coefficients from Table 2.

Table B3: Gender and race/ethnicity coefficients from Table 3

	No research controls	With research controls	
	(1)	(2)	(3)
Panel A: Tenure institution rank (log)			
Gender (omitted category: male)			
Female	-0.0247	-0.0918***	-0.0881**
	(0.039)	(0.035)	(0.035)
Race/ethnicity (omitted category: White Non-Hispanic)			
Asian, Non-Hispanic	0.127	0.0690	0.0932
	(0.10)	(0.097)	(0.095)
Black, Non-Hispanic	0.0974	-0.198**	-0.181**
	(0.092)	(0.081)	(0.083)
Hispanic, All Races	0.0644	-0.0500	-0.0655
	(0.070)	(0.065)	(0.065)
Other, Non-Hispanic	0.00184	-0.125	-0.106
	(0.10)	(0.100)	(0.10)
Panel B: Got tenure, conditional on tenure-track institution			
Gender (omitted category: male)			
Female	-0.00377	0.00598	0.0122
	(0.018)	(0.018)	(0.018)
Race/ethnicity (omitted category: White non-Hispanic)			
Asian, Non-Hispanic	0.0885**	0.0889**	0.0660
	(0.044)	(0.044)	(0.042)
Black, Non-Hispanic	-0.0280	-0.00252	-0.0105
	(0.041)	(0.040)	(0.042)
Hispanic, All Races	-0.00854	0.00165	0.00652
	(0.038)	(0.038)	(0.038)
Other, Non-Hispanic	0.0542	0.0607	0.0659
	(0.047)	(0.042)	(0.045)

Source: SDR 2015-2021, matched with Web of Science and NSF Awards. *Notes:* Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Shows gender and race coefficients from Table 3.

Table B4: Gender and race/ethnicity coefficients for Table 6

Dep. var: Log earnings	(1)	(2)	(3)	(4)	(5)
Sector	Tenure-track academia	Industry	Government	Non-tenure-track education	Tenure track, w/ institution FEs
Gender (omitted category: male)					
Female	-0.0922***	-0.268***	-0.0897***	-0.213***	-0.0735***
	(0.0061)	(0.0087)	(0.010)	(0.0091)	(0.0054)
Race/ethnicity (omitted category: White Non-Hispanic)					
Asian, Non-Hispanic	0.0173	0.00864	-0.0366*	0.0148	-0.0138
	(0.016)	(0.017)	(0.021)	(0.021)	(0.013)
Black, Non-Hispanic	0.000576	-0.0245	-0.0159	0.0182	0.0122
	(0.014)	(0.020)	(0.021)	(0.022)	(0.012)
Hispanic, All Races	-0.00613	-0.0531***	-0.0186	-0.0595***	0.00461
	(0.011)	(0.017)	(0.018)	(0.018)	(0.010)
Other, Non-Hispanic	-0.00603	-0.00766	-0.0529**	-0.0180	-0.00585
	(0.024)	(0.023)	(0.025)	(0.027)	(0.019)

Source: SDR 1993-2021. *Notes:* Standard errors, clustered at individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Shows gender and race coefficients from Table 6.

C Appendix: Data

Parental Education: The Survey of Earned Doctorates (SED) asks respondents to indicate the highest level of education of their two parents separately.[46] We generate a 4-level categorical variable by determining the highest level of education between the two parents, or the level of education of one parent if only one is reported. The four categories of this variable are mutually exclusive and collectively exhaustive: No parent with a bachelor's degree or higher, at least one parent with a bachelor's degree / four-year college degree, at least one parent with a graduate degree that is not a PhD, and at least one parent with a PhD. 9.7% of unique individuals in our 1993-2021 SDR sample have no information on parental education; we drop them from all analyses.

Gender: We use the GENDER variable from the SDR which indicates if the respondent reports identifying as male or female at the time of the survey. Among those who are not missing parental education, there are no observations missing gender. 64% of observations are male.

Race: Our race dependent variable is a 5-level categorical variable generated from the RACE variable in the SED. The categories are as follows, with their share of observations listed in parentheses: White Non-Hispanic (64.9%), Black Non-Hispanic (5.7%), Asian Non-Hispanic (19.5%), Other Non-Hispanic (2.3%), and Hispanic All Races (7.6%). These categories are mutually exclusive and collectively exhaustive. Other Non-Hispanic includes American Indian/Alaskan Native, Multiple races, and individuals who didn't answer the RACE question in the SED but indicated not Hispanic on the Hispanic indicator. We drop any individuals who report neither race nor ethnicity, which accounts for an additional 55,619 observations (9% of the sample who are not missing parental education). We follow the National Science Foundation classification in defining Under-Represented Minorities (URM) as

[46] Prior to 2018, the SED asked respondents specifically to indicate the highest level of education of their mother and father. Starting in 2018, respondents were asked to report up to two parents' or guardians' highest level of education, regardless of gender. In either instance, the two variables used to report parental education are EDFATHER and EDMOTHER.

Black Non-Hispanic or Hispanic of All Races.

Birth Region: We created this variable using the place of birth (BIRTHPL) variable from the SED, which has state of birth for those born in the US and country of birth for those born outside the US. Since the SED has been surveying respondents for many decades, the reporting of countries has changed, and in some years people reported only region of birth rather than country of birth. For all our baseline specifications, we use a variable we construct to capture the region of birth for respondents. This is a 14-level categorical variable, with categories as follows (and their share of observations listed in parentheses): US (68.1%), Eastern Europe (1.9%), Western Europe (3.2%), East Asia (11.2%), Southeast Asia (1.4%), South Asia (5.0%), West and Central Asia (1.5%), North America excluding the US (2.0%), South America (2.4%), Central America (0.4%), Caribbean (0.7%), Africa (1.9%), Oceania (0.3%), and missing (0.15%). (Missing includes unknown country, skipped question, or at sea).

PhD Field: We use four different levels of granularity of PhD field:

- *PhD Field Group:* 3 categories: Biological Sciences (includes Health, Agricultural, Environmental), Physical Sciences (includes Math, Computer Science, Engineering), Social Sciences (includes Psychology). We use this categorization for our regressions with research controls, where we interacted our research control variables with PhD Field Group (Table 3). We also use this for heterogeneity analysis of our main results, shown in Appendix Figure A4.
- *Broad PhD Field:* 10 categories. This follows the NSF's grouping of PhD fields into broad fields, but breaks out Economics separately from the other Social Sciences. The categories are: Agricultural and Environmental Sciences; Biological Sciences; Health Sciences; Engineering; Computer and Information Sciences; Mathematics and Statistics; Physical, Geological, Atmospheric, and Ocean Sciences; Psychology; Social Sciences excluding Economics; Economics. We use this broad PhD field definition to calculate field-specific percentile ranks of our research output measures (publications,

CNCI, journal impact factor, etc) for regressions using research either as dependent variables (Appendix Table A5) or controls (Table 3).

- *PhD Field:* 75 categories. **This is our baseline PhD field definition**, which we use for our fixed effects in all our regressions (except a robustness check in Table A2, where we use Narrow PhD Field). We construct this field definition using the first two digits of the NSF's 3-digit PhD field classification (described below as "narrow PhD field").
- *Narrow PhD Field:* 267 categories. This is the NSF-provided PhD field definition (and thus the narrowest classification available in our data). The full list is available in the SED 2021 codebook Appendix F ("Historical SED Field of Study/Specialties List"). We only use this narrow field definition in a robustness check in Table A2.

Earnings: The SDR earnings variable indicates total earned income before deductions in the year prior to the survey. Earnings is available starting in survey year 1995. We adjust earnings to 2021 US dollars using the CPI. Among all individuals in our sample (1995-2021) who were working in the US, 0.56% are missing earnings. For those in the 2021 SDR, the median earnings was $115,000, with the 25th percentile $80,000 and the 75th percentile $168,646.

Debt: The SED contains variables which indicate the level of undergraduate and graduate debt. Over 90% of respondents with PhDs in 2000 or later have information for undergraduate and graduate debt (and almost noone prior to 2000). These variables designate debt in five or ten thousand dollar buckets. The exact buckets depend on the year the SED was taken. We impute debt using the midpoint of all buckets; for the highest buckets, we impute a value. We then add imputed undergraduate and graduate debt to get a measure of total student debt.

Institution code imputation: The SDR includes institution codes (IPEDS codes) for the institution at which each respondent is currently employed if they are working for an academic institution in the survey year. This variable, INSTCOD, however, is occasionally missing and/or uses outdated institution codes in earlier years. Since institution codes are important for our analyses and for generating our ranking variables (see the next session), we impute INSTCOD where we can. This primarily involved imputing institution code for survey waves w where we observe the individual at the same institution wave $w-1$ and $w+1$, and with the same tenure status in all three waves. We also recoded any institution codes that changed over time due to universities combining together, changing their name, or closing altogether, in order to match in institution ranks and Carnegie classifications using modern institution codes.

Institution ranks: Our core measure of institution rank is the field-specific graduate program rank from *US News and World Report*. In 2023 we downloaded the most recent program rankings for as many relevant fields as possible: audiology, biology, business, chemistry, computer science, criminology, earth science, economics, engineering, history, mathematics, medicine, nursing, physics, political science, psychology, public health, public policy, sociology, and statistics. We matched these institutions to their IPEDS codes. Since there are several PhD fields for which we are missing field-specific ranks, we imputed ranks for certain missing fields, using the average rank for each broad PhD field for each institution (weighting the field-specific ranks by the number of individuals in each of those fields at that institution, and excluding any fields missing rank information). This means for example that an institution which has an average ranking of N across the social sciences for which we have ranks would also receive that same rank N in the smaller social sciences for which we are missing ranks (like anthropology, gender studies, area studies, and demography). We then merge these field-specific ranks into our SED-SDR data (for both PhD institutions and current employer institutions), using the PhD field of the individual in question. Note that this will give us accurate rankings for the PhD program an individual attended, but means that if someone is employed in an academic department which is *not* the field of their PhD, we may erroneously impute a higher or lower field-specific rank for their institution than is appropriate for the department they are employed in. In all we obtain PhD program ranks for 94.3% of individuals, and institution ranks for 48% of the individuals we observe on the tenure track at a named US institution.[47]

Carnegie classifications: One of our main dependent variables is whether or not an institution is an R1 institution. This is a Carnegie classification, which categorize accredited, degree-granting colleges and universities in the US on various institutional characteristics for the purposes of academic research. We focus in this paper on the classifications based on research activity, in particular R1 institutions, defined as doctorate-granting institutions that have very high research activity.[48] We primarily use the 2015 Carnegie Classification, but supplement it with the 1994 Carnegie Classification. Among those who are on the tenure track working at a named US institution, we have Carnegie classifications for 99% of observations.

Inferring tenure decision dates: Our full matched SED SDR dataset contains a panel of academics, but is not a complete career history: we have data in roughly biannual surveys from 1993 to 2021, but most individuals in the data answer no more than two or three surveys throughout this period. Therefore we frequently only observe snapshots of someone's career: we always observe their PhD year and information, and then observe a few later snapshots in later surveys (the median person in our data answers 3 surveys; the 90th percentile is 7). For our main "got tenure" analysis (Table 2, column 4), we need to know when someone received tenure. For tenured faculty who filled out the SDR in 2010 or later, the year they received tenure is asked directly. For other tenured faculty, and for anyone in other positions (non-tenure track, tenure-track without tenure, or employed outside academia), there is no question asking whether or when a tenure decision was taken. As such, we need to infer the likely tenure decision year for this group.

[47] Since we do not have rankings for all institutions, we also supplement our field-specific rankings with US News and World Report's 2022 undergraduate institution rankings in a robustness check. We observe undergraduate institution ranks for 52% of the individuals we observe on the tenure track at a named US institution. The institutions for which there are ranks on one or the other metric are not fully overlapping: around 4.5% of tenure-track observations at a named US institution have a field-specific graduate program ranking but no undergraduate institution ranking, and about 8.5% for the converse.

[48] An R2 institution is a doctorate-granting institution that has high research activity, and a research institution is any doctorate-granting doctoral or professional university. The Carnegie Commissions use measures such as research expenditure, number of research doctorates awarded, and number of research-focused faculty to determine the level of research activity at institutions.

For this "got tenure" analysis, we restrict our sample to individuals who we observe in a non-tenured tenure-track academic job and then later again after the tenure decision has likely occurred. For our analysis, we need to identify the last year we observe the individual in the SDR on the tenure track before the tenure decision, and the first year we observe the individual in the SDR after the tenure decision. We identify the last year in which we observe individual p in a non-tenured tenure-track job at institution i, denoting this year t. If year t is more than 5 years since the individual's PhD receipt, and if we observe the individual again no more than 5 years later in another SDR survey wave, we denote year $t+1$ the likely tenure decision year. (Typically, there are two years between SDR survey waves, so this gives us the year between the two closest observations of the same individual). We limit only to those on the tenure track at a US institution. For about 5% of individuals in this sub-sample, this process gives us more than one tenure decision year. This could reflect moves where an individual left a tenure-track job without facing a tenure decision, *or* moves where an individual left a tenure-track job because they did not get tenure. In our baseline analyses, we limit to the last tenure decision year we observe.

Web of Science bibliometric data: To construct publication-level variables, we gained access to author-publication level Web of Science bibliometric data that was linked to the SDR by NCSES. Web of Science (WoS), owned by Clarivate, is a widely used database of bibliographic and citation information for over 250 fields and over 21,000 journals, conferences, and books from 1900 to present. Clarivate collaborated with NCSES to collect publication metrics for respondents in the SDR, which was done using a two-stage machine learning algorithm to match each individual respondent to their publications in WoS. Due to various resource constraints, Clarivate has provided NCSES with publication data matched to the 78,320 respondents in the 2015 SDR (Ginther et al., 2023). This data contains metrics for items published from January 1990 to December 2017.

These variables include the publication year and type, the number of authors and each author's position, and the number of first-5-year citations and the CNCI for each publication.

CNCI or Category Normalized Citation Impact is defined by Clarivate as an indicator of the number of citations normalized by subject category, time, and document type. For publications from 1997 onwards they also include the journal impact factor, defined by Clarivate as the frequency with which the average article in a journal has been cited in a particular year. Not all journals are given impact factors by Clarivate.

NSF Award data: NCSES has matched data on all NSF Awards awarded to individuals in the 2015 SDR survey. Our baseline variable using this data is a categorical variable of the number of NSF awards broken down into 0 awards, 1 award, 2 or 3 awards, and 4 or more awards. The majority of researchers in our data have 0 NSF awards; very few have 4 or more. For our baseline analysis sample with research controls (e.g. Table **??**), 66% of the sample have no NSF awards, 10% have 1 NSF award, 10% have 2-3 NSF awards, and 14% have 4 or more NSF awards.

D Appendix: Additional Discussions

D.1 Differences in endowments of research ability within PhD program

Consider in what ways the endowment of research ability might differ, by SEB, for two graduates of the same PhD program. Note that both of these individuals were admitted to and chose to enter the same PhD program, suggesting both that (i) the admissions committees deemed them relatively similar on future research ability and (ii) the individuals thought this program was their best available option. Denote the information observed by the admissions committee as the vector $\mathbf{s}$, which they aggregate into index S and use to form an expectation of future research ability r.

First, it is possible that the admissions committee uses different cutoff rules for lower-SEB vs. higher-SEB students, such that for high-SEB students, all students with $\underline{S_1} < S < \bar{S}$ are admitted, but for low-SEB students, all students with $\underline{S_2} < S < \bar{S}$ are admitted, wherethe cutoff for lower-SEB students is lower than for higher-SEB students, $\underline{S_2} < \underline{S_1}$. This could be a result of affirmative action for low-SEB students, for example. We believe, however, that this is unlikely: Posselt (2016)'s detailed ethnographic study of elite PhD admissions found no evidence of affirmative action based on socioeconomic background, and, indeed, socioeconomic background is rarely observable to PhD admission committees.[49]

Second, it is possible that the admissions committee uses the same cutoff rules for lower-SEB and higher-SEB students, but the lower-SEB students happen to be the more "marginal admits" in any given PhD program: that the observed characteristics S for lower-SEB students may be systematically at the lower end of the interval $\{\underline{S}, \bar{S}\}$. This may be true of large PhD programs, but seems less likely to be true of small programs.

Third, it is possible that the observed characteristics S may on average be the same for higher and lower SEB students within a given PhD program, but that there are other characteristics which are unobservable to the PhD admissions committee, but reflect research

[49] Similarly, Lamont (2009)'s examination of academic grant-making found that very few panelists on grant committees consider class diversity.

ability, which are positively correlated with SEB even conditional on observables. That is, the PhD admissions committee sees the same *expected* research potential in their lower-SEB and higher-SEB admits, but in fact the higher-SEB has more research potential that is unobservable to the PhD admissions committee. This might be, for example, that when comparing a high-SEB individual and a low-SEB individual with the same grades, GRE scores, prior research experience, and recommendation letters, the high-SEB individual may have greater tacit knowledge of how to write well or greater experience with the creative part of the research process.[50] The reverse, however, seems equally plausible: to have obtained equivalently good *observable* measures of academic success S pre-PhD, it seems a priori more likely that lower-SEB individuals would have had to exhibit more determination, hard work, and entrepreneurial spirit than their higher-SEB colleagues, and one would also expect these characteristics to make someone a successful researcher.

Unfortunately, we have no data that enables us to test these possibilities. A test of the first and second, but not third, possibilities above would be to see whether lower-SEB admits are on average worse on observables, such as pre-PhD grades, GRE scores, research experience, or recommendation letters, than their higher-SEB counterparts from the same PhD program. This presents a useful opportunity for further study.

[50] Note that we exclude social and cultural capital from consideration here. We see these as factors which are correlated with SEB and enable researchers to produce better research in future, but do not reflect higher underlying research ability.