The Class Gap in Career Progression: Evidence from US academia

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Unlike gender or race, class background is rarely a focus of research on career progression, or of DEI efforts in elite occupations. Should it be? In this paper we document a large class gap in career progression in one occupation - US tenure-track academia – using parental education to proxy for class background. First-generation college graduates are 10% less likely to be tenured at an R1, are tenured at institutions ranked 11% lower, earn 3% less, and report 5% lower job satisfaction, than their former PhD classmates (from the same institution and field) with a parent with a non-PhD graduate degree. Neither selection out of academia nor different preferences explain this gap; differential research productivity also plays little role. Instead, likely drivers are differences in cultural and social capital. We also find a class gap in career progression for PhDs who work in industry, suggesting this phenomenon generalizes outside academia.

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"Education is a great equalizer. SES is an important element in access to higher education, but conditional on access, most differences wash out."

"[Class] is the most important thing missing from our understanding of advantages/disadvantages in academia."
- quotes from economics professors in our faculty survey, Spring 2025

1 Introduction

Unlike gender or race, class background is rarely a focus of academic research on career progression, or of diversity, equity, and inclusion efforts in elite occupations and organizations.[1] While there is a large literature showing how socioeconomic background affects someone's career starting point, including whether and where they go to college, there is a common assumption that any impacts of class are washed out beyond that point (Laurison and Friedman, 2024). This assumption is incorrect.

In this paper, we show that socioeconomic background is an important determinant of career progression, not just career starting point – using US tenure-track academia as a case study. Specifically, we find that first-generation college graduates are less likely to end up tenured at research-intensive or highly-ranked institutions, earn less, and are less satisfied with their jobs, as compared to their former PhD program classmates from more advantaged backgrounds.

Why study tenure-track academia? It is interesting in itself, as professors' backgrounds may impact their research and teaching. But more importantly, tenure-track academia is uniquely suited for a detailed, quantitative case study of class background and career progression, with: (i) standardized hiring and promotion prcesses (tenure-track job market and tenure), (ii) quantifiable productivity (research output), and

[1] For example, among large US companies with public DEI goals or reporting in 2024, all discussed gender and race, and the vast majority also discussed LGBTQ, disability, and veteran status – but only 6% made any mention of socioeconomic background (Figure 1). See also Ingram (2021).

(iii) proxies for employer quality (research-intensiveness and rank). Thus, tenure-track academia can shed light on how class gaps may emerge in elite occupations in general. Indeed, it may be a lower bound: class likely matters more in other occupations where productivity is less measurable, promotion is less meritocratic, and elite networks are more important.

In Section 2, we outline our empirical setting. Our main data set is the NSF Survey of Doctorate Recipients (1993-2021), a large representative survey of US PhD recipients in the sciences and social sciences. We proxy for socioeconomic background using parental education.[2] Our main focus is the "class gap in career progression": the gap in outcomes between the least and most socioeconomically advantaged groups, conditional on their career starting point. In our setting, this is the gap between first-generation college graduates, and those with a parent with a non-PhD graduate degree (e.g. JD, MD, MBA), conditional on PhD program attended.[3]

Our main results, in Section 3, show a large class gap in career progression in tenure-track academia. Among tenured professors, and conditional on fixed effects for PhD institution, field, race, gender, and birth country, first-gen college grads are 10% less likely to be tenured at a highly research-intensive university (an "R1" according to the Carnegie classification), are tenured at institutions ranked 11% lower, earn 3% less, and are 5% less satisfied with their jobs, than those with a parent with a non-PhD graduate degree. That is, across a range of metrics first-gen college grads seem to have less successful academic careers than their former PhD classmates from more advantaged backgrounds.

[2]We use "class background" and "socioeconomic background" ("SEB") interchangeably. Parental education is one of the three most commonly used measures of class background in academic research, alongside family income/wealth and parental occupation.

[3]We estimate outcomes for four groups by highest level of parental education: less than a college degree, four-year college degree, non-PhD graduate degree, and PhD. Our core "class gap" comparison excludes those with a parent with a PhD because we are interested in the role of generalized socioeconomic advantage, and not academia-specific advantages.

At what point in the career trajectory does this class gap emerge? It is not a result of lower-SEB PhD recipients disproportionately choosing to leave academia for industry: there is no class gap in whether someone leaves academia, conditional on our baseline fixed effects. That is, socioeconomic background does not affect the extensive margin of *whether* someone stays in academia, but does affect the intensive margin of *where* they end up. Moreover, we find a class gap at both major junctures in the PhD to tenure pipeline: in post-PhD placement in tenure-track jobs, as well as in whether someone gets tenure (conditional on tenure-track institution).

What explains this class gap in tenure outcomes? In Section 4 we explore three mechanisms: research productivity, preferences, and social and cultural capital.

First, we consider research productivity. This has only limited explanatory power: detailed field-specific controls for research quantity and quality explain at most two-fifths of the class gap in tenure institution rank, and less than one-fifth of the class gap in the rate of getting tenure. Thus, first-gen college grads are "underplaced" at lower-ranked institutions than would be predicted by their research output.

Second, we explore preferences. These have even less explanatory power: we find no evidence consistent with lower-SEB academics trading off employer prestige in order to be closer to family or community, to prioritize higher paying jobs, to prioritize family care needs, or to work at an institution with a stronger social mission.

Third, we explore cultural and social capital. Limited cultural and social capital may mean lower-SEB academics have greater difficulties forming valuable professional relationships, gaining professional recognition, and navigating academia's "hidden curriculum". While we cannot directly test the role of cultural or social capital in tenure outcomes, we show evidence consistent with them being important: lower-SEB academics have fewer and less well-published coauthors, and are more likely to coauthor with other lower-SEB academics (who are relatively scarce in elite academia), suggesting difficulties building relationships; lower-SEB academics receive fewer NSF awards and citations than their publication record would predict, suggesting difficulties gaining recognition; and in a survey of over 2,000 US academics, respondents overwhelmingly emphasize the importance of cultural capital and social capital when discussing how their own socioeconomic background affected their careers.

How do class gaps compare to race and gender gaps? Strikingly, we find that the class gaps in tenure-track academia are as large as or larger than analogous race or gender gaps. Moreover, the drivers of class gaps likely differ from drivers of race or gender gaps: race and gender gaps in academia exist on both extensive and intensive margins (compared to a class gap only on the intensive margin), and many race and gender gaps are closed by research controls while class gaps are not.

Finally, we examine the generalizability of our findings outside academia, investigating PhDs who work in industry. Conditional on our baseline fixed effects, we find a class gap in (i) earnings, which widens with years of experience; (ii) job satisfaction, particularly with the level of responsibility and opportunities for advancement; and (iii) the likelihood of becoming a manager. Thus, tenure-track academia is not unique: a class gap in career progression also exists for PhDs in industry – and likely in other elite US occupations as well.

Related literature. There is very little research on the role of class in career outcomes like hiring, pay, or promotion - in contrast to a large literature on gender and race.[4] In economics, our work is most closely related to Zimmerman (2019) and Michelman et al. (2022), who show how social ties affect elite graduates' job outcomes; Shukla (2022), who finds caste-based hiring discrimination based on "fit"; and Staiger (2023), who finds family ties affect access to high-paying jobs. In sociology, our work

[4] While a large literature shows how socioeconomic background affects college attainment (e.g. Chetty et al., 2020), there is almost no work on whether it affects career progression after graduation.

builds on qualitative work on the "class ceiling" in elite UK occupations (Friedman and Laurison, 2020; Friedman, 2023) and on hiring in elite US occupations (Rivera, 2012); resume audit studies finding class-based discrimination (Rivera and Tilcsik, 2016; Galos, 2024); and documentation of within-occupation pay gaps by class origin.[5]

Our contribution is threefold. First, we are the first paper to provide detailed, large-scale, quantitative evidence of a class gap in career progression in any elite occupation.[6] Second, we can quantify multiple aspects of career progression: not just pay but also promotion and the quality of the employer. Third, we can investigate mechanisms in detail – in particular, the role of productivity.

In focusing specifically on academia, we build on recent work documenting the underrepresentation of low-SES individuals in US academia (Morgan et al., 2022; Stansbury and Schultz, 2023; Airoldi and Moser, 2024). More broadly, our work speaks to the large literature on demographic disparities in elite career progression, which is almost entirely focused on gender and race.[7]

Socioeconomic background is rarely considered in DEI efforts in either academia or other elite US occupations. Our findings suggest researchers and practitioners should consider socioeconomic background – alongside race and gender – as an important axis of advantage in elite career progression, and demonstrate a need for more research to document and understand the class gap in career progression.

[5] For the US, see Laurison and Friedman (2024), Witteveen and Attewell (2017), Torche (2011); for non-US see Friedman and Laurison (2020), Falcon and Bataille (2018), Hällsten (2013), and Núñez and Gutiérrez (2004), as well as Engzell and Wilmers (2021) on the role of firm pay premia.

[6] Specifically, we estimate class gaps conditional on detailed educational attainment and career starting point (PhD program or tenure-track job). Estimated class pay gaps in earlier work may be driven by lower-SEB individuals starting on a worse footing (e.g. a worse college or initial employer).

[7] In particular, in finding an important role for networks, subjective performance evaluation, and homophily, our work relates to Cullen and Perez-Truglia (2023), Benson et al. (2024), and Linos et al. (2023). In academia specifically, research has found gender differences in reference letters, recognition or evaluation of work, coauthorship, and citations (Eberhardt et al., 2023; Sarsons et al., 2021; Card et al., 2020; Hengel, 2022; Ross et al., 2022; Davies, 2022; Koffi, 2021); and racial differences in funding awards and citation patterns (Ginther et al., 2018; 2011; Koffi et al., 2024).

2 Background and Empirical Setting

Our main dataset is the National Science Foundation's Survey of Doctorate Recipients ("SDR"), a biennial representative survey of people who received a US PhD in a science, social science, engineering, or health field. The SDR provides data on individuals' employment sector, salary, job satisfaction, and their institution and position if in academia. We combine this data with the NSF's Survey of Earned Doctorates ("SED"), an annual census of US PhD recipients, which provides data on parental education, other demographics, and PhD field and institution. To study research productivity, we use new linkages between the 2015 wave of the SDR and (1) the Web of Science bibliometric database, as well as (2) a database of NSF award receipt.

For most of our analyses, we use the 1993-2021 SDR surveys. This comprises 14 survey waves, with about 30,000 individuals per wave for 1993-2013 and 80,000 per wave for 2015-2021. The median respondent appears in 3 survey waves. We weight our regressions with NSF-provided survey weights, and cluster standard errors at the PhD program cohort level.[8] We restrict the sample to those living in the US.

To proxy for 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. All of these groups are meaningfully represented among PhD recipients: in our baseline sample in the 2021 SDR, 34% were first-gen college grads, 24% had a parent with at most a four-year college degree, 29% had a parent with

[8]NSF survey weights adjust for differential sampling and nonresponse rates by gender, race/ethnicity, location, PhD year, and PhD field. SDR response rates are around two thirds. Clustered standard errors at PhD program cohort level (PhD field by institution by year) adjust for correlation between the same individual's responses over different waves, as well as between members of the same PhD program cohort. We show our results are robust to alternative weighting and clustering in Appendix B, and provide more detail on the data in Appendix C.

at most a non-PhD graduate degree, and 13% had a parent with a PhD (Figure 2). While we compare all four parental education groups, our main focus is the "class gap" in outcomes between the least and most socioeconomically advantaged groups: first-generation college graduates and people with a parent with a non-PhD graduate degree.[9] We do not focus on those 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 advantages.[10] In the academic literature, parental education is one of the three most commonly used indicators of socioeconomic background, alongside family income and parental occupations (which are not available in our data). Parental education is an effective proxy for socioeconomic background, both because it is a strong predictor of family income (e.g. Sirin, 2005),[11] and because parental education itself can provide students with a better understanding of how to access and succeed in elite occupations.

3 Empirical Analysis

This paper asks whether there is a class gap in career progression in US tenure track academia. The raw data suggests there may be: tenured professors, particularly at elite institutions, are more socioeconomically advantaged than the population of PhD recipients (Table 1). But this could simply be caused by a class gap in career *starting point*: prior research shows that lower-SEB individuals are more likely to do their PhDs at lower-ranked programs which send fewer graduates to elite tenure-track

[9] In the US, non-PhD graduate degrees are primarily professionally-oriented degrees in medicine, law, business, psychology, education, and social work (Appendix Table A1). Among the parents of academics in our survey, the non-PhD graduate degrees were primarily in medicine, law, and business, or masters' degrees in STEM and non-STEM fields (Appendix Table E3).

[10] 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).

[11] For example, in 1992 the average income of a household where neither parent had a college degree was $29,300, vs. $66,200 if a parent had a non-PhD graduate degree (Appendix Table A2).

jobs (Stansbury and Schultz, 2023). We are interested in whether there is also a class gap in *career progression*: are lower-SEB individuals less likely to end up tenured at elite institutions even conditional on the PhD program they attended?

3.1 Empirical Strategy

For SDR respondents who are 10-39 years post-PhD,[12] we estimate

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

with five core dependent variables $DepVar_i$. First, we estimate the *extensive margin*, capturing whether there are socioeconomic gaps in the likelihood of staying in tenured academia at all, with dependent variable:

1. *Tenure anywhere*, a binary dependent variable taking value 1 if someone is in a tenured academic job and 0 if in any other job.

Next, we estimate four *intensive margin* regressions, limiting the sample to tenured academics and capturing whether there are socioeconomic gaps in the quality of these jobs, using dependent variables:

2. *Tenure at an R1,* a binary dependent variable taking value 1 if someone is tenured at an R1 per Carnegie Classification and 0 otherwise;
3. *(Log) Tenure institution rank*, measured as the most recent field-specific graduate program ranking from *US News and World Report* ("USNWR");
4. *(Log) Earnings*; and
5. *Job Satisfaction*, self-reported on a four-point scale.

All regressions include fixed effects for PhD institution, PhD field, survey year, years since PhD, year of PhD receipt (in 5-year buckets), birth country, gender,

[12] Starting at 10 years so that most people have faced a tenure decision, and ending at 39 years to avoid differential retirement decisions by SEB.

and race/ethnicity (X_i). We refer to this set of fixed effects as our *baseline fixed effects* and use them in all analyses unless noted otherwise. Our fixed effects hold constant any differences in socioeconomic background and tenure rates by PhD field, PhD institution, or PhD year, roughly comparing people who got their PhD in the same program.[13] Our fixed effects also mean that any class gap in career progression we identify is a gap based on differences in parental education alone, and *not* arising from correlated differences in race/ethnicity or country of origin.

3.2 Main Results

Table 2 shows our main results. Our core comparison of interest – the "class gap" – is between first-gen college grads (denoted "Less than college") and those with a parent with a non-PhD graduate degree (the omitted category).

Extensive margin. Conditional on our baseline fixed effects, there is no class gap in the likelihood of ending up a tenured academic (column 1).[14] The point estimate is very close to zero (-0.002) and the 95% confidence interval rules out more than a one percentage point difference in either direction – a small margin when compared to the 27% of our sample who are tenured.

Intensive margin. In contrast, we find a large class gap on the "intensive margin" – the quality of the job, among tenured academics. Conditional on PhD institution and field fixed effects, first-gen college grads are 4.2 percentage points (10%) less likely to be tenured at an R1, as compared to those with a parent with a non-PhD graduate degree (column 2); they are tenured at institutions ranked 10.8 log points lower (column 3); they earn 3.1 log points less (column 4); and they report 5% lower

[13] In a robustness check, we also estimate with fixed effects for PhD field *by* institution *by* decade, directly comparing people from the same PhD program.

[14] Indeed there are no class differences in the likelihood of working in any sector: tenure-track or tenured academia, non-tenure-track academia, industry, or government (Appendix Table A3).

job satisfaction (column 5).[15]

Thus, our results show that, conditioning on the institution and field where someone got their PhD, there is a large "class gap" in career progression. This class gap exists entirely on the intensive margin: there is no class gap on the extensive margin (no differential selection into tenured academia).

Notably, for all four intensive margin results, the coefficient estimates for those with a parent with a college degree only are between first-gen college grads and those with a parent with a non-PhD graduate degree, suggestive of a monotonic class advantage across parental education groups. And, while not our main focus, we note that those with PhD parents have better outcomes even than those with a parent with a non-PhD graduate degree, suggestive of academia-specific advantages which matter even beyond generalized socioeconomic advantage.

Robustness. These main results are robust to using coarser parental education categories, alternative measures for tenure institution research-intensiveness or rank, sub-samples over time, and alternate regression specifications. Notably, there is still a large class gap in all four intensive margin variables even controlling for PhD program fixed effects – directly comparing individuals who graduated from the same PhD program in the same decade.[16] For full robustness checks, see Appendix B.

The pipeline: getting tenure-track jobs and getting tenure. Our baseline analysis asks if there is a class gap in where someone *ends up* in their career, conditional on PhD program: do they end up a tenured professor, and if so at what kind of institution? There are two key points between PhD and tenure where this gap could arise:

[15] The class earnings gap mostly closes when controlling for current institution, suggesting it is driven by lower-SEB academics being tenured at lower-paying institutions. The job satisfaction gap of 5% is calculated as the coefficient of 0.0294 applied to average job satisfaction of 1.52.

[16] See Appendix Table B1. We do not use PhD program fixed effects at baseline to ensure consistency across regressions: in our later regressions where we condition on research output (particularly Table 5), the sample size is too small to include PhD program fixed effects.

on the tenure-track job market, or at the point of the tenure decision. Unfortunately, since the SDR is not a full panel we cannot observe these two junctures for much of our sample. We therefore analyze each juncture with smaller subsamples.

To examine the tenure-track job market, we limit our sample to those 1-9 years after their PhD, and run an analogous set of regressions to those in Table 2 columns 1-3, but using tenure-track positions instead of tenured positions. Results are shown in Table 3, columns 1-3. We again find no class gap on the extensive margin (the likelihood of being on the tenure track), but large class gaps on the intensive margin.

To examine the tenure decision juncture, we limit our sample to the small subset who we observe shortly before and shortly after the (inferred) tenure decision year. We define "getting tenure", following Sarsons et al. (2021), as being observed with tenure at an institution ranked higher or up to 5 rank points lower than the tenure-track institution. We regress this "getting tenure" dependent variable on parental education and our baseline fixed effects with one alteration: we use fixed effects for tenure-track institution instead of PhD institution, implicitly comparing individuals who are tenure-track in the same department. We find a large class gap: first-gen college grads are 6.6 percentage points (9%) less likely to get tenure, compared to someone with a parent with a non-PhD graduate degree who was tenure-track at the same institution (Table 3, col. 4).[17]

4 Mechanisms

Our results in section 3 showed that, conditional on PhD program attended, there is a large class gap in tenure institution type: first-gen college grads end up tenured at less research-intensive, lower-ranked institutions. We also showed that this is

[17] First-gen college grads instead are more likely to move to non-tenure-track academic jobs or industry (Appendix Table A4). Note: our "getting tenure" variable limits our sample to those at ranked institutions. For those at non-ranked institutions, we show other outcomes in Appendix Table A5.

not driven by the extensive margin (there is no differential selection out of tenured academia),[18] and that there is a class gap in outcomes at both key junctures for career progression: the tenure-track job market, and the tenure decision. In this section, we examine three possible mechanisms for this class gap in career progression: (1) Productivity (proxied by research output), (2) Preferences, and (3) Social and Cultural Capital. We find that research output can explain at most one-to-two fifths of the class gap, preferences can explain none, and the residual is therefore likely explained by social and cultural capital.

4.1 Research Output

Lower-SEB academics may end up with tenure at less prestigious institutions if they have produced less or lower-quality research. This may be because of differential endowments (if, e.g., lower-SEB individuals enter PhD programs with fewer research-relevant skills),[19] skill development (if, e.g., lower-SEB individuals receive less mentorship or have less time to build skills during their PhD), or constraints (if, e.g., lower-SEB individuals need to earn extra money or attend to family responsibilities, reducing time for research (Lee, 2017; Waterfield et al., 2019)).

To evaluate whether differential research output explains the class gap in academia, we re-run our main regressions with research controls, using our linked 2015 SDR - Web of Science - NSF award sample. The Web of Science data gives us a close-to-exhaustive set of the observable measures of research quantity, quality, and individual contribution, while the NSF data gives a good proxy for funding success. Note that this sample is substantially smaller than our main sample, because only the 2015 SDR

[18] While there is no difference in the overall likelihood of leaving tenured academia, there may still be differential selection gradients by ability within each socioeconomic group. In Appendix D.2 we use Lee-style bounds (Lee, 2009) to show that this is unlikely to explain the class gaps we see.

[19] Since we condition on PhD institution and field fixed effects, this channel requires differential prior preparation or ability *within PhD program cohorts*. See Appendix D.1 for further discussion.

survey wave is linked to the Web of Science data.

Tenure institution rank regressions. We first re-run our baseline regression for (log) tenure institution rank (Table 2, column 3), controlling for detailed measures of research output. This regression asks "are low-SEB academics tenured at lower-ranked institutions – as compared to what you would predict based on their PhD institution and field, other demographics, *and* research output?" Note that this is an upper bound estimate. It will over-estimate the explanatory power of research, since the relationship between tenure institution rank and research output goes in both directions: an academic with less research output will likely end up tenured at a lower-ranked institution, but also an academic who has been working for many years at a lower-ranked institution has likely had less time or funding for research, or less incentive to prioritize research, and so may have produced less research than if they had been employed at a higher-ranked institution (independent of their initial research ability).[20] To avoid this problem, we would ideally control for research output at the time of the hiring or tenure decision, but for most academics in our sample we do not have this information.

We show results in Table 4, Panel A (and visualize in Figure 3). Column 1 presents the baseline results without research controls, for this more limited sample. Column 2 incorporates our baseline research controls: second order polynomials in publications, average CNCI citations, average journal impact factor, and average number of authors per paper. Column 3 incorporates additional research controls: second order polynomials in first-author publications and in last-author publications,

[20]Indeed, conditional on PhD institution and field, we do find that tenured academics who are first-gen college grads have fewer publications, fewer citations, and lower average journal impact factors than those with a parent with a non-PhD graduate degree (Appendix Table A6). But as discussed in the text, this research gap could be an outcome, not a cause, of the class gap in tenure institution type. This is why we do not run our baseline "tenure anywhere" or "tenure at R1" regressions controlling for research output: because those who are either non-tenured or tenured at non-R1s will have substantially less time, resources, and incentive to produce research.

the number of NSF awards (bucketed), and two measures of the share of publications that were "hits" (share in the top 10 percent CNCI, and share in high impact journals). All research controls are interacted with PhD field group.[21]

If socioeconomic background *only* affects tenure outcomes through its effect on research productivity, we should see no significant relationship between tenure institution rank and parental education when controlling for research output. This is not the case. Controlling for even our most detailed measures of research quantity and quality explains at most two-fifths of the class gap: in this sample there is a 15.7 log point class gap in tenure institution rank with our baseline fixed effects, which falls to 9.3 log points with the full suite of research controls, remaining statistically significant at the 5% level. Lower-SEB academics are "underplaced", tenured at substantially lower ranked institutions than their research output would suggest.[22]

"Got tenure" regressions. We also re-run our "got tenure" regressions (Table 3 col. 4), controlling for detailed measures of research output *at the time of the tenure decision.*[23] We show these results in Table 5 (and visualize in Figure 3). Controlling for research reduces the class gap in the rate of "getting tenure", conditional on tenure track institution, but by less than one fifth: with our baseline fixed effects, the class gap in "getting tenure" in this sample is 8.2pp; with our full suite of research controls, it falls to 6.8pp, and – despite the small sample and hundreds of fixed effects – remains

[21] "CNCI", or Category Normalized Citation Impact, is the number of citations normalized by subject category, time, and document type. We use three PhD field groups: biological, physical, and social sciences. For the number of publications, first-author pubs, last-author pubs, CNCI, impact factor, and authors per paper, we use the field-specific percentile rank rather than the raw number given the highly-skewed distributions and large number of zeroes. In Appendix Table B7 we show very similar results using raw numbers instead.

[22] In fact, the difference is more pronounced in the likelihood of "overplacement". In Figure 4, we show that higher-SEB academics are much more likely than lower-SEB academics to be "overplaced" at institutions that are better-ranked than their research record would predict.

[23] Unlike the rank regressions, this regression does not suffer from the reverse causality problem because we are able to control for research at the time of the tenure decision itself. Since our sample size is small and fixed effects are highly saturated, instead of a fixed effect for PhD field, we include a control for the field-specific mean tenure rate.

statistically significant at the 10% level. Thus, lower-SEB academics are less likely to get tenure than their more-advantaged peers at the same tenure track institution, even controlling for their research output.

Unobservable aspects of research quality. Our research measures cover almost all possible observable measures of research quality and quantity, including the key quantifiable measures central to tenure decisions (Schimanski and Alperin, 2018). But some aspects of research quality may be unobservable to us. For this to explain the large residual class gap, it would need to be the case that higher-SEB academics have better unobservable research quality than lower-SEB academics, conditional on all observable measures of research quantity and quality. The relative stability of the class gap coefficient when moving from our baseline to full research controls makes this unlikely: adding information on authorship contribution, NSF awards, and "hit" publications neither increases the explanatory power nor closes the class gap, so additional (unobservable) research quality would need to be uncorrelated with all of these to close the class gap further. If we do assume unobservable research quality is uncorrelated with observed research output, we can bound the degree to which this may explain our class gap using Oster (2019)'s bias correction: even under conservative assumptions, we still estimate large class gaps.[24]

4.2 Preferences

In this section we explore reasons lower-SEB academics may be more likely to *choose* lower-ranked or less-research-intensive tenured jobs, relative to their higher-SEB peers with similar job options.

Distance from home. Lower-SEB academics may prefer to live closer to home

[24]Specifically, assuming the explanatory power of unobservable research quality is half the explanatory power of all observable research measures combined, we still only close the class gap in tenure institution rank by three-fifths and in "getting tenure" by one quarter. See Appendix D.3.

– e.g. because of family commitments or financial constraints – even at the cost of job quality (Gardner, 2013). We find no evidence that this explains the class gap in tenure institution type: 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 (Appendix Figure A1).[25] 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 A3).

Financial constraints. Lower-SEB academics may face greater financial constraints, so may be willing to trade off tenure institution prestige for higher pay.[26] But in tenure-track academia there is no such tradeoff: higher-ranked, more research-intensive institutions pay more.[27] Moreover, the class gap is unchanged when controlling for a third-order polynomial in student debt – a proxy for financial constraint (Appendix Figure A1).

Family constraints. Lower-SEB academics may make different trade-offs between career and family, or face greater constraints e.g. around childcare. But, re-running our baseline regressions separately for those with or without children, we find that class gaps are similar for both groups, suggesting different career-family tradeoffs do not explain the class gap in tenure institution type (Appendix Figure A1).

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-

[25] 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 (Appendix Table B4).

[26] Indeed, in SDR questions about importance of job components, lower-SEB academics rank pay and benefits as more important than their higher-SEB colleagues (Appendix Figure A3).

[27] In our data, tenure-track jobs at R1 institutions pay on average 25 log points more, and each 10-rank-point increment pays 1.9 log points more, conditional on fixed effects for survey year, 5-year PhD group, years since PhD, and PhD field.

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.[28] Moreover, we find no class gap in respondents' rating of the importance of a job's contribution to society (Appendix Figure A3).

Other explorations. We find similar-sized class gaps for each of the three field groups (biological, physical, and social sciences), suggesting that factors common across fields are the key drivers. 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 A1).

4.3 Social and Cultural Capital

Differences in research output and preferences cannot explain the bulk of the class gap. Thus, other factors must explain the finding that lower-SEB academics end up tenured at less research-intensive, lower-ranked institutions. We propose that the residual class gap can be explained by limited social and cultural capital. Following Bourdieu (1986), we define social capital as relationships which can provide useful professional resources, advantages, and knowledge;[29] and define cultural capital as the tastes, ideas, habits, and behaviors which confer status or recognition in academia.

Lower-SEB academics likely start their careers with less social capital: fewer pre-existing relationships with academics, through family or community. Lower-SEB academics likely also start their careers with less cultural capital: through their upbringing, they may have less familiarity with upper-middle class norms or cultural experiences (Bourdieu, 1986). This can make it difficult to form new professional relationships, both because of simple cultural distance as well as because of implicit

[28] 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.

[29] Note that this definition of social capital is the common definition in sociology, but *differs* from that of Putnam (1995), which focuses on social trust. See Siisiainen (2003).

or explicit biases around what kinds of speech, dress, and behaviors represent "professional", "brilliant", or "polished" individuals (Friedman and Laurison, 2020).

By limiting the scope of professional networks, limited social and cultural capital can matter for research output (e.g. via advising or coauthorships). But even conditional on research output, more limited professional networks likely matter for hiring and tenure decisions for two reasons: (i) influential sponsors: limited networks may mean that lower-SEB academics are less likely to receive strong recommendation or tenure letters;[30] and (ii) the "hidden curriculum": limited networks make it harder for lower-SEB academics to learn how to navigate the academic profession (Calarco, 2020). Even beyond its effect on professional networks, cultural capital can matter for two additional reasons: (iii) implicit or explicit bias: judgments about academic excellence can be subconsciously influenced by subtle speech or behavioral signals;[31] and (iv) "fit": perceived "fit" is important for hiring and tenure decisions (Rivera, 2017; White-Lewis, 2020), and is likely affected by cultural capital, particularly at highly-ranked institutions where most faculty are from advantaged backgrounds.

While we cannot examine all of these aspects directly with our data, we provide three pieces of evidence which suggest limited social and cultural capital are important drivers of the class gap. First, lower-SEB academics' coauthorship networks are consistent with greater difficulties forming professional relationships. Second, NSF awards and citations provide suggestive evidence that lower-SEB academics receive less professional recognition. Third, academics' own survey responses about the role of socioeconomic background in their careers emphasize cultural and social capital.

Relationships: Coauthor networks. For every individual in the linked 2015 SDR-

[30] Rivera (2017) finds that the prestige of the institution a letter writer comes from, and the reputation of the writer, are both weighed heavily in tenure-track hiring decisions.

[31] Lamont (2009)'s research on grant-making found that judgments of excellence were often influenced by cultural capital, and by perceived fit with subjective notions of "flair, elegance, and spark".

Web of Science data, we observe the number of coauthors on each paper, and detailed information about the subset of these coauthors who are also in the 2015 SDR.[32] We find (i) homophily by socioeconomic background: first-gen college grads' coauthors are more likely to also be first-gen college grads than you would predict, given these coauthors' other characteristics (Table 6 Panel A),[33] which restricts the potential size and value of professional networks because academics at elite institutions are rarely from lower-SEB backgrounds; (ii) first-gen college grads' coauthors are less well-published and well-cited than would be predicted by these coauthors' other characteristics (Table 6 Panel B);[34] and (iii) lower-SEB academics have fewer coauthors per paper, conditional on our baseline fixed effects (Appendix Table A6). Together, these findings suggest greater frictions in forming valuable professional relationships.

Recognition: NSF awards and citations. We also find suggestive evidence that lower-SEB academics' work gains less recognition. First, conditional on highly granular measures of research output as well as prior NSF award receipt, we find that first-gen college grads are 3.8 percentage points (18%) less likely to receive an NSF award than their tenure-track or tenured peers *at the same institution and in the same field* with a parent with a non-PhD graduate degree (Table 7). Second, we find that publications where the author is a first-gen college grad are less well cited than you would predict from the publication's field, year, type, and journal impact factor, as well as the author's other demographics, seniority, and employer institution (Table 8). While these gaps could be consistent with lower-quality work, given the highly detailed research controls it seems more likely that they reflect a lower likelihood

[32] We can observe at least one coauthor in the SDR for over 23,000 individuals.

[33] For each individual, we residualize a dummy for whether they are a first-gen college grad on fixed effects for gender, race/ethnicity, birth country, PhD year, PhD field, and PhD institution. We take the average of this residual across each individual i's coauthors (weighted by authorship share). We regress this average coauthor residual on a dummy for the first-gen status of individual i.

[34] As above, we residualize each research measure on parental education and our baseline fixed effects, calculate the weighted average residual across coauthors, and regress this on parental education.

of receiving recognition conditional on research quality. Reduced recognition could reflect more limited networks, and/or implicit bias based on limited cultural capital.

Survey evidence. To further explore potential drivers of the class gap, we ran our own survey of US academics in Spring 2025, receiving over 2,000 responses.[35] We asked respondents multiple choice and open-ended questions about the class gap in tenure-track academia in general, as well as how their own socioeconomic background affected their career progression during and after their PhD. Two core themes were present: cultural capital and social capital.[36]

Survey evidence: cultural capital. In the multiple choice questions, while we did not ask about cultural capital directly, 92% of the first-gen or low-income respondents who thought their background had hindered their academic career selected at least one of the three mechanisms most closely related to cultural capital (limited knowledge of academic norms and soft skills, impostor syndrome, or outright bias).[37]

In the open-ended responses, cultural capital emerged as an overwhelming theme. First-gen respondents explained ways in which limited cultural capital manifested. One major theme was norms of speech, dress, and behavior: a biologist, for example, discussed the academic "dress code and speaking code that is difficult to learn unless you are raised with it", while an ecologist wrote that "My speech was colloquial. I did not know how to verbally talk academic-ese". A second major theme was cultural knowledge or experiences, particularly around international travel and "high culture", such as literature, classical music, and poetry. A first-gen chemist, for example, wrote that "I was not 'well traveled' and did not have much experience of other cultures,

[35] This reflects a response rate of 12%. We provide full survey details in Appendix E.

[36] As also found in qualitative studies on first-gen or working-class academics (Gardner and Holley, 2011; Haney, 2015; Warnock, 2016; Lee, 2017; Waterfield et al., 2019).

[37] While impostor syndrome may not always reflect limited cultural capital, the open-ended responses suggest that a lack of cultural fit was a key trigger for impostor syndrome; other qualitative analyses of working-class and first-gen academics suggest similarly (e.g. Warnock, 2016).

ideas, diversity, so felt 'stupid' and out-of-place".

Not knowing these norms mattered professionally. In part, this was because it made it more difficult to form professional relationships: a first-gen industrial engineer from a low-income background wrote, for example, that "I do not always know proper "social graces" to fit in with the class of people I work with, and this... reduces my ability to create useful connections", and a first-gen economist from a low-income background wrote that "my family background affected my ability to network in the profession... the 'small talk game' (talking about specific books/music/readings/world travels...) intimidated me". In part, it was because certain behaviors are considered "signals of academic potential": a first-gen political scientist, for example, explained that "Folks who grew up in households saturated in cultural capital...have a way of conducting themselves that gives them some advantage: how they speak ...how to conduct themselves in seminars and other academic settings; how to ask a question; how to drop names; how their body postures project confidence". And in part, it was because of outright bias: a mathematician, for example, found that "Being from a blue-collar background, my natural accent is generally regarded as indicative of being witless or slow", and a biologist who grew up on a farm in Iowa said that "many, many colleagues would make snide remarks about Iowa and farmers". Many respondents said they had changed their accent, dress, or behavior, or hid details about their background, to avoid being judged by colleagues.

Feeling excluded from "upper-middle class" or "elite East Coast" norms was not just common for first-gen or low-income academics, but also for those from middle-class and/or rural backgrounds. A biologist, for example, noted that despite growing up "solidly middle class" she did not "know the rules about how to interact in what feels like the upper-middle class setting of academia". Meanwhile, some academics from advantaged backgrounds were aware that their cultural capital made it easier for them to be seen as professional or polished: another biologist noted "I was well socialized in conducting myself in ways that are coded as 'professional' ", and a biomedical engineer said "The way that I speak makes a difference. I can 'sound smart' ".[38]

Survey evidence: social capital. Social capital emerged as the other overwhelming theme from our survey, in both open-ended and multiple choice questions. 67% of the first-gen or low-income respondents who thought their background had hindered their academic career selected either limited networks and/or weaker mentorship as an important reason. In open-ended responses, first-gen or low-income respondents discussed both having less pre-existing social capital, and finding it harder to build new professional relationships (perhaps because of limited cultural capital). A biologist from a low-income background, for example, wrote that he "failed to develop a network of supportive older colleagues to advance my career opportunities."

Respondents identified several ways in which social capital mattered for their careers. The most common was demystifying the "hidden curriculum": the knowledge that is required to navigate an academic career succesfully (Calarco, 2020). In multiple choice questions, 70% of the first-gen or low-income respondents who thought their background had hindered their career selected the hidden curriculum as an important mechanism. First-gen respondents discussed many aspects of an academic career which they were unaware of, including "how to create helpful professional networks, how to publish early, how to negotiate for contracts, how to play the game to obtain pay raises" (Sociology); "how tenure worked" (Mechanical Engineering); "how to approach other faculty in grad school to learn new techniques or to find better men-

[38] While lower-SEB respondents frequently identified their lack of cultural capital as a disadvantage, relatively few higher-SEB respondents identified their cultural capital as an advantage. Most of these were social scientists, particularly sociologists. This does not seem to reflect the fact that cultural capital is less important in the hard sciences: many lower-SEB hard scientists discussed their lack of cultural capital. Instead, it may reflect greater awareness among social scientists of the advantage their cultural capital has given them.

tors" (Biology); as well as whether and how to apply for awards, how the academic hierarchy worked, how academic publishing worked, and how universities functioned administratively. Even the need for this knowledge remained hidden: according to a first-gen mechanical engineer "The problem was that everyone assumed I knew all that and thus didn't think to ask me if I understood. I didn't know what I didn't know". One mathematician gave an evocative metaphor: "Pursuing an academic career as someone from a low-income background or as a first-generation college student is like trying to find your way through a dark room by feeling along the walls—while your peers navigate the same space with a bright light powered by a generator".

Respondents with a parent with a PhD emphasized the value of their academic social capital in helping them navigate the hidden curriculum.[39] Those without family in academia had to learn how to navigate the hidden curriculum from mentors. Here, socioeconomic background also mattered: higher-SEB respondents without family in academia were more able to form these valuable mentorship relationships. For example, a sociologist explained that "Because of the ways my background has affected how I move through the world, I find that I often interact with more senior people than my peers, giving me opportunities for learning the unwritten rules of how academia works, and advantages of powerful networks. These are not due to my background directly, but because of my background I have a leg up in building networks and navigating systems". On the other hand, lower-SEB academics had neither pre-existing relationships in academia, nor were able to as easily form new mentorship relationships, making the hidden curriculum particularly difficult to learn.

[39] Some examples of many, include: "how to manage my work, my time, how to write paper, how to apply to academic jobs", "how to select a postdoc, what to put in a faculty application", "about academic processes, grant writing, student advising, understanding academic environment, structure of universities, science organization and management, role of different professional societies", "how to seek out training and mentorship and to build alliances in university settings.", "what to expect during a PhD, how to allocate time, what are priorities", "how to choose a research advisor/area", "about hiring processes and decisions", and "advice on negotiating".

Discrimination. To what extent does the class gap in career progression in academia reflect discrimination? Following Bohren et al. (2023) in defining discrimination as "group-based disparities among equally qualified individuals", our findings suggest some combination of direct and systemic discrimination against lower-SEB academics. While socioeconomic background is rarely as directly observable as gender or race, direct discrimination still seems to occur: our survey respondents frequently discussed bias against class-coded norms of speech, dress, and behavior. And our evidence on networks suggests systemic discrimination, if lower-SEB academics are less able to form valuable professional networks than their higher-SEB peers of equivalent ability, and this reduces their ability to get good jobs later.

5 Class, Race, and Gender

In this section, we compare the class gap to gender and racial gaps, which have been the focus of most prior research on disparities in career progression. Strikingly, across most main outcomes the class gap is as large as, or larger than, the analogous gender and racial gaps.[40] Moreover, these gaps often look different, illustrating that class gaps at least in part have different drivers than race and gender gaps.

First, while the class gap emerges only on the intensive margin, this is not the case for race or gender (Table 2). The gender gap arises entirely at the extensive margin (the "leaky pipeline"): among the women who stay in tenured academia, there is no gender gap in the likelihood of ending up tenured at an R1 or in the rank of tenure institution. Racial and ethnic disparities in tenure outcomes arise both at the extensive and intensive margin, but in different ways depending on the group.[41]

[40] As discussed in section 3, all our estimated class gaps are conditional on gender and race/ethnicity fixed effects, and vice versa. We estimate outcomes for five racial/ethnic groups: White non-Hispanic, Asian non-Hispanic, Black non-Hispanic, Hispanic of all races, and Other non-Hispanic.

[41] Black and Hispanic PhDs are more likely to go into tenured academia as compared to White non-Hispanic PhDs, conditional on our fixed effects; but among those who do, they are at lower-ranked institutions. On the other hand, Asian PhDs are less likely to go into tenured academia than White

And while there is a large class gap in the rate of "getting tenure", conditional on tenure track institution, only Black academics see a similarly large gap; there is no statistically detectable gap for women or for other racial groups.[42]

Second, class gaps are persistently large across our full range of outcomes even conditioning on research record; this is not the case for most gender or racial gaps. When conditioning on research output, women are actually tenured at higher-ranked institutions than men (Table 4), and there is no gender gap in the rate of "getting tenure" (Table 5), NSF award receipt (Table 7), or citations (Table 8). This is also the case for Hispanic vs. White non-Hispanic PhDs. For Black PhDs, the picture is more mixed: when conditioning on research output, Black non-Hispanic PhDs are tenured at higher-ranked institutions than White non-Hispanic PhDs, and there is no racial gap in NSF award receipt – but, there is a large Black-White gap in "getting tenure" even conditional on research record, and a large gap in citations.

Third, class gaps in earnings and job satisfaction are smaller than analogous gender gaps (Table 2): the gender gap in earnings in tenure-track academia is 3x larger than the class gap, and the gender gap in job satisfaction is 2x larger. We see no racial earnings gaps in tenure-track academia, but we do see large job satisfaction gaps: Black academics are 6% less satisfied than their White counterparts.

Fourth, note that the combination of race and class likely matters. Our estimated race gaps control for parental education, but Black and Hispanic academics are also more likely to be first-gen college grads, meaning that they will be disproportionately affected by class gaps too. Moreover, intersectionality suggests academics who are both first-gen and racial minorities face an even greater disadvantage than either characteristic independently would predict.

non-Hispanic PhDs, but among those who do, there are no gaps in institution rank.

[42] No gender gap in "getting tenure" is consistent with Ginther and Kahn (2014); Ceci et al. (2023).

Overall 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 race.

6 Beyond Academia: Class gap in industry

Only about 30% of our SDR sample are tenured or tenure-track. Most of the rest work in industry (45%) with the remainder in non-tenure-track academia and government. While we have less information on the SDR recipients working in these sectors, we examine the available data to understand whether our results on the class gap in career progression generalize to other sectors of the US economy.

For each other sector – industry, government, and non-tenure-track academia – we repeat our baseline earnings and job satisfaction regressions, showing results in Table 9. We find class gaps in industry, with first-gen college grads earning 1.9 log points less and reporting 1% lower job satisfaction than people with a parent with a non-PhD graduate degree (conditional on our baseline fixed effects). The class gap in job satisfaction in industry is particularly pronounced in three categories which closely reflect career progression: opportunities for advancement, intellectual challenge, and level of responsibility (Appendix Figure A3). In contrast, we find no class gaps in earnings or job satisfaction in government or non-tenure-track academia.[43]

Next, we further examine the class gap in career progression in industry. We re-run our baseline earnings gap regressions interacting parental education and years since PhD (in 5-year buckets). We find large increases in the class earnings gap over the course of a career (Figure 5). This may reflect slower progression for lower-SEB

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

individuals to senior positions. Confirming this, we also find a growing class gap in the likelihood of being in a managerial role over the course of the career. Together, these show that a class gap in career progression also exists for PhDs in private industry – and thus, likely exists in many elite occupations outside academia.

7 Conclusion

Research and DEI efforts rarely focus on the role of class in career progression – unlike gender or race. This paper documents large, persistent disparities in career outcomes by socioeconomic background in one elite US occupation: tenure-track academia. Specifically, we show that when comparing two PhD recipients from the *same institution and same field*, those from less advantaged socioeconomic backgrounds on average end up tenured at less research-intensive and lower-ranked institutions, earn less, and are less satisfied with their jobs.

Disparities in research output explain no more than 20-40% of the class gap in tenure institution type, suggesting that lower SEB academics are "underplaced" relative to their research record. Further, we find no evidence that different preferences cause lower-SEB academics to trade off job prestige or quality for other factors, like location or pay. The residual class gap must therefore be explained by something else. Our evidence suggests limited social and cultural capital are important, reducing lower-SEB academics' ability to form valuable professional relationships, gain recognition, and navigate academia's "hidden curriculum".

Finally, we find class gaps in pay, job satisfaction, and progression to managerial responsibilities among PhDs in industry. Thus, class background likely matters for career progression in many elite occupations, not just academia.

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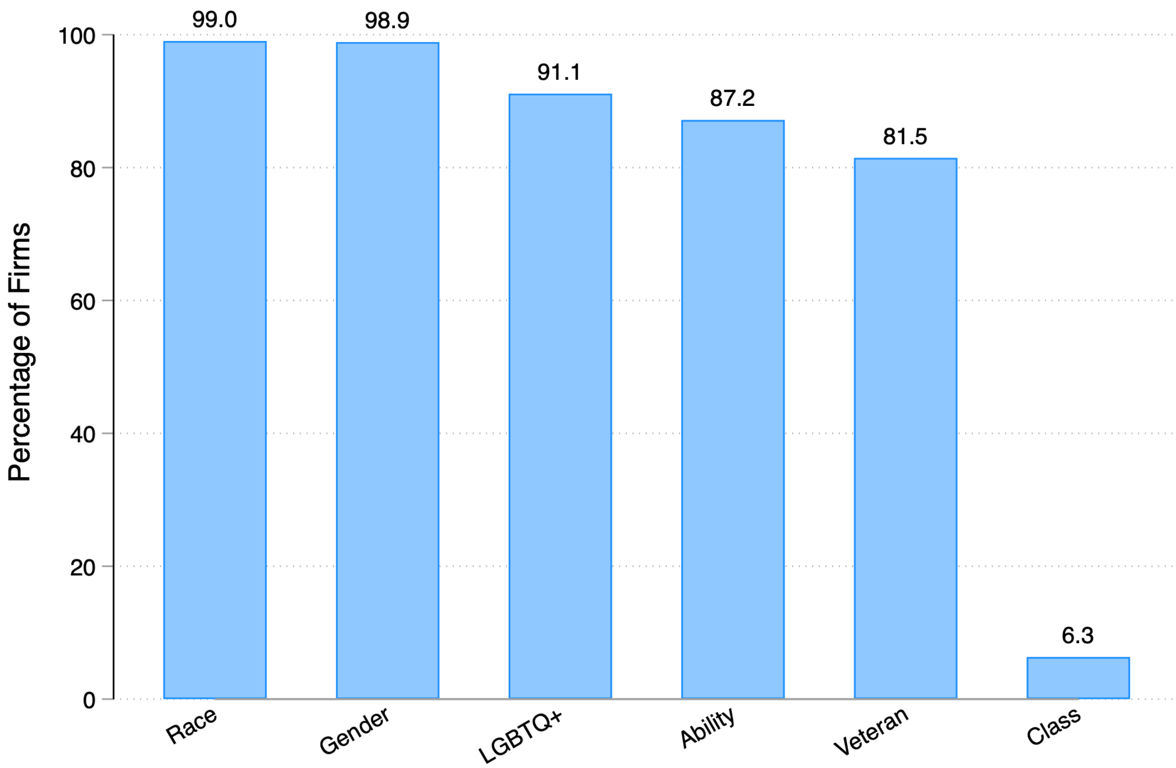
Tables and Figures

Figure 1: Large US companies' DEI reporting



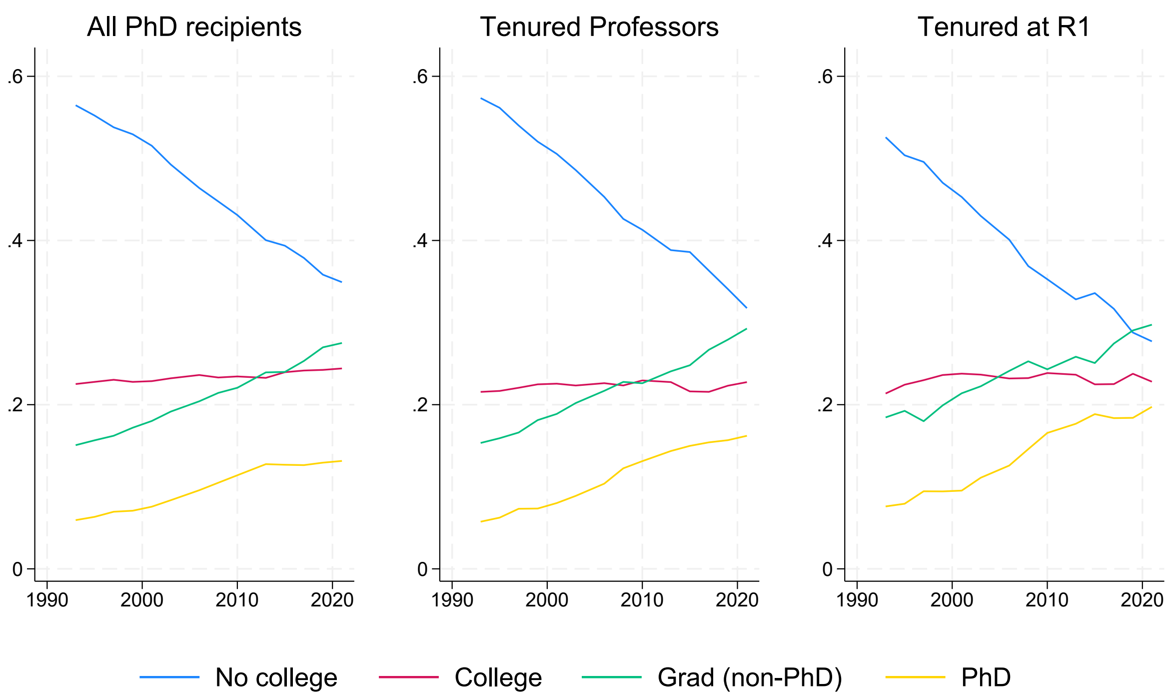
Source: Companies' websites and DEI reports, scraped September 2024. *Notes:* Figure shows the share of large US firms which have any goals, reporting on, or discussion of each of the listed groups in the context of diversity, equity, or inclusion. Sample was initially defined by all firms in any of: S&P 500, Forbes 100 largest private companies by revenue, Y Combinator top 50 companies by revenue, and TIME America top law firms with revenue >$1bn, which resulted in 708 total firms. This figure's sample comprises only the 631 US firms that publicly report on DEI. "Class" keywords include: First Generation, Socioeconomic, Parental Education, Low Income, Working class, Social Class, Pell Grant (and variations in spelling, e.g. "first-gen", "socio-economic").

Table 1: Tenure outcomes of US SEH PhD recipients, by parental education group

Parental education	Share tenured anywhere	Share tenured at R1	Share tenured at top 50
Less than college	29.4%	10.4%	5.4%
College	27.0%	11.2%	6.2%
Non-PhD Grad Degree	28.5%	12.3%	7.3%
PhD	30.3%	14.9%	10.0%

Source: SDR 2021, matched with SED 2021. *Notes:* "SEH" refers to Science, Engineering, or Health fields (including social sciences). Sample limited to those 10-39 years since PhD receipt and working in the US to match our main analysis sample in Table 2. Table shows shares among each parental education group who are, respectively, tenured, tenured at an R1 institution, and tenured at a top 50 ranked institution (per *USNWR* field-specific graduate program rank). Weighted by NSF-provided survey weights.

Figure 2: Parental education shares of PhD recipients and tenured professors in SEH fields



Source: SDR 1993-2021. *Notes:* Population: those with a US PhD in a Science, Engineering, or Health field (including social sciences). Sample limited to those 10-39 years since PhD receipt and working in the US to match our main analysis sample in Table 2. "PhD recipients" refers to the population in year y who have a PhD (not the population who graduate with a PhD in year y). Weighted by NSF-provided survey weights.

Table 2: Main Results: Tenure outcomes, conditional on PhD institution and field

Sample:	*All (Ext. margin)*	*Tenured only (Intensive margin)*			
Dep var:	Tenure Anywhere	Tenure at R1	Log Tenure Inst. Rank	Log Earnings	Job Satisfaction
Parental education (omitted category: non-PhD graduate degree)					
Less than college	-0.00166	-0.0424***	-0.108***	-0.0307***	-0.0294**
	(0.0055)	(0.011)	(0.033)	(0.010)	(0.012)
College	-0.00484	-0.0112	-0.0384	-0.0164	-0.0232*
	(0.0059)	(0.013)	(0.037)	(0.011)	(0.014)
PhD	0.0126*	0.0407***	0.155***	0.0187	0.0110
	(0.0072)	(0.014)	(0.044)	(0.013)	(0.015)
Gender (omitted category: Male)					
Female	-0.0253***	-0.00827	0.0221	-0.0915***	-0.0629***
	(0.0045)	(0.0093)	(0.030)	(0.0083)	(0.011)
Race/ethnicity (omitted category: White Non-Hispanic)					
Asian, Non-Hispanic	-0.0398***	0.000958	0.0860	0.00972	-0.0430
	(0.011)	(0.027)	(0.081)	(0.023)	(0.032)
Black, Non-Hispanic	0.0551***	-0.0237	-0.0988	-0.0181	-0.0859***
	(0.011)	(0.019)	(0.071)	(0.021)	(0.022)
Hispanic, All Races	0.0328***	-0.0463**	-0.137**	-0.00143	0.00606
	(0.010)	(0.020)	(0.058)	(0.017)	(0.022)
Other, Non-Hispanic	-0.0269*	-0.00513	-0.0290	-0.0390	-0.00933
	(0.015)	(0.033)	(0.11)	(0.033)	(0.039)
PhD Field FE	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.27	0.41	-3.90	11.7	-1.52
Observations	269,823	74,473	37,079	71,153	61,214
Unique Individuals	83,154	22,741	12,019	22,382	21,633
Absorbed DF	648	555	491	554	547

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variables are: (1) Binary variable taking value 1 if individual is tenured anywhere and 0 if in any other job; (2) Binary variable taking value 1 if individual is tenured at an R1 and 0 if tenured elsewhere; (3) Minus log rank of tenure institution (such that a negative coefficient means a lower rank); (4) Log earnings; (5) Minus job satisfaction (1-4 scale, such that a negative coefficient means less satisfied). Sample for all columns is restricted to people 10-39 years since PhD receipt, currently working in the US. Sample in columns 2-5 is restricted only to those tenured somewhere (and in column 3 to those tenured at ranked institutions, by definition of the dependent variable). Rank is unavailable for 1993 and 1995; Earnings is unavailable for 1995; Job Satisfaction is unavailable for 1993, 1995, 1999, and 2001. Regressions weighted by NSF-provided survey weights. 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 3: Where in the pipeline does the class gap appear?

Juncture	Tenure track job market			Getting tenure
	(1)	(2)	(3)	(4)
Dep var:	TT anywhere	TT at R1	Log TT Inst. Rank	Got Tenure
Parental education (omitted category: non-PhD graduate degree)				
Less than college	-0.00383	-0.0353***	-0.0667*	-0.0664***
	(0.0045)	(0.010)	(0.035)	(0.025)
College	-0.00503	-0.0300***	-0.0162	-0.0403
	(0.0047)	(0.011)	(0.040)	(0.025)
PhD	0.00637	0.0529***	0.116**	0.0207
	(0.0058)	(0.014)	(0.048)	(0.026)
Gender (omitted category: Male)				
Female	-0.0134***	-0.0240***	-0.0433	-0.0304
	(0.0037)	(0.0086)	(0.030)	(0.020)
Race/ethnicity (omitted category: White Non-Hispanic)				
Asian, Non-Hispanic	-0.0362***	0.0204	0.0418	0.0363
	(0.0077)	(0.023)	(0.085)	(0.049)
Black, Non-Hispanic	0.0303***	0.0795***	0.254***	-0.113***
	(0.0090)	(0.017)	(0.066)	(0.043)
Hispanic, All Races	0.0488***	-0.0261*	-0.00523	-0.0472
	(0.0080)	(0.016)	(0.061)	(0.042)
Other, Non-Hispanic	-0.0172*	-0.00371	-0.0303	0.0362
	(0.010)	(0.024)	(0.087)	(0.056)
PhD Field FE	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	
TT Institution FE				Yes
Time FE	Yes	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes	Yes
Dep Var Mean	0.22	0.35	-3.84	0.72
Observations	177,843	39,433	16,077	3,563
Unique Individuals	82,411	20,224	8,824	3,563
Absorbed DF	677	582	489	355

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows regressions for the tenure track job market juncture (columns 1-3) and getting tenure juncture (column 4). *Tenure track job market juncture:* Dep vars are: (1) Binary variable taking value 1 if individual is on the tenure track (or tenured) anywhere and 0 if in any other job; (2) Binary variable taking value 1 if individual is on the tenure track (or tenured) at an R1 and 0 if on the tenure track (or tenured) elsewhere; (3) Minus log rank of tenure-track institution (such that a negative coefficient means a lower rank). Sample for columns 1-3 is restricted to people 1-9 years since PhD receipt, currently working in the US. Sample in column 2 is restricted to those on the tenure track, and in column 3 to those on the tenure track at ranked institutions (by definition of the dependent variable). *Getting tenure juncture:* Dep var 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:* Rank is not available for 1993 or 1995. Regressions weighted by NSF-provided survey weights. 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 4: Tenure institution rank, with research controls

Dep var:	Log Tenure Inst. Rank		
	No research controls	Research controls	
	(1)	(2)	(3)
Parental education (omitted category: non-PhD graduate degree)			
Less than college	-0.157***	-0.0973**	-0.0932**
	(0.050)	(0.046)	(0.046)
College	-0.0581	-0.0434	-0.0544
	(0.052)	(0.048)	(0.048)
PhD	0.0638	0.0416	0.0291
	(0.057)	(0.051)	(0.050)
Gender (omitted category: Male)			
Female	0.0299	0.0955***	0.0886**
	(0.040)	(0.037)	(0.037)
Race/ethnicity (omitted category: White Non-Hispanic)			
Asian, Non-Hispanic	-0.0401	0.0108	-0.0203
	(0.12)	(0.11)	(0.11)
Black, Non-Hispanic	-0.0804	0.197**	0.177*
	(0.10)	(0.092)	(0.095)
Hispanic, All Races	-0.0250	0.140**	0.166**
	(0.079)	(0.071)	(0.071)
Other, Non-Hispanic	-0.0136	0.117	0.105
	(0.12)	(0.12)	(0.12)
PhD Field FE	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes
Baseline Research Controls		Yes	Yes
Add'l Research Controls			Yes
Dep Var Mean	-3.82	-3.82	-3.82
Observations	5,927	5,884	5,884
R-Squared	0.27	0.38	0.40
Adjusted R-Squared	0.22	0.34	0.35
Absorbed DF	382	381	381

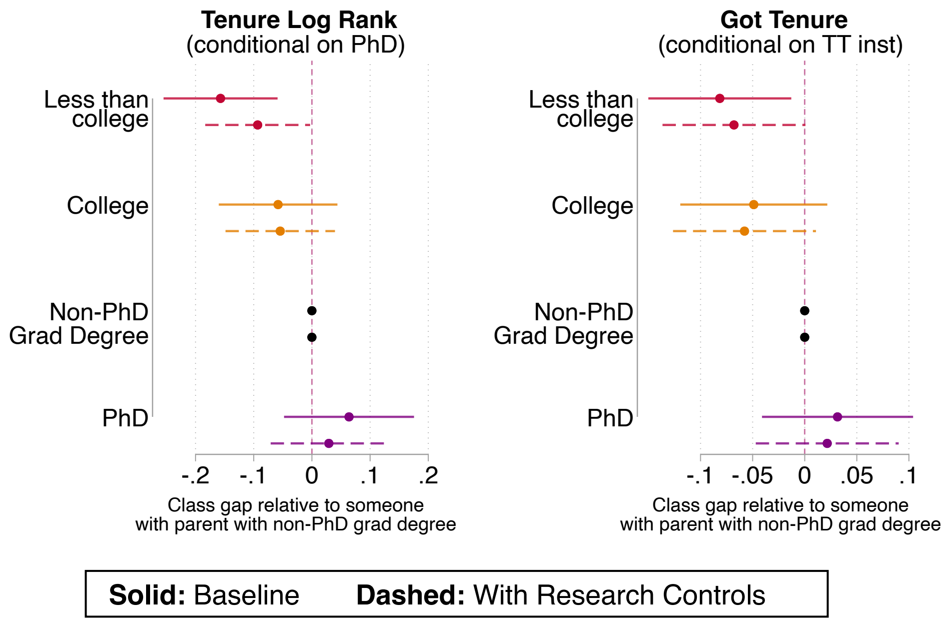
Source: SDR 2015-2021, matched with Web of Science and NSF Awards. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table replicates our baseline tenure institution rank regression in Table 2, column 3, but with controls for research output. Because the WoS/NSF link is only available for the 2015 SDR, sample is 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). Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group). 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 weights.

Table 5: Got tenure (conditional on tenure-track institution), with research controls

Dep var:	Got tenure		
	No research controls	Research controls	
	(1)	(2)	(3)
Parental education (omitted category: non-PhD graduate degree)			
Less than college	-0.0815**	-0.0642*	-0.0679*
	(0.035)	(0.036)	(0.035)
College	-0.0489	-0.0505	-0.0578*
	(0.036)	(0.036)	(0.035)
PhD	0.0315	0.0398	0.0216
	(0.037)	(0.036)	(0.035)
Gender (omitted category: Male)			
Female	0.000699	0.0314	0.0423
	(0.027)	(0.027)	(0.027)
Race/ethnicity (omitted category: White Non-Hispanic)			
Asian, Non-Hispanic	-0.00836	0.0203	-0.00949
	(0.068)	(0.074)	(0.069)
Black, Non-Hispanic	-0.0827	-0.0489	-0.0750
	(0.068)	(0.066)	(0.067)
Hispanic, All Races	-0.0460	-0.0167	-0.000264
	(0.063)	(0.062)	(0.063)
Other, Non-Hispanic	0.0791	0.103	0.115
	(0.073)	(0.071)	(0.077)
PhD Field Control	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes
Current Institution FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes
Baseline Research Controls		Yes	Yes
Add'l Research Controls			Yes
Dep Var Mean	0.75	0.76	0.76
Observations	1,842	1,830	1,830
R-Squared	0.24	0.28	0.33
Adjusted R-Squared	0.12	0.15	0.20
Absorbed DF	243	243	243

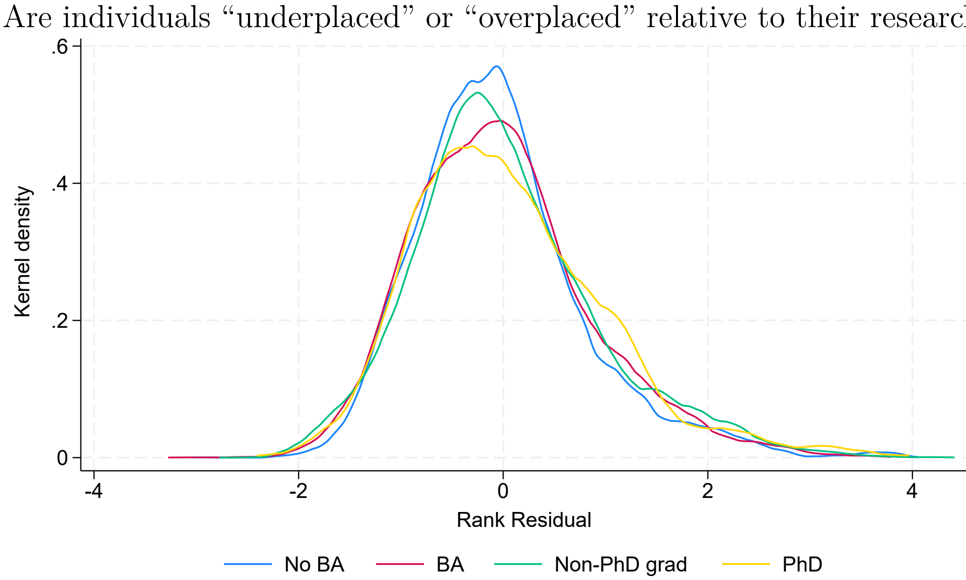
Source: SDR 2015-2021, matched with Web of Science and NSF Awards. *Notes:* Standard errors in parentheses (clustered at current institution by field by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table replicates our baseline "got tenure" regression in Table 3, column 4, but with 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. Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group). PhD field controls are a control for the mean tenure rate in the field. 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.

Figure 3: Tenure outcomes with research controls



Source: SDR 2015-2021, matched with Web of Science and NSF Awards. *Notes:* Figure shows point estimates and 95% confidence intervals. Tenure Rank subplot and Got Tenure subplot show coefficients from Table 4 and 5 respectively. Coefficients are relative to the omitted category: people with a parent with a non-PhD graduate degree. Tenure rank regressions include our baseline fixed effects: gender, race/ethnicity, birth country, time, PhD institution, PhD field. "Got tenure" regressions 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 Tables 4 and 5.

Figure 4: 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 4, Panel A, column 3, but excluding parental education). Regressions weighted by NSF-provided survey weight. Positive residuals reflect "overplacement" relative to a prediction based on research output and educational history.

Table 6: Coauthor characteristics

Panel A: Coauthor homophily						
Dep var:	First gen		Female		URM	
	(1)	(2)	(3)	(4)	(5)	(6)
Parental education (omitted category: at least a college degree)						
First-gen college grad	0.0100***	0.0173***				
	(0.0038)	(0.0058)				
Gender (omitted category: male)						
Female			0.0335***	0.0367***		
			(0.0032)	(0.0054)		
Race/ethnicity (omitted category: all other)						
Under-Represented Minority (Black or Hispanic)					0.0335***	0.0266***
					(0.0031)	(0.0056)
Observations	23,177	8,808	23,177	8,808	23,177	8,808
Current Institution FE		Yes		Yes		Yes

Panel B: Coauthor research output						
Dep var:	Cumulative Publications		Cumulative Citations (CNCI)		Average Journal Impact Factor	
	(1)	(2)	(3)	(4)	(5)	(6)
Parental education (omitted category: non-PhD graduate degree)						
Less than college	-0.00271*	-0.00287	-0.00538***	-0.00512**	-0.00642***	-0.00172
	(0.0016)	(0.0025)	(0.0017)	(0.0026)	(0.0018)	(0.0028)
College	0.000183	-0.00214	-0.00260	-0.00496*	-0.00290	-0.000745
	(0.0017)	(0.0027)	(0.0018)	(0.0028)	(0.0019)	(0.0031)
PhD	0.000519	-0.00000274	0.000968	0.000792	0.00231	0.00453
	(0.0020)	(0.0030)	(0.0021)	(0.0031)	(0.0023)	(0.0035)
Observations	23,151	8,649	23,151	8,649	23,151	8,649
Current Institution FE		Yes		Yes		Yes

Source: Web of Science matched with 2015 SDR. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions are at author level, weighted by NSF survey weight. 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 an Under-Represented Racial or Ethnic Minority ("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). We define "URM" following the NSF as anyone who lists their race as Black and/or American Indian and Alaska Native, and/or their ethnicity as Hispanic. 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 7: NSF Award Receipt, conditional on research output

Dep var:	Receipt of NSF award 2016-2020 (Binary: 1 if yes)			
	No research controls	Research controls		
	(1)	(2)	(3)	(4)
Parental education (omitted category: non-PhD graduate degree)				
Less than college	-0.0441*	-0.0474**	-0.0464**	-0.0382*
	(0.023)	(0.023)	(0.022)	(0.022)
College	-0.0292	-0.0330	-0.0270	-0.0344
	(0.025)	(0.025)	(0.024)	(0.023)
PhD	-0.00879	-0.00181	0.00705	0.0126
	(0.027)	(0.027)	(0.027)	(0.025)
Gender (omitted category: male)				
Female	0.0149	0.0278	0.0237	0.00976
	(0.019)	(0.019)	(0.019)	(0.018)
Race/ethnicity (omitted category: neither Black nor Hispanic)				
Asian, Non-Hispanic	0.0577	0.0593	0.0615	0.0746
	(0.066)	(0.065)	(0.064)	(0.062)
Black, Non-Hispanic	-0.0183	0.0309	0.0378	0.0304
	(0.043)	(0.042)	(0.041)	(0.040)
Hispanic, All Races	-0.00180	-0.00177	0.00693	0.0351
	(0.045)	(0.044)	(0.044)	(0.042)
Other, Non-Hispanic	0.0145	0.00546	0.00220	-0.0755
	(0.060)	(0.061)	(0.061)	(0.053)
Current Institution X Field FE	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Birth Country 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	0.21	0.21	0.21	0.21
Observations	4,840	4,761	4,761	4,761
R-Squared	0.66	0.68	0.69	0.74
Adjusted R-Squared	0.38	0.40	0.41	0.51
Absorbed DF	305	304	304	304

Source: 2015 SDR matched with Web of Science and NSF awards. *Notes:* Standard errors in parentheses (clustered at current institution by PhD field by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 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. Time FE are fixed effects for years since PhD (5-year group) and PhD year (5-year group). Research controls defined as in Table 5, with the exception that "Add'l Research Controls" does *not* include prior NSF awards in column 3; column 4 then adds fixed effects for prior NSF award receipt. Sample size is small because of institution-by-field fixed effects; when including instead institution and field fixed effects separately, sample is greater than 10,000 individuals and coefficients remain similar.

Table 8: Citations per publication

	(1)	(2)	(3)	(4)	(5)
Dep var	Any Cites	Log(Cites(5y))	Log(1+Cites(5y))	Log(CNCI)	Log(1+CNCI)
Parental education (omitted category: non-PhD graduate degree)					
Less than college	-0.00387**	-0.0270*	-0.0303**	-0.0355**	-0.0415**
	(0.0019)	(0.016)	(0.015)	(0.017)	(0.019)
College	-0.00509**	-0.0103	-0.0177	-0.0308*	-0.0408**
	(0.0022)	(0.015)	(0.014)	(0.016)	(0.019)
PhD	-0.00106	0.000431	-0.00134	-0.0176	-0.0192
	(0.0021)	(0.017)	(0.016)	(0.019)	(0.021)
Gender (omitted category: Male)					
Female	0.0000665	-0.0199	-0.0200	-0.0140	-0.0200
	(0.0016)	(0.013)	(0.013)	(0.015)	(0.017)
Race/ethnicity (omitted category: White Non-Hispanic)					
Asian, Non-Hispanic	0.00130	-0.00309	0.00901	-0.00771	0.00844
	(0.0046)	(0.036)	(0.035)	(0.042)	(0.048)
Black, Non-Hispanic	-0.0136**	-0.0851**	-0.105***	-0.0859*	-0.152***
	(0.0062)	(0.038)	(0.035)	(0.044)	(0.049)
Hispanic, All Races	0.00650	-0.0286	-0.0132	-0.0210	-0.0160
	(0.0043)	(0.028)	(0.028)	(0.032)	(0.036)
Other, Non-Hispanic	0.0000146	-0.0417	-0.0408	-0.0219	-0.0176
	(0.0046)	(0.037)	(0.033)	(0.042)	(0.043)
PhD Field FE	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes	Yes	Yes
Current Institution FE	Yes	Yes	Yes	Yes	Yes
Pub. Year FE	Yes	Yes	Yes	Yes	Yes
Pub. Type FE	Yes	Yes	Yes	Yes	Yes
Pub. Field FE	Yes	Yes	Yes	Yes	Yes
Num. Authors FE	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.95	2.50	2.51	-0.20	4.28
Observations	261,431	248,499	261,431	252,745	261,431

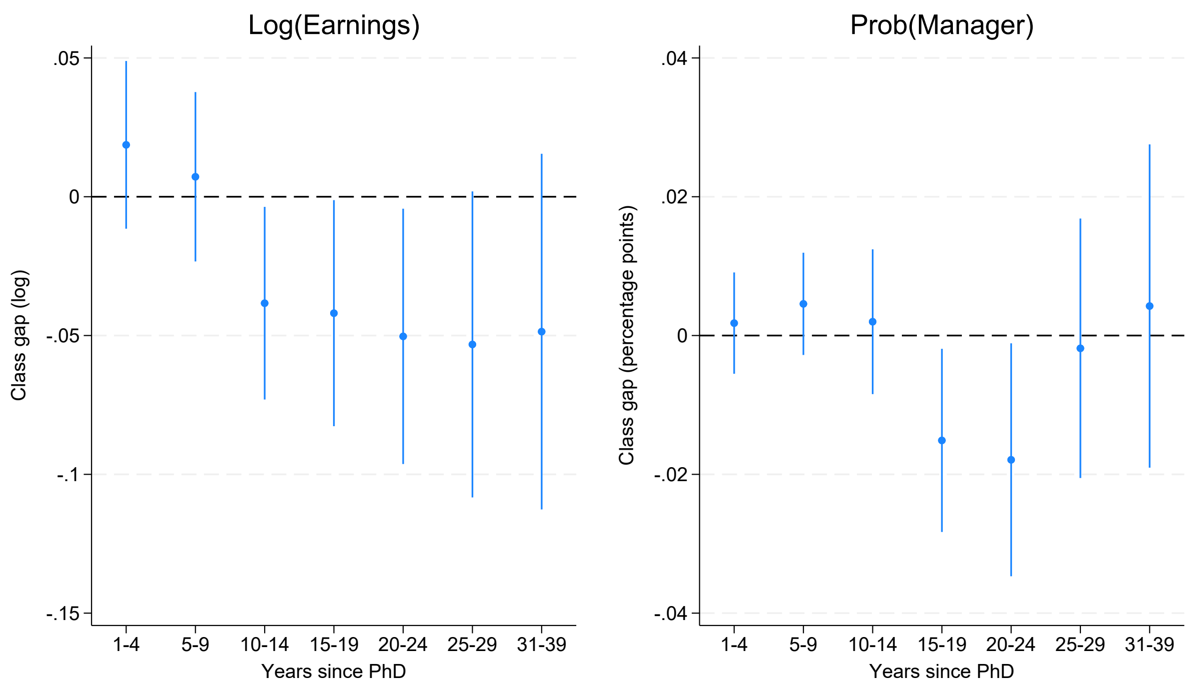
Source: Web of Science bibliometric data, matched with 2015 SDR. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions are run at the publication-author level. The dependent variables are: (1) Any Cites = a binary variable 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 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). Time FE are fixed effects for years since PhD (5-year group), PhD year (5-year group) and 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), indicators for whether the publication was in a high impact or a low impact journal (or neither), and fixed effects for the decile of the journal's impact factor within the PhD field group. 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+). Weighted by NSF provided survey weights.

Table 9: Earnings and Job Satisfaction Across Sectors

	Tenure Track Academia		Industry		Government		Non-TT Academia	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep var:	Log Earnings	Job Satis.	Log Earnings	Job Satis.	Log Earnings	Job Satis.	Log Earnings	Job Satis.
Parental education (omitted category: non-PhD graduate degree)								
Less than college	-0.0254***	-0.0414***	-0.0194**	-0.0145*	-0.00694	0.0118	-0.0162	-0.00718
	(0.0075)	(0.0098)	(0.0094)	(0.0078)	(0.011)	(0.016)	(0.011)	(0.012)
College	-0.0159*	-0.0302***	-0.0143	-0.00655	-0.00607	0.00821	-0.0396***	0.00783
	(0.0083)	(0.011)	(0.0097)	(0.0080)	(0.011)	(0.017)	(0.012)	(0.012)
PhD	0.0185*	0.00342	-0.000730	0.00384	0.0160	0.0294	-0.0246*	0.0185
	(0.0097)	(0.012)	(0.012)	(0.0099)	(0.014)	(0.021)	(0.015)	(0.015)
Gender (omitted category: Male)								
Female	-0.0912***	-0.0522***	-0.273***	-0.00696	-0.0884***	-0.0149	-0.207***	-0.0148
	(0.0060)	(0.0084)	(0.0086)	(0.0066)	(0.0096)	(0.014)	(0.0090)	(0.0095)
Race/ethnicity (omitted category: White Non-Hispanic)								
Asian, Non-Hispanic	0.000252	-0.0663***	-0.00129	-0.0554***	-0.0175	-0.0148	0.00249	-0.0433**
	(0.017)	(0.024)	(0.018)	(0.015)	(0.023)	(0.031)	(0.021)	(0.022)
Black, Non-Hispanic	0.00197	-0.0943***	-0.0312	-0.0694***	-0.00959	-0.0994***	0.0117	-0.127***
	(0.014)	(0.017)	(0.021)	(0.018)	(0.023)	(0.030)	(0.023)	(0.021)
Hispanic, All Races	0.000191	-0.00969	-0.0475**	-0.0136	-0.0156	0.0123	-0.0484***	-0.0672***
	(0.011)	(0.017)	(0.019)	(0.016)	(0.017)	(0.028)	(0.018)	(0.020)
Other, Non-Hispanic	-0.00364	-0.0175	-0.0279	-0.0275	-0.0406*	-0.137***	-0.0106	-0.0563**
	(0.021)	(0.026)	(0.023)	(0.022)	(0.023)	(0.042)	(0.025)	(0.027)
PhD Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	11.6	-1.55	11.7	-1.62	11.6	-1.60	11.1	-1.72
Observations	115,835	97,317	177,912	150,950	43,432	36,898	83,658	71,717

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This regression replicates Table 2, columns 4 and 5, with dependent variables log earnings and job satisfaction respectively, but with each column restricting sample to sector in title (Cols 1-2: Tenure track academia (incl. tenured). Cols 3-4: Industry. Cols 5-6: Government. Cols 7-8: Non-tenure track academia.) Job satisfaction is answered on a 1 to 4 scale with 1 the best; it is coded negatively such that a negative regression coefficient indicates being less satisfied. Earnings is unavailable for 1993; Job satisfaction is unavailable for 1993, 1995, 1999, and 2001. Time FE are fixed effects for survey year, years since PhD, and PhD year (5-year group). Sample restricted to people less than 40 years since PhD receipt, currently working in the US; regressions weighted by NSF-provided survey weight.

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 – log earnings and the probability of being a manager – 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 PhD program by year level; sample limited to people working in Industry in the US, less than 40 years since PhD receipt. Regressions weighted by NSF-provided survey weight. "Prob(Manager)" is a dummy taking value 1 if occupation is a top-level managerial, executive, or administrative occupation (CEO, COO, CFO, president, district or general manager, etc), representing about 7% of those working in industry.

Online Appendix

A Appendix: Additional Tables and Figures

Table A1: Degree types of non-PhD graduate degree holders, 1993

Degree type	Share of non-PhD graduate degree holders
Business, law, or medical	38%
Psychology, education, or social work	32%
STEM masters	16%
Non-STEM masters or professional degree	16%

Source: National Survey of College Graduates 1993. *Notes:* Our SDR data does not tell us what kind of non-PhD graduate degree a person's parent received. In this table, we show the breakdown of non-PhD graduate degree holders in the US population as per the 1993 National Survey of College Graduates. This may roughly reflect the degree breakdown for the parents of people in our sample. We show a similar breakdown for the parents of academics in our survey in Appendix Table E3.

Table A2: Parental education and household income for households with children, 1992

Highest education level of adult in household	Average household income
Less than college	\$29,300
College only	\$52,600
Non-PhD graduate degree	\$66,200
PhD	\$76,600

Source: Current Population Survey 1992. *Notes:* Our SDR data does not contain information on childhood family income. In this table, we show the average household income of households with children in the 1992 Current Population Survey, separately by the highest education level of any adult in the household. This table illustrates that parental education levels translate on average to large income differences.

Table A3: Sector of Employment, 10-39 years post PhD

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	Any Academia	Tenured	Tenure-Track	Non-TT Academia	Industry	Government
Parental education (omitted category: non-PhD graduate degree)						
Less than college	-0.000548	-0.00166	-0.00227	0.00338	-0.00356	0.00411
	(0.0060)	(0.0055)	(0.0014)	(0.0039)	(0.0059)	(0.0036)
College	-0.00527	-0.00484	-0.000454	0.0000178	0.00268	0.00259
	(0.0065)	(0.0059)	(0.0016)	(0.0042)	(0.0065)	(0.0039)
PhD	0.0187**	0.0126*	0.000966	0.00515	-0.0242***	0.00542
	(0.0078)	(0.0072)	(0.0020)	(0.0052)	(0.0076)	(0.0047)
Gender (omitted category: Male)						
Female	0.0325***	-0.0253***	-0.00173	0.0595***	-0.0283***	-0.00420
	(0.0050)	(0.0045)	(0.0013)	(0.0036)	(0.0049)	(0.0031)
Race/ethnicity (omitted category: White Non-Hispanic)						
Asian, Non-Hispanic	-0.0392***	-0.0398***	0.00440	-0.00378	0.0317***	0.00748
	(0.012)	(0.011)	(0.0036)	(0.0076)	(0.012)	(0.0070)
Black, Non-Hispanic	0.0954***	0.0551***	0.0188***	0.0215**	-0.125***	0.0291***
	(0.012)	(0.011)	(0.0035)	(0.0091)	(0.012)	(0.0085)
Hispanic, All Races	0.0355***	0.0328***	0.00979***	-0.00709	-0.0368***	0.00130
	(0.011)	(0.010)	(0.0036)	(0.0077)	(0.011)	(0.0069)
Other, Non-Hispanic	-0.0369**	-0.0269*	0.00302	-0.0130	0.0237	0.0132
	(0.017)	(0.015)	(0.0046)	(0.010)	(0.017)	(0.011)
PhD Field FE	Yes	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.44	0.27	0.031	0.14	0.46	0.099
Observations	269,823	269,823	269,823	269,823	269,823	269,823

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This runs the analogous regressions to Table 2, column 1, but with additional "extensive margin" sector of employment dependent variables: 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. Sample is restricted to individuals who received their PhD between 10-39 years prior to the survey year, are currently working, and are located in the US. Dependent variable takes value 1 if person is employed in the sector in title and zero otherwise (Col 1: Any academia, Col 2: Tenured academia, Col 3: Tenure-track academia, Col 4: Non-tenure-track academia, Col 5: Industry, Col 6: Government). Outcomes in columns 2-6 are mutually exclusive and collectively exhaustive. Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group). Regressions are weighted using NSF-provided survey weights.

Table A4: Outcomes after tenure decision (Sample: those on tenure track at ranked institutions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep var:	"Got Tenure"	Tenure Elsewhere	Tenure Track	Industry	Government	Non-TT Ed.	Not Working
Parental education (omitted category: non-PhD graduate degree)							
Less than college	-0.0664***	-0.00284	0.00938	0.0199	0.00534	0.0271	0.00757
	(0.025)	(0.012)	(0.011)	(0.013)	(0.0074)	(0.017)	(0.0091)
College	-0.0403	0.00153	0.00459	0.0173	0.00623	0.0156	-0.00498
	(0.025)	(0.012)	(0.012)	(0.013)	(0.0062)	(0.019)	(0.0079)
PhD	0.0207	-0.00880	-0.0180*	0.0155	-0.00831*	-0.0119	0.0107
	(0.026)	(0.013)	(0.011)	(0.013)	(0.0050)	(0.018)	(0.0095)
Gender (omitted category: Male)							
Female	-0.0304	0.0115	-0.00201	0.00387	-0.00232	0.00669	0.0126*
	(0.020)	(0.0094)	(0.0091)	(0.010)	(0.0044)	(0.014)	(0.0069)
Race/ethnicity (omitted category: White Non-Hispanic)							
Asian, Non-Hispanic	0.0363	0.0113	-0.00757	0.00331	0.0219*	-0.0445*	-0.0206
	(0.049)	(0.020)	(0.027)	(0.023)	(0.013)	(0.026)	(0.013)
Black, Non-Hispanic	-0.113***	-0.00349	0.0407	-0.0163	0.00424	0.0816**	0.00590
	(0.043)	(0.020)	(0.025)	(0.020)	(0.0090)	(0.035)	(0.019)
Hispanic, All Races	-0.0472	0.0312	0.0188	-0.0117	0.0261*	-0.0151	-0.00204
	(0.042)	(0.022)	(0.023)	(0.018)	(0.013)	(0.029)	(0.013)
Other, Non-Hispanic	0.0362	0.0162	0.00443	0.0151	-0.00785	-0.0802***	0.0161
	(0.056)	(0.028)	(0.022)	(0.035)	(0.0062)	(0.022)	(0.018)
PhD Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TT Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.72	0.046	0.043	0.054	0.014	0.10	0.023
Observations	3,563	3,563	3,563	3,563	3,563	3,563	3,563

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 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 1-7 are mutually exclusive and collectively exhaustive. Col 1 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 3 column 4 in the main paper. 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. Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group). Analogous outcomes from those on the tenure-track at non-ranked institutions shown in Appendix Table A5.

Table A5: Outcomes after tenure decision
(Sample: those on tenure track at non-ranked institutions)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	Tenure	Tenure Track	Industry	Government	Non-TT Ed.	Not Working
Parental education (omitted category: non-PhD graduate degree)						
Less than college	-0.0420	-0.000841	-0.00698	-0.00320	0.0300	0.0230*
	(0.030)	(0.018)	(0.015)	(0.0083)	(0.019)	(0.013)
College	-0.0264	-0.0126	0.0104	-0.00308	0.0167	0.0149
	(0.032)	(0.020)	(0.017)	(0.0093)	(0.022)	(0.0098)
PhD	-0.0687*	0.000871	0.0311	0.0197	0.00234	0.0147
	(0.040)	(0.017)	(0.021)	(0.018)	(0.025)	(0.013)
Gender (omitted category: Male)						
Female	-0.0418	-0.00113	-0.00650	-0.0104	0.0443**	0.0155
	(0.027)	(0.013)	(0.012)	(0.010)	(0.018)	(0.010)
Race/ethnicity (omitted category: White Non-Hispanic)						
Asian, Non-Hispanic	-0.0570	0.0125	0.0141	0.00357	0.0268	0.0000604
	(0.064)	(0.036)	(0.042)	(0.027)	(0.064)	(0.011)
Black, Non-Hispanic	-0.129*	0.0637	0.0243	0.0465*	-0.0197	0.0138
	(0.069)	(0.047)	(0.044)	(0.024)	(0.042)	(0.028)
Hispanic, All Races	-0.0528	0.00647	0.00695	0.0173	-0.00256	0.0246
	(0.051)	(0.027)	(0.023)	(0.014)	(0.033)	(0.023)
Other, Non-Hispanic	0.101	0.0318	-0.0224	-0.0440	-0.0653	-0.00115
	(0.069)	(0.033)	(0.034)	(0.031)	(0.047)	(0.016)
PhD Field FE	Yes	Yes	Yes	Yes	Yes	Yes
TT Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.82	0.049	0.035	0.015	0.064	0.016
Observations	1,612	1,612	1,612	1,612	1,612	1,612

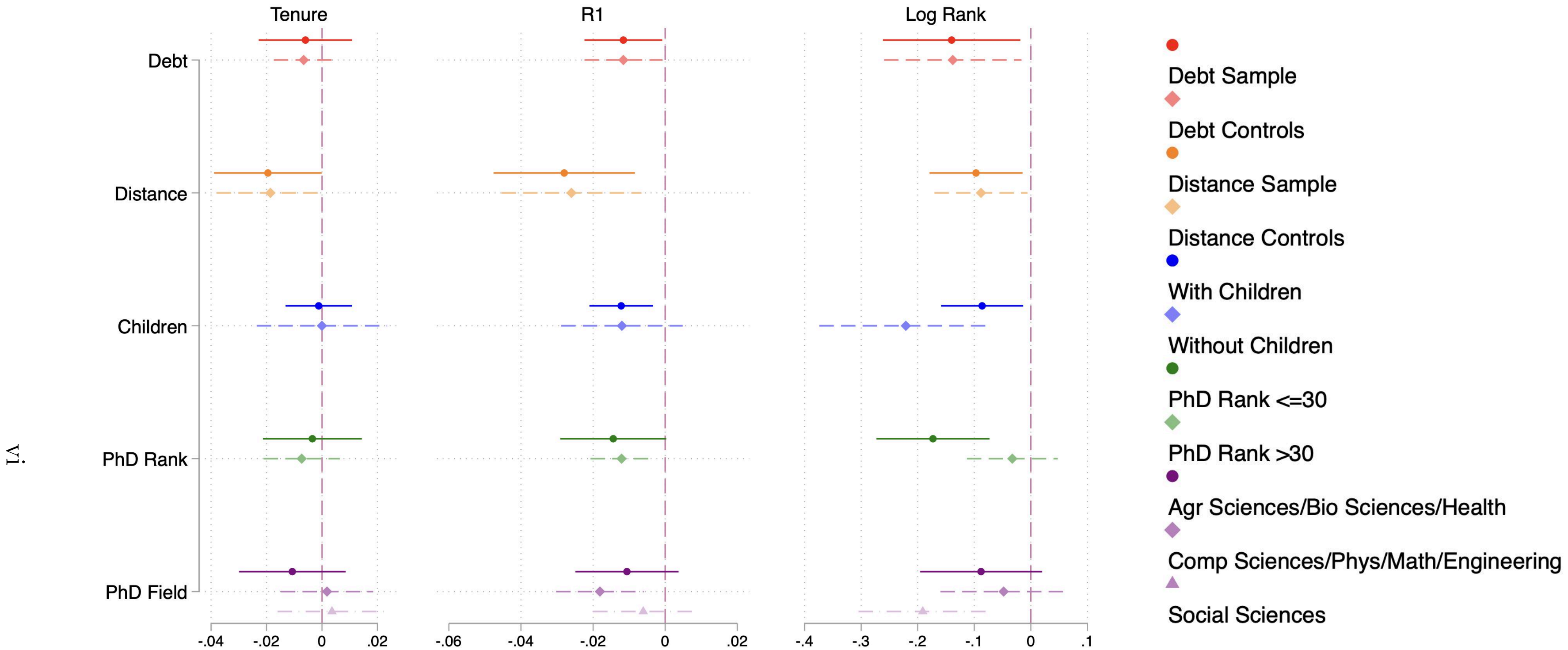
Source: SDR 1993-2021. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dep vars are binary variables taking value 1 if the individual is working in that job type / industry in the next survey observation after the inferred tenure decision year. Outcomes in the columns are mutually exclusive and collectively exhaustive. Col 1 refers to having tenure anywhere, col 2 refers to tenure track without tenure. 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. Fixed effects are included for the tenure track institution. Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group).

Table A6: Research output of tenured professors, conditional on PhD institution and field

	(1) Publications	(2) First Auth. Pubs	(3) Last Auth. Pubs	(4) Average CNCI	(5) Avg Impact Factor	(6) NSF Awards	(7) Top 10% CNCI	(8) High Impact Journal Share	(9) Avg. Auth. Per Pub
Parental education (omitted category: non-PhD graduate degree)									
Less than college	-0.0417***	-0.0254***	-0.0431***	-0.0337***	-0.0213**	-0.0829***	-0.0155***	-0.0118**	-0.0185**
	(0.0087)	(0.0091)	(0.0084)	(0.0090)	(0.0086)	(0.032)	(0.0048)	(0.0057)	(0.0090)
College	-0.0200**	-0.0159*	-0.0234***	-0.0131	0.0120	0.0119	-0.00680	0.00700	-0.00280
	(0.0094)	(0.0096)	(0.0089)	(0.0096)	(0.0090)	(0.035)	(0.0054)	(0.0063)	(0.0096)
PhD	0.0110	-0.000318	0.0139	0.0135	0.0259**	0.0351	-0.00115	0.0143**	0.00783
	(0.011)	(0.011)	(0.010)	(0.011)	(0.010)	(0.040)	(0.0061)	(0.0070)	(0.011)
Gender (omitted category: Male)									
Female	-0.0552***	-0.0489***	-0.0512***	-0.0263***	-0.0185***	-0.0413*	-0.0158***	-0.0133***	-0.00148
	(0.0069)	(0.0070)	(0.0067)	(0.0074)	(0.0069)	(0.024)	(0.0041)	(0.0050)	(0.0072)
Race/ethnicity (omitted category: White Non-Hispanic)									
Asian, Non-Hispanic	-0.0450**	-0.0613***	-0.0335	-0.0592***	-0.0514**	-0.166**	-0.0206*	-0.0221	0.000758
	(0.023)	(0.023)	(0.022)	(0.023)	(0.021)	(0.077)	(0.012)	(0.016)	(0.023)
Black, Non-Hispanic	-0.141***	-0.166***	-0.120***	-0.106***	-0.0790***	-0.0628	-0.0390***	-0.0323***	0.00547
	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)	(0.077)	(0.0096)	(0.0091)	(0.017)
Hispanic, All Races	-0.0576***	-0.0510***	-0.0604***	-0.0669***	-0.0539***	0.0204	-0.0321***	-0.0277**	-0.000488
	(0.015)	(0.018)	(0.015)	(0.017)	(0.015)	(0.055)	(0.0099)	(0.011)	(0.016)
Other, Non-Hispanic	-0.0322	-0.0355	-0.0117	-0.0522**	-0.0196	0.103	-0.0236*	-0.00816	0.000521
	(0.020)	(0.023)	(0.021)	(0.024)	(0.021)	(0.080)	(0.013)	(0.016)	(0.024)
PhD Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,267	12,267	12,267	12,267	12,049	12,267	12,267	12,267	12,267

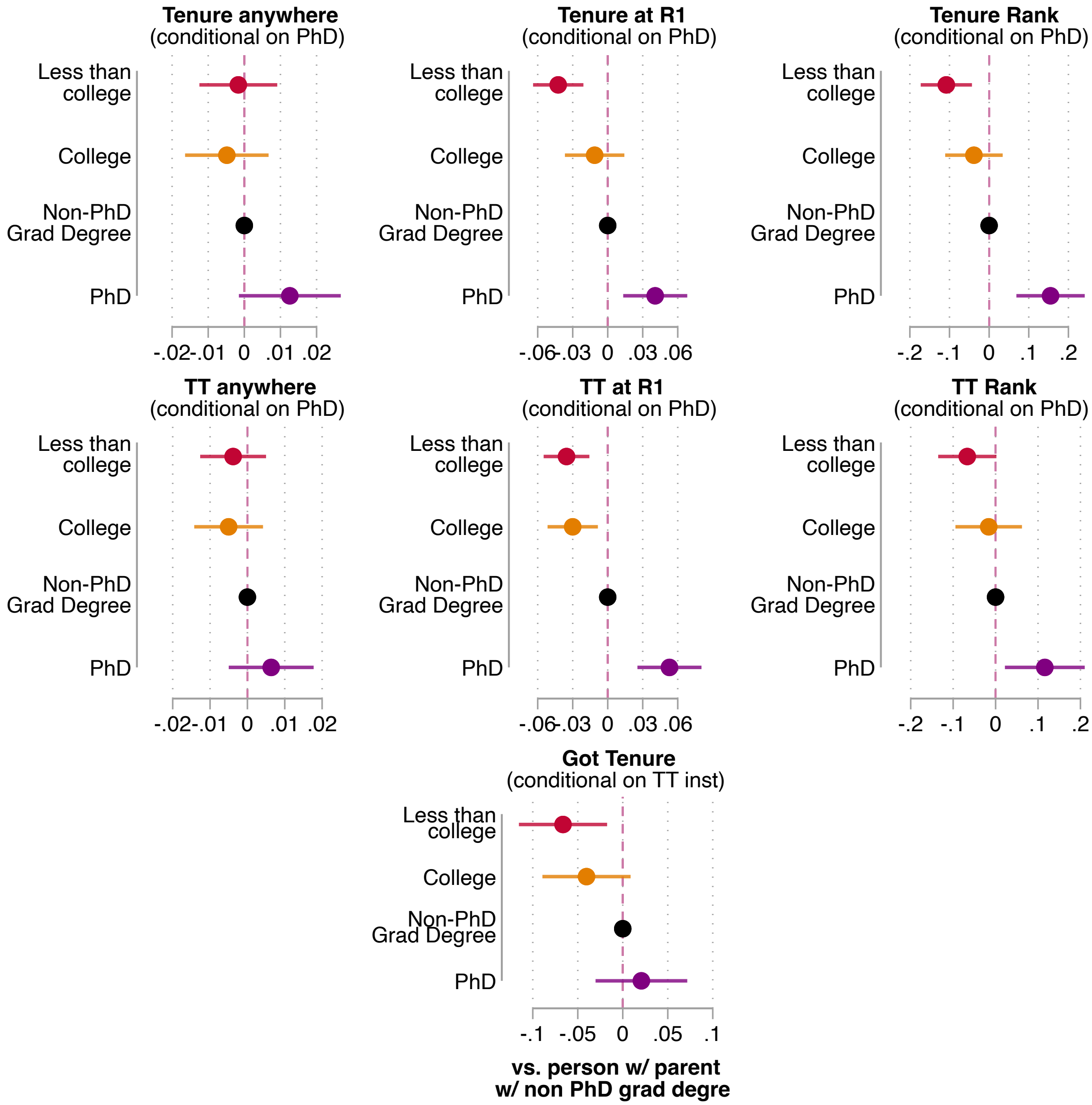
Source: SDR 2015-2021, matched with Web of Science and NSF Awards. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample restricted to 2015 SDR respondents who were tenured at a US institution in 2015, or in the first SDR year we observe them with tenure after 2015. Individuals are matched to their publication record as of 2015 (for 2015 SDR observations) or 2017 (for later SDR waves). Dep vars for cols 1-5 are respectively: total publications, first author publications, last author publications, avg. CNCI (category normalized citation count) across all publications, average journal impact factor across all publications (all using the field-specific percentile rank "fspr"). Col 6 is a categorical variable for number of NSF awards: 0, 1, 2 or 3, and greater than 4. Cols 7 & 8 are the share of publications that were in the top 10% CNCI, or in a high impact journal, respectively. Col 9 is the fspr of the average authors per publication. Regressions weighted by NSF-provided survey weight. Time FE are fixed effects for survey year, years since PhD (5-year group), and PhD year (5-year group).

Figure A1: 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



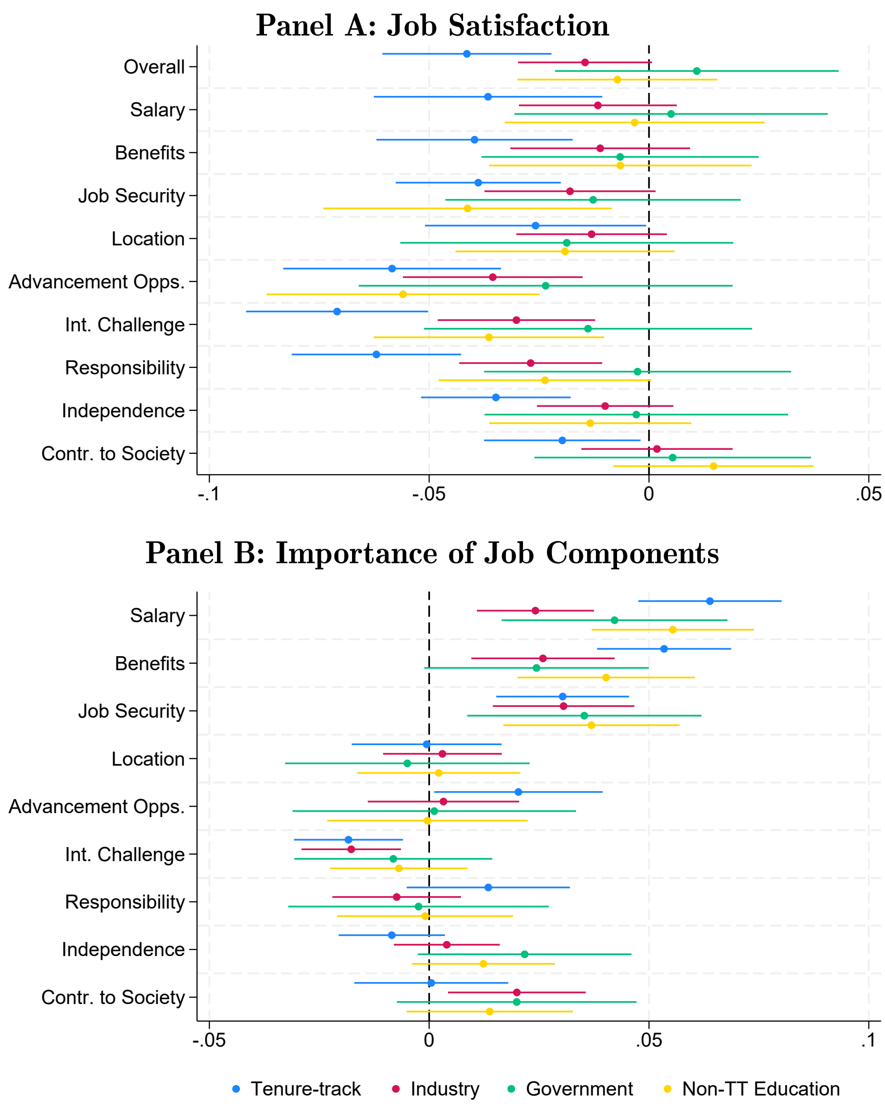
Source: SDR 1993-2021. *Notes:* Each sub-plot is a coefficient plot showing coefficients and 95% confidence intervals from regressions of the dependent variable (sub-plot title) on parental education and our baseline fixed effects, with regressions weighted by survey weights and standard errors clustered at PhD program by year level. Only the coefficient on first-generation college graduates is shown, compared to the omitted category of people with no parent with a graduate degree. Dependent variables are our three baseline (Tenure anywhere, Tenure at R1, and Log Tenure Institution 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 A2: Main regression results – Visualization



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 2, "TT" plots in the second row show coefficients from Table 3 Columns 1-3, and "Got Tenure" plot in the third row shows coefficients from Table 3 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 (using minus log rank so that a negative coefficient represents a worse (lower-ranked) outcome). Coefficients are relative to the omitted category: people with a parent with a non-PhD graduate degree which are represented by the circular points on the vertical dashed line at zero. Estimates for tenure and TT regressions are conditional on our baseline fixed effects: gender, race/ethnicity, birth country, 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.

Figure A3: Class gap in job satisfaction and importance of job components, by sector (Difference between first-generation college graduates and people with a parent with a non-PhD graduate degree, conditional on our baseline fixed effects)



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 PhD program-by-year level; sample limited to people working in the US, less than 40 years since PhD receipt. Panel A shows Job Satisfaction: Dep vars, listed on y-axis, are continuous variables taking values 1 to 4, with 1 very satisfied, 2 somewhat satisfied, 3 somewhat dissatisfied, and 4 very dissatisfied (negatively coded so that a negative coefficient means less satisfied). Respondents are asked each question separately: the "overall" job satisfaction number reflects a specific question asked about respondents' "overall" job satisfaction, and not an index of the sub-components. Panel B shows Perceived Importance of Job Components: Dep vars, listed on y-axis, are continuous variables taking values 1 to 4, with 1 very important, 2 somewhat important, 3 somewhat unimportant, and 4 not important at all (negatively coded so that a negative coefficient means less important). (Advancement Opps. = Opportunities for advancement; Int. challenge = intellectual challenge; Contr. to society = contribution to society). Regressions weighted by NSF provided survey weights. Variables unavailable for 1993, 1995, 1999, and 2001.

B Appendix: Robustness

We ran several robustness checks on our baseline regression results shown in Table 2. We outline these checks briefly in the main text and in more detail here.

Alternate regression specifications. For all five of our baseline dependent variables, we show in Figure B1 that our coefficients are robust to alternate regression specifications: (i) including fixed effects for PhD field by institution by decade (directly comparing individuals who graduated from the same PhD program in the same decade) (also in Table B1); (ii) 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); (iii) including fixed effects for narrow PhD field instead of our baseline PhD field definition; (iv) not using survey weights, and (iv) clustering standard errors at PhD program or PhD program by decade level rather than at the individual level.

Separate regressions by survey year. We also ran our baseline regressions separately for each SDR survey year. The class gap remains relatively consistent across time (Figure B2).

Alternate parental education splits. In Table B2 we show our baseline results separating only by first-gen vs non-first-gen college grads, or by those with or without a parent with any graduate degree, rather than estimating separately for each of the four parental education groups. We find consistently that there is no class gap on the extensive margin, but large class gaps on all four intensive margin measures.

Alternate subsamples. In Table B3 we show our baseline results, limiting our sample only to White non-Hispanic individuals who were born in the US. We find no class gap on the extensive margin but large class gaps on the intensive margin, further emphasizing that our findings are not driven by correlated differences by race/ethnicity or birth country. In Table B4 we show our baseline results, limiting our sample only to US-born individuals in Panel A and foreign-born individuals in Panel B. We find similar class gaps for both groups.

Alternate measures for tenure institution type. There may be a concern that our finding of a class gap in tenure institution type depends on the choice of measure for the dependent variable. In our main regression, these measures are: whether the tenure institution is an R1, and the log rank (field-specific graduate program rank). In Table B5 we use alternative dependent variables measuring tenure institution research-intensiveness or rank. Specifically, these alternative measures are: whether an institution is an R1 or R2, or whether it is research-intensive at all; whether an institution is ranked in the top 50; using the rank itself (the number) as the dependent variable rather than the log of rank; using rank groups rather than a continuous rank measure; and using a different measure of the institution rank – the rank of the tenure institution in *USNWR*'s undergraduate institution rankings, rather than its graduate program rankings. Across all these measures we find large, statistically significant class gaps, suggesting that our main results are not artefacts of specific definitions of tenure institution type.

As an alternate approach, we create dependent variables representing a mutually exclusive, collectively exhaustive set of rank categories for the rank of the tenure institution: top 10, 11-25, 26-50, 51-100, 100+, and non-ranked. Specifically for each of these, we construct a binary dependent variable taking the value 1 if an individual has tenure at one of these institutions and 0 if not (limiting our sample to the "intensive margin", i.e. those who have tenure anywhere). We show results in Table B6. This shows that the underrepresentation of first-gen college grads at high-ranked schools is particularly pronounced at the top 10 and top 25 schools, and overrepresentation of first-gen college grads is particularly pronounced in non-ranked schools.

Regressions with research controls. In Table B7, we repeat our regressions for tenure institution rank and "got tenure" with research controls (Tables 4 and 5), with alternate specifications of the research controls. Specifically, we use the raw number rather than field-specific percentile rank for our controls for publications, citations, journal impact factor, etc. Results remain very similar.

Figure B1: Tenure outcomes - Robustness - Alternate specifications

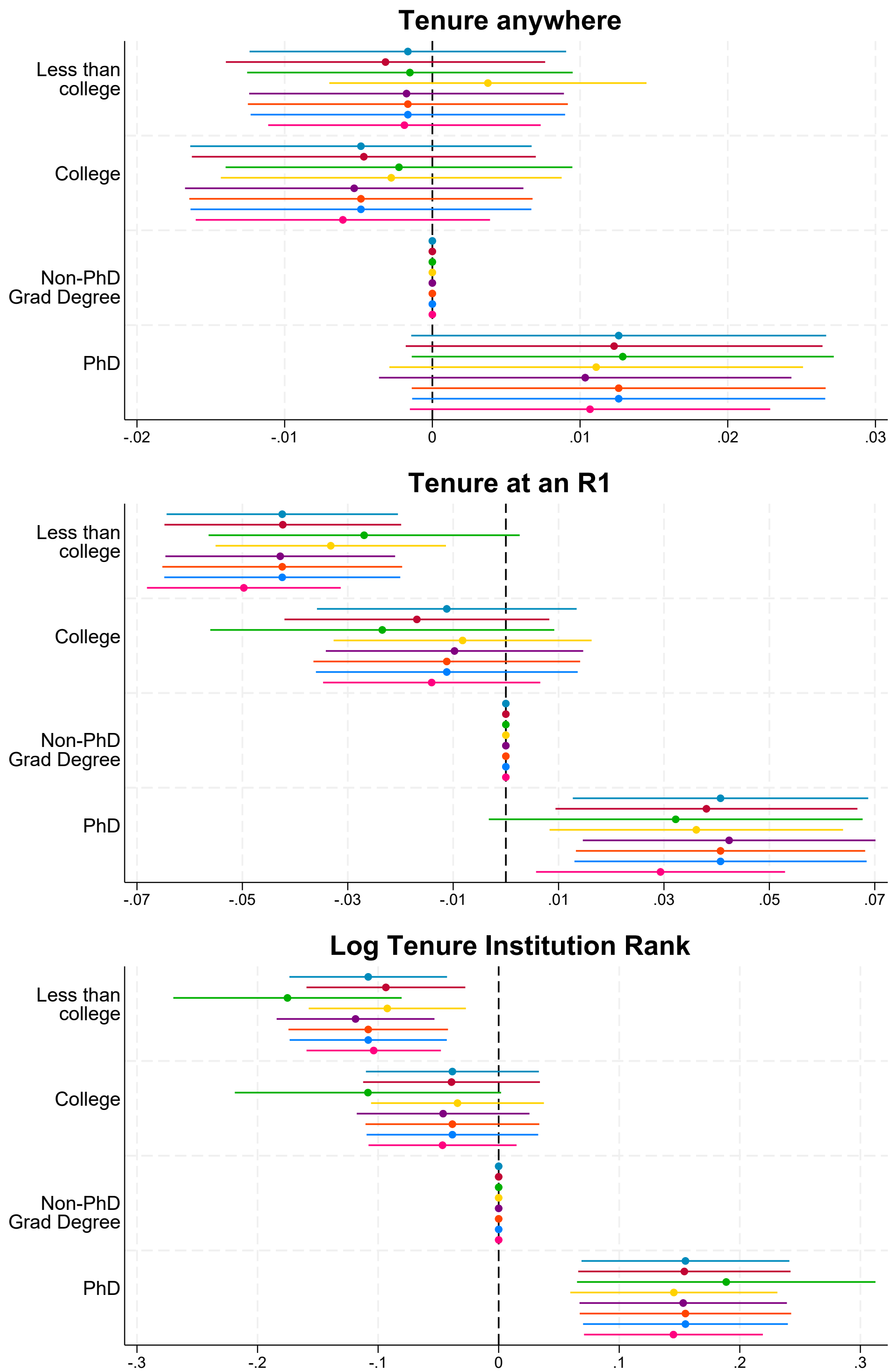
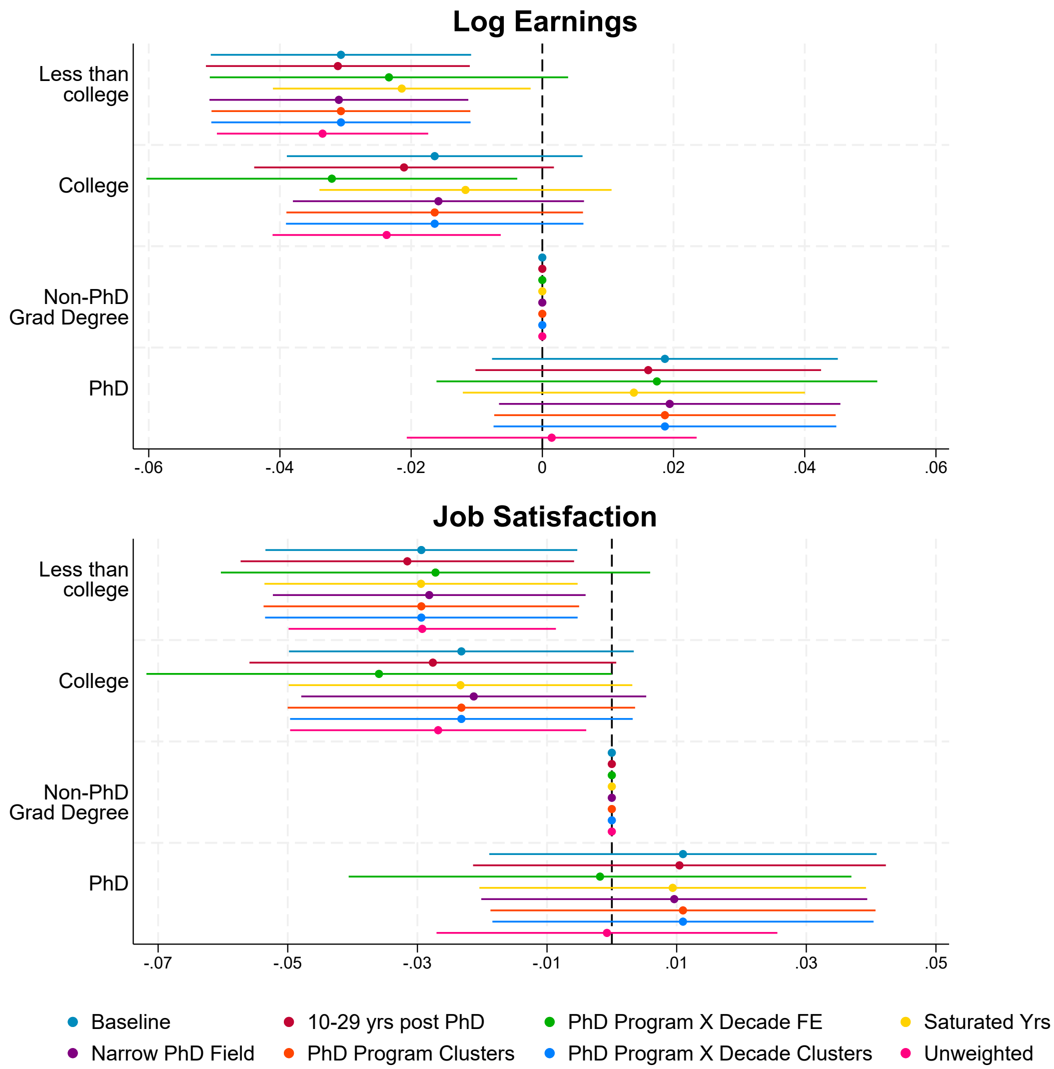


Figure B1 (continued)



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 2. Dependent variables and sample restrictions are as in Table 2. Each color represents a different regression specification, which modifies our baseline specification in some way. All controls and fixed effects are as in Table 2 except the modifications, listed in order: Blue: Baseline. Maroon: 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: Standard errors clustered at PhD program level. Light blue: Standard errors clustered at PhD program by decade level. Pink: Unweighted regressions.

Figure B2: Tenure outcomes - Robustness - Year-by-year regressions

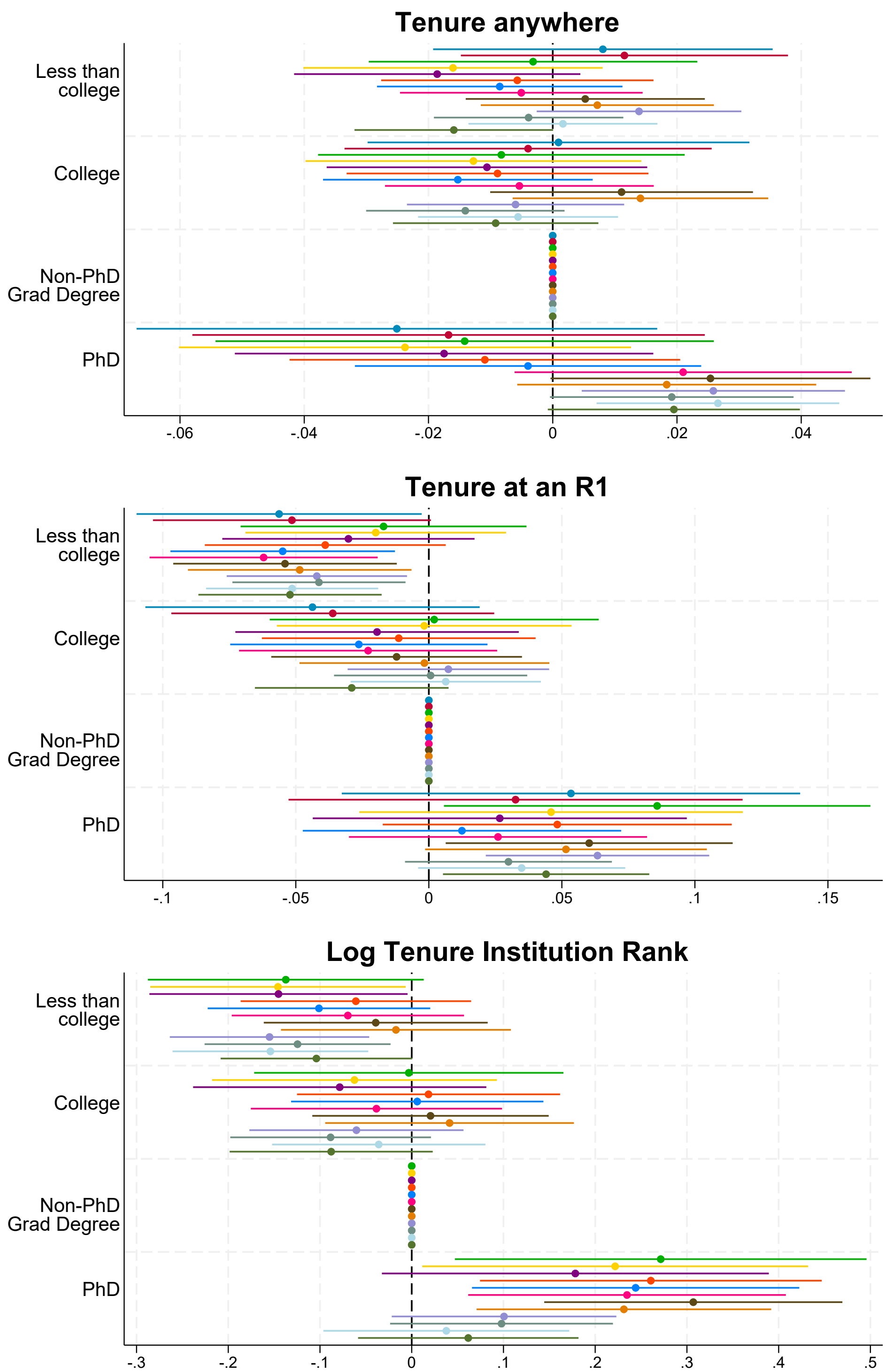
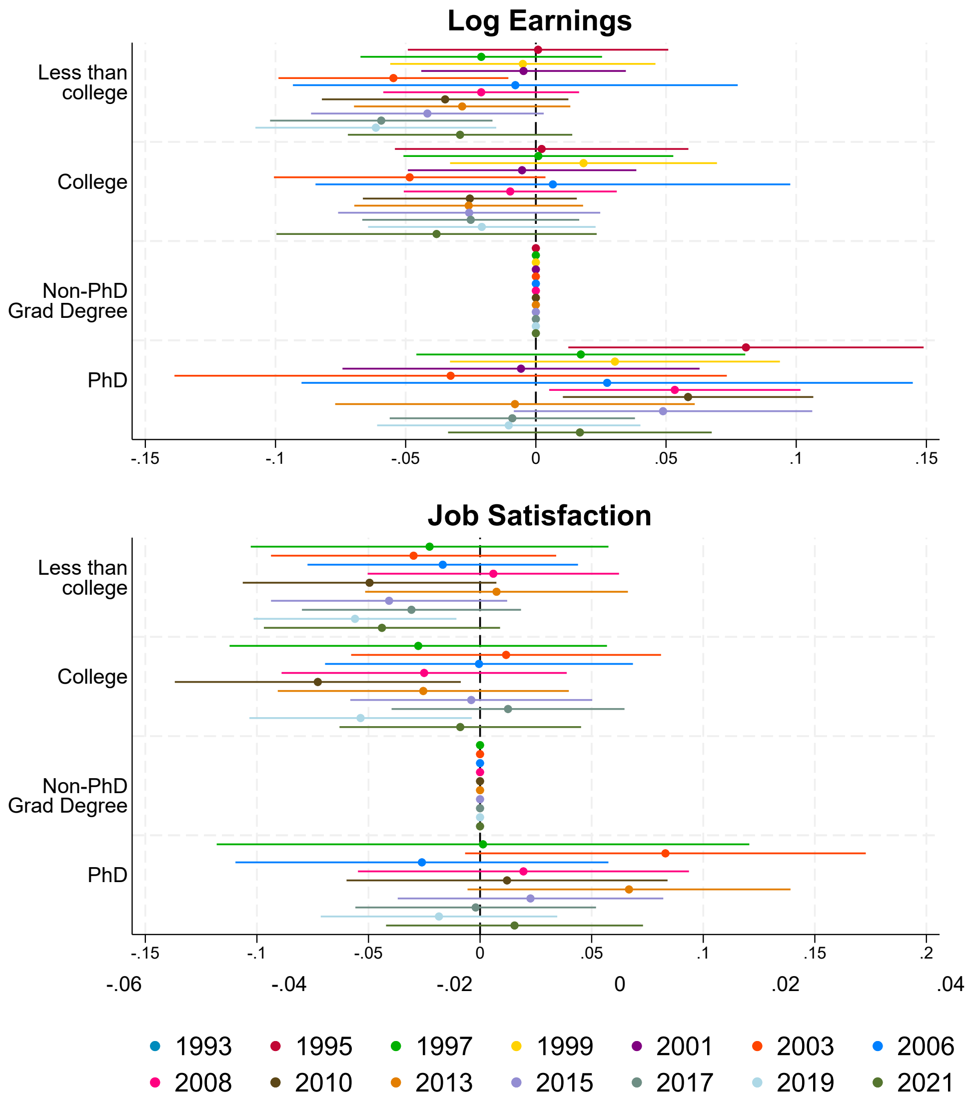


Figure B2 (continued)



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 2. Each regression limits the sample to one survey year as indicated in the legend. Dependent variables and sample restrictions are as in Table 2. lnEARN = log earnings. JOBSATIS_num = job satisfaction on a numeric scale. Each color represents a regression run on one specific survey year, as denoted in the legend.

Table B1: Main Outcomes, conditional on PhD program by decade FEs

Sample:	*All (Ext. margin)*	*Tenured only (Intensive margin)*			
Dep var:	Tenure Anywhere	Tenure at R1	Log Tenure Inst. Rank	Log Earnings	Job Satisfaction
Parental education (omitted category: non-PhD graduate degree)					
Less than college	-0.00152	-0.0269*	-0.175***	-0.0234*	-0.0272
	(0.0056)	(0.015)	(0.048)	(0.014)	(0.017)
College	-0.00226	-0.0235	-0.108*	-0.0321**	-0.0359**
	(0.0060)	(0.017)	(0.056)	(0.014)	(0.018)
PhD	0.0129*	0.0322*	0.189***	0.0175	-0.00182
	(0.0073)	(0.018)	(0.063)	(0.017)	(0.020)
Observations	266,501	72,463	35,574	69,100	58,830

Source: SDR 1993-2021. *Notes:* This table replicates Table 2, but with PhD program by decade fixed effects (PhD institution by field by decade) instead of separate PhD institution and PhD field fixed effects. Weighting, clustering, and other fixed effects as in Table 2.

Table B2: Main Outcomes: Alternate Parental Education Categories

	(1)	(2)	(3)	(4)	(5)
Dep var:	Tenure Anywhere	Tenure at R1	Log Tenure Inst. Rank	Log Earnings	Job Satisfaction
Panel A: First-gen vs. Non-First gen					
Parental education (omitted category: Parent with college degree or more)					
Less than college	-0.00173	-0.0453***	-0.122***	-0.0273***	-0.0220**
	(0.0044)	(0.0089)	(0.026)	(0.0083)	(0.010)
Panel B: No graduate degree vs. Any graduate degree					
Parental education (omitted category: Parent with any graduate degree)					
Parents with no graduate degree	-0.00696	-0.0438***	-0.133***	-0.0313***	-0.0307***
	(0.0045)	(0.0092)	(0.028)	(0.0083)	(0.0100)
Observations	269,823	74,473	37,079	71,153	61,214

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table replicates Table 2 using an alternate categorization of parental education. Weighting, clustering, and fixed effects as in Table 2.

Table B3: Main Outcomes: Sample limited to White non-Hispanic US-born

	(1)	(2)	(3)	(4)	(5)
Dep var:	Tenure Anywhere	Tenure at R1	Log Tenure Inst. Rank	Log Earnings	Job Satisfaction
Parental education (omitted category: non-PhD graduate degree)					
Less than college	-0.00560	-0.0403***	-0.0913**	-0.0192	-0.0324**
	(0.0068)	(0.013)	(0.040)	(0.012)	(0.015)
College	-0.00616	-0.00551	-0.0648	-0.000978	-0.0146
	(0.0074)	(0.015)	(0.044)	(0.013)	(0.016)
PhD	0.0148*	0.0440***	0.153***	0.0183	0.00818
	(0.0089)	(0.017)	(0.054)	(0.016)	(0.018)
Observations	168,850	48,015	23,326	45,693	38,940

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table replicates Table 2 but limits the sample only to White Non-Hispanic US-born individuals. Weighting, clustering, and fixed effects as in Table 2.

Table B4: Main Outcomes: Separate estimation for US-born and foreign-born

	(1)	(2)	(3)	(4)	(5)
Dep var:	Tenure Anywhere	Tenure at R1	Log Tenure Inst. Rank	Log Earnings	Job Satisfaction
Panel A: US-born only					
Parental education (omitted category: non-PhD graduate degree)					
Less than college	-0.00591	-0.0445***	-0.103***	-0.0203*	-0.0358**
	(0.0064)	(0.013)	(0.038)	(0.012)	(0.014)
College	-0.00616	-0.00903	-0.0636	-0.000650	-0.0153
	(0.0071)	(0.014)	(0.042)	(0.012)	(0.015)
PhD	0.0125	0.0394**	0.154***	0.0216	0.00677
	(0.0083)	(0.016)	(0.050)	(0.015)	(0.017)
Observations	200,666	57,787	27,834	54,931	46,511
Panel B: foreign-born only					
Parental education (omitted category: non-PhD graduate degree)					
Less than college	0.0113	-0.0493**	-0.106	-0.0844***	0.00612
	(0.010)	(0.023)	(0.072)	(0.021)	(0.026)
College	0.00144	-0.0430*	0.0239	-0.0790***	-0.0378
	(0.010)	(0.025)	(0.077)	(0.025)	(0.030)
PhD	0.0159	0.0433	0.109	0.00596	0.0464
	(0.014)	(0.029)	(0.090)	(0.029)	(0.033)
Observations	69,147	16,665	9,231	16,200	14,684

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table replicates Table 2 but limits the sample only to US-born individuals in Panel A and foreign-born individuals in Panel B. Weighting, clustering, and fixed effects as in Table 2.

Table B5: Tenure Institution Type - Robustness Check with Different DVs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep var:	Research	R1 or R2	Top 50	Top 50 (Any)	Rank Group	Rank	BA Rank	Log BA Rank
Parental education (omitted category: non-PhD graduate degree)								
Less than college	-0.0228**	-0.0336***	-0.0350***	-0.0341***	-5.298***	-5.368***	-10.93***	-0.137***
	(0.011)	(0.011)	(0.010)	(0.010)	(1.83)	(1.83)	(2.43)	(0.030)
College	-0.00658	-0.00459	-0.0104	-0.00969	-1.398	-1.614	-3.736	-0.0517
	(0.012)	(0.013)	(0.011)	(0.012)	(1.93)	(1.93)	(2.62)	(0.034)
PhD	0.0254*	0.0352**	0.0470***	0.0532***	5.421***	5.359***	7.279**	0.128***
	(0.014)	(0.014)	(0.014)	(0.014)	(2.02)	(2.02)	(2.88)	(0.042)
Dep Var Mean	0.58	0.54	0.24	0.26	-72.7	-76.0	-111.6	-4.32
Observations	74,473	74,473	68,074	68,074	37,079	37,079	40,051	40,051

Source: SDR 1993-2021. *Notes:* Standard errors in parentheses (clustered at PhD program by year level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dep vars for cols 1-5 are binaries taking value 1 if individual is tenured at a research institution (col 1), at an R1 or R2 (col 2), a top-50 ranked institution by field-specific graduate program rank (col 3) a top-50 ranked institution by either graduate or undergraduate rank (col 4), and a top-20 ranked institution by graduate program rank (col 5), and 0 if in any other kind of job. Cols. 6, 7, and 8 show the the overall ranking, undergraduate institution ranking, or the log undergraduate institution rank of the tenure institution, respectively. (Ranks from *USNWR*; "undergraduate institution rank" refers to the *USNWR* undergraduate institution rankings, as applied to the individual's tenure institution). Sample for all cols is restricted to tenured individuals who are 10-39 years since PhD receipt, currently working in the US. Cols 1 and 2 cover SDR years 1993-2021 and cols 3-8 years 1997-2021 inclusive because rank is unavailable in 1993 and 1995. Sample in cols 5-8 is restricted only to those tenured at ranked institutions. Regressions weighted by NSF-provided survey weight. All regressions include baseline fixed effects: PhD field, PhD institution, time, birth country, race, gender.

Table B6: Rank Group of Tenure Institution

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	Top 10	11-25	26-50	51-100	101+	Non-ranked
Parental education (omitted category: non-PhD graduate degree)						
Less than college	-0.00942**	-0.0164***	-0.00599	-0.00267	-0.00344	0.0371***
	(0.0048)	(0.0063)	(0.0074)	(0.0086)	(0.0082)	(0.011)
College	-0.00137	-0.0132*	0.00369	-0.000685	0.00108	0.00987
	(0.0055)	(0.0070)	(0.0084)	(0.0097)	(0.0090)	(0.012)
PhD	0.0253***	0.0188**	0.000697	-0.00884	-0.00852	-0.0312**
	(0.0079)	(0.0092)	(0.0097)	(0.011)	(0.0098)	(0.014)
Dep Var Mean	0.046	0.076	0.100	0.15	0.14	0.49
Observations	74,473	74,473	74,473	74,473	74,473	74,473

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 1-6 are binary variables taking value 1 if individual is tenured at a top-10 ranked institution (col 1), an institution ranking between 11-25 (col 2), an institution ranking between 26-50 (col 3), an institution ranking between 51-100 (col 4), an institution ranked over 100 (col 5), or an unranked institution (col 6). The ranking are by field-specific graduate program rank (Ranks from *USNWR*). Sample for all cols is restricted to tenured individuals who are 10-39 years since PhD receipt, currently working in the US. All cols cover SDR years 1997-2021 inclusive since rank is not available for 1993 and 1995. Regressions weighted by NSF-provided survey weight. All regressions include baseline fixed effects: PhD field, PhD institution, time, birth country, race, gender.

Table B7: Tenure outcomes with research controls - robustness

	No research controls	With research controls	
	(1)	(2)	(3)
Panel A: Dep. var.: Tenure institution rank (log)			
Parental education (omitted category: non-PhD graduate degree)			
Less than college	-0.157***	-0.114**	-0.114**
	(0.050)	(0.047)	(0.046)
College	-0.0581	-0.0493	-0.0535
	(0.052)	(0.048)	(0.048)
PhD	0.0638	0.0561	0.0419
	(0.057)	(0.051)	(0.050)
Observations	5,927	5,884	5,884
R-Squared	0.27	0.38	0.40
Adjusted R-Squared	0.22	0.33	0.35
PhD Institution FE	Yes	Yes	Yes
Panel B: Dep. var. : Got tenure			
Parental education (omitted category: non-PhD graduate degree)			
Less than college	-0.0815**	-0.0678*	-0.0585
	(0.035)	(0.036)	(0.036)
College	-0.0489	-0.0535	-0.0455
	(0.036)	(0.036)	(0.034)
PhD	0.0315	0.0404	0.0308
	(0.037)	(0.036)	(0.035)
Observations	1,842	1,830	1,830
R-Squared	0.24	0.27	0.32
Adjusted R-Squared	0.12	0.14	0.19
TT Institution FE	Yes	Yes	Yes
Fixed effects and controls in both panels			
PhD Field FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Birth Country FE	Yes	Yes	Yes
Race & Gender 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:* Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel A replicates Table 4, and Panel B replicates Table 5, but using raw numbers rather than field-specific percentile rank for research control variables in Columns 2 and 3.

C Appendix: Data

Parental Education: The Survey of Earned Doctorates (SED) asks respondents the highest level of education of each parent or guardian.[44] Our categorical parental education variable reflects the highest level of education of either parent, or the level of education of one parent if only one is reported. The four categories are mutually exclusive and collectively exhaustive. 9.7% of individuals in our 1993-2021 SDR sample have no information on parental education; we drop them from all analyses.

Gender: We use the SDR GENDER variable, where respondents select their gender as either male or female (at the time of the survey). 64% are male.

Race: We use the SED race/ethnicity variable to construct five mutually exclusive and collectively exhaustive categories: 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%). 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 (9% of the sample who are not missing parental education).

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

- *PhD Field Group:* 3 Science categories: Biological (incl. Health, Agricultural, Environmental), Physical (incl. Math, Computer Science, Engineering), Social (incl. Psychology). We use PhD field group interacted with research controls in section 4.1 and for heterogeneity analysis in Figure A1.
- *Broad PhD Field:* 10 categories. This uses the NSF's 9 "broad fields", but breaks out Economics separately from the other Social Sciences.[45] We use this to calculate field-

[44] Pre-2018 it asked about mother and father. From 2018, it asked for up to two parents' or guardians' highest level of education, regardless of gender.

[45] 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.

specific percentile ranks of our research output measures (publications, CNCI, journal impact factor, etc) in section 4.1.

- *PhD Field:* 75 categories. **This is our baseline PhD field definition**, which we use for our fixed effects in all regressions. We construct this using the first two digits of the NSF's 3-digit "narrow PhD field" classification.
- *Narrow PhD Field:* 267 categories. This is the NSF-provided PhD field definition (and thus the narrowest classification available in our data).[46] We use narrow PhD field fixed effects in a robustness check in Figure B1.

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. Less than 1% of our sample are missing earnings. For those in the 2021 SDR, the median earnings was $115,000, the 25th percentile $80,000, and the 75th percentile $169,000.

Debt: In recent years the SED has asked individuals their level of undergraduate and graduate debt. Over 90% of respondents with PhDs in 2000 or later have this information. The SED variables designate debt in five or ten thousand dollar buckets. To generate a continuous estimate for total debt, we impute using the midpoint of each bucket. We then add imputed undergraduate and graduate debt to generate total debt.

Institution code imputation: The SDR includes institution codes (IPEDS codes) for academic employer institutions, but this variable (INSTCOD) is occasionally missing and/or uses outdated institution codes in earlier years. We impute INSTCOD where we can. This primarily involves imputing institution code for survey wave w where INSTCOD is missing in wave w, but INSTCOD is the same in waves $w-1$ and $w+1$, and the respondent has the same tenure status in all three waves.

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 pro-

[46]See SED 2021 codebook Appendix F ("Historical SED Field of Study/Specialties List").

gram 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. For the fields without *USNWR* rankings, we imputed ranks 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).[47] We merge these field-specific ranks into our SED-SDR data using the PhD field of the individual in question. In all we obtained institution ranks for 48% of the individuals on the tenure track at a named US institution.[48]

Carnegie classifications: One of our main dependent variables is whether an institution is an R1. This is a Carnegie classification, which defines R1 institutions as doctorate-granting institutions that have very high research activity.[49] We primarily use the 2015 Carnegie Classification as provided by the NSF, but supplement it with the 1994 Carnegie Classification. We have Carnegie classifications for 99% of individuals who are on the tenure track at a US institution with a valid institution code.

Inferring tenure decision dates: For our main "got tenure" analysis (Table 3, column 4), we needed to know when someone went up for 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 many respondents.

[47] This means for example that an institution which has an average ranking of N across the social sciences for which we have ranks, like sociology and economics, would also receive that rank N in the smaller social sciences for which we are missing ranks (like anthropology or demography).

[48] 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 (Appendix Table B5) We observe undergraduate institution ranks for 52% of the individuals we observe on the tenure track at a named US institution.

[49] 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.

To do this, we define year t as the last year in which we observe individual p in a non-tenured tenure-track job at institution i. If year t is more than 5 years since the individual's PhD receipt, and if we observe the individual again in a different position no more than 5 years later in another SDR survey wave, we denote year $t+1$ the likely tenure decision year.[50]

Web of Science bibliometric data: To construct publication-level variables, we gained access to the NSF's restricted dataset which matches the 2015 SDR with the author-publication level Web of Science bibliometric data (Ginther et al., 2023). Web of Science (WoS) is a widely used database of bibliographic and citation information for over 250 fields and over 21,000 journals, conferences, and books. Our data contains WoS metrics for items published from January 1990 to December 2017.

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. For our analysis with research controls (e.g. Table 4), these reflect 66%, 10%, 10%, and 14% of the sample respectively.

[50]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. Our baseline analyses limit to the last tenure decision year observed.

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, where the 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. Since our regressions all condition on race and ethnicity, this affirmative action would need to happen by SEB within race/ethnic groups (and thus cannot be driven by affirmative action on race or ethnicity). We believe that substantial affirmative action on SEB in PhD admissions is unlikely through most of the time period we study: 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.[51]

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 $\{\underline{S}, \bar{S}\}$.

Third, it is possible that the observed characteristics S may on average be the same

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

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 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.[52] 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.

D.2 Differential selection by ability out of tenure-track academia

In Table 2 we find that there is no class gap in whether or not someone ends up a tenured professor (extensive margin), conditional on our baseline fixed effects, but that among those tenured there is a large class gap in whether they end up at an R1 or highly ranked institution (intensive margin). The fact that there is no extensive margin class gap suggests

[52]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.

that differential selection out of academia probably does not explain our results. However *differential selection gradients on ability within parental education group* could reconcile the absence of an extensive margin class gap with the large intensive margin class gap. This would be possible if the highest-ability first-gen college grads are more likely to select out of academia, and vice versa, while the highest-ability people with a parent with a non-PhD graduate degree are more likely to select into academia, and vice versa – and, crucially, if this differential gradient in selection out of academia by ability nets out at no aggregate differences in the share ending up in tenured academia.

Three of our core empirical findings suggest this differential selection on ability is unlikely to explain our findings. First, we find a class gap not just at the point of the tenure-track job market, but also at the point of getting tenure, *conditional on tenure-track institution* fixed effects (Table 3 column 4). It seems much less likely that among professors who are already on the tenure track at the same institution (i.e. who selected into academia after their PhD), there is differential selection on ability to leave the tenure track.

Second, we find large class gaps even conditional on detailed measures of research output (Tables 4 and 5). Thus, to explain the large class gap conditional on research output, we would need to believe there is differential selection by parental education group on *unobservable* research ability among people with a similar observable research record.

Third, we find a class gap in salary and career progression for PhDs in private industry, conditional on our baseline fixed effects (Table 9). If the higher-ability first-gen college grads were more likely to select out of academia and into (higher-paying) industry jobs, we should expect to see the opposite.

We also carry out two additional explorations to test this. To the extent that financial constraints motivate selection out of academia, we might expect to see that the degree of selection out of tenure-track academia for first-gen college grads is greater in fields where the salary gap between tenure-track academic jobs and industry jobs is greater. We estimate the log salary gap between tenure-track academia and industry, conditional our baseline fixed effects, separately for each of the 10 broad PhD fields. We also estimate our baseline extensive margin regression in Table 2 column 1 separately for each of the 10 broad PhD fields. We find no evidence that the class gap in selection out of tenure-track academia is greater for the fields where there is a larger industry-academia salary gap. Similarly, we might expect to see that differential financial constraints mediate the extensive margin class gap. Re-estimating our baseline extensive margin regression controlling for a third order polynomial in total student debt, we find no evidence for this: the coefficient stays almost identical to that in the baseline regression (Appendix Figure B1).

Finally, it is possible to bound the degree of differential selection on ability out of tenure-track academia which would be consistent with our findings. To do so, we carry out an exercise inspired by Lee (2009), asking: What degree of differential selection on ability would there need to be to explain our baseline results? Specifically, we run our baseline regression from Table 2 column 3, but exclude parental education (regressing log tenure institution rank on our baseline fixed effects). We extract the residuals, and denote individuals with a negative residual "high ability" (a negative residual means that an individual's tenure institution rank is higher ranked than their demographics and PhD program would predict). We then randomly drop $x\%$ of high-ability individuals from the group with a parent with a non-PhD graduate degree (mimicking a scenario where these high-ability individuals were more likely to select into industry). We re-run our baseline regression to estimate the class gap in tenure institution type conditional on our baseline fixed effects. We run this 100 times for values of x between 5% and 25% and estimate the average class gap for each x across each set of 100 iterations, as shown in the table below. The class gap is closed only when 25% of the high-ability set of people with a parent with a non-PhD graduate degree are dropped. This means that to explain the class gap in tenure institution rank by differential selection on ability within PhD program across parental education group, you would need to believe that high-ability people with a parent with a non-PhD graduate degree are around 25% more likely to select into academia than their similarly high-ability PhD classmates who are first-gen college grads, even though there is no difference in the average likelihood of people from these different groups going into academia.

Table D1: Estimated class gap in tenure institution rank under different assumptions about selection on ability

x	0	5%	10%	15%	20%	25%
Class gap coefficient	-0.108	-0.096	-0.076	-0.055	-0.031	-0.007

D.3 Bounding the role of unobservable research output

In the main text we argue that unobservable differences in research output are unlikely to explain the class gap in tenure institution rank or in "getting tenure". Specifically, recall that our baseline research controls are second order polynomials in: number of publications, average citations (CNCI) per paper, average number of authors per publication, average impact factor per publication. Our additional research controls are: second order polynomials in first author publications and in last author publications, as well as NSF award buckets, share of publications in top 10% CNCI, and share of publications in high impact journals. Denote our baseline research controls R_b, our additional research controls R_a and unobservable research measures U (which are assumed to be unobservable to us but observable to tenure committees). Controlling for our baseline research controls R_b increases the R-squared of both our tenure institution rank regression and our "got tenure" regression, showing that the measures of research we use are important in explaining tenure outcomes. Controlling for R_b also reduces the class gap in both regressions, since lower-SEB individuals in academia have less impressive research records even conditional on our baseline fixed effects. However, adding our vast suite of additional research controls R_a does little to explain the class gap above and beyond the baseline research controls R_b: in the tenure institution rank regressions, the estimated class gap coefficient barely changes, and the estimated R-squared increases by only 0.02,[53] while in the "got tenure" regression, the estimated class

[53]This is presumably because these additional research measures are sufficiently correlated with our baseline research measures, such that adding them does not further shift either the explanatory power of our

gap coefficient actually *grows* with the extra research controls. In order for unobservable research measures U to explain a large share of the residual class gap when controlling for R_b and R_a, it would need to be the case that these measures are (1) highly uncorrelated with our existing suite of research measures R_b and R_a, (2) highly correlated with socioeconomic background even conditional on our research measures and baseline fixed effects, and (3) important for tenure outcomes. The fact that R_a adds very little explanatory power relative to R_b – despite the fact that it incorporates a wide range of additional important outcomes like NSF award receipt, first- and last-author publications, and the share of "hit" publications – suggests to us that unobservable research quality U is similarly unlikely to fulfill assumptions (1)-(3) above.

Even if unobservable research quality U is substantively uncorrelated with our existing regressors, however, we can attempt to bound the degree to which it might bias upward our coefficient on the class gap using the method developed by Oster (2019). Oster shows that under certain assumptions, the bias-adjusted coefficient β^* can be approximated as

$$\beta^* \approx \tilde{\beta} - \delta \left[\mathring{\beta} - \tilde{\beta}\right] \frac{R_{max} - \tilde{R}}{\tilde{R} - \mathring{R}} \tag{1}$$

where $\mathring{\beta}$ and $\mathring{R}$ are the coefficient and R-squared of the regression without the observed controls, $\tilde{\beta}$ and $\tilde{R}$ are the coefficient and R-squared of the regression *with* the observed controls, R_{max} is the maximum possible R-squared from a hypothetical regression where the relevant unobserved controls are included, and δ is the coefficient of proportional selection across observables and unobservables. Using our baseline regressions (Table 4 column 1, Table 5 column 1) as the regressions without the observed controls, and our regressions with full research controls (Table 4 column 3, Table 5 column 3) as the regression with the observed controls, we can bound the possible bias arising from being unable to control for unobservable aspects of research quality which are (i) unobservable to us, (ii) observable to

regressions or our estimate of the class gap.

the tenure committee, and (iii) uncorrelated with existing regressors. To do so, we also need to select values for R_{max} and δ. Oster suggests setting $\delta = 1$, reflecting an assumption that the observables are at least as important as the unobservables (in our case, that the detailed observable measures of research output we have – publications, citations, journal impact factor, authorship position and contribution, NSF awards – are at least as important as unobservable research quality in affecting the tenure decision or tenure institution). We then follow Oster in estimating a bias-adjusted class gap, under four different values of R_{max}. For our first three scenarios, we set $R_{max} = \tilde{R} + k \cdot (\tilde{R} - \mathring{R})$, for three values of k: 0.25, 0.5, and 1. These assume, respectively, that the incremental explanatory power of unobservable research quality in tenure decisions is one quarter of, one half of, or equal to, the explanatory power of our observable research measures. In Scenario 4, we instead follow Oster's benchmark recommendation in setting $R_{max} = 1.25\tilde{R}$, which assumes that the addition of unobservable research quality measures would increase the explanatory power of our regression by 1.25 times (relative to our regression which *already* included all our detailed measures of research quantity and quality as well as PhD institution, field, and researcher demographics). Table D2 shows these assumptions and the bias-corrected coefficient estimates β^* under the three scenarios. We see scenarios 1 or 2 as the most plausible, since we think it likely that all our combined observable research quality measures have more explanatory power for the tenure decision, collectively, than unobservable research quality. But even in the more conservative scenarios 3 and 4, the class gap remains substantial.

Table D2: Bias-corrected class gaps under different assumptions

	Log tenure rank	Got tenure
Parameters from regression output		
$\mathring{\beta}$	-0.157	-0.0815
$\mathring{R}$	0.27	0.24
$\tilde{\beta}$	-0.0932	-0.0679
$\tilde{R}$	0.38	0.33
Scenario 1: $R_{max} = \tilde{R} + 0.25(\tilde{R} - \mathring{R})$		
R_{max}	0.408	0.353
β^*	-0.077	-0.065
Scenario 2: $R_{max} = \tilde{R} + 0.5(\tilde{R} - \mathring{R})$		
R_{max}	0.435	0.375
β^*	-0.061	-0.061
Scenario 3: $R_{max} = \tilde{R} + (\tilde{R} - \mathring{R})$		
R_{max}	0.490	0.420
β^*	-0.029	-0.054
Scenario 4: $R_{max} = 1.25\tilde{R}$		
R_{max}	0.475	0.413
β^*	-0.038	-0.055

E Appendix: Survey

E.1 Survey overview

We fielded a survey to around 18,000 academics in the spring of 2025.[54] The first wave contacted academics in Economics departments, and the second wave ("Multi-disciplinary") contacted academics within a broader range of science and social science disciplines: Computer Science, Political Science, Sociology, Biology, Physics, Mathematics, and Engineering. We selected institutions using the U.S. News & World Report rankings as of August 2024: specifically, we contacted academics who were faculty at departments which had one of the top 30 U.S. graduate programs in their field (or top 50 in economics).[55] Table E1 reports the number of departments and email addresses contacted in each discipline ("unique emails" shows the total number once removing duplicate email addresses or department contacts).

Table E1: Survey Population

Field	**Nb. Departments**	**Nb. Emails**
Economics	51	2,588
Computer Science	30	2,037
Political Science	38	1,205
Sociology	32	895
Biology	33	1,878
Physics	36	2,212
Mathematics	30	2,001
Engineering	29	6,224
Total	**228**	**19,040**
Unique Emails		**18,350**

Our Economics survey was fielded during February and March 2025.[56] Our Multi-

[54] The survey received an Exempt determination from MIT's Committee on the Use of Humans as Experimental Subjects (Determination E-5808).

[55] The exact number of departments contacted varied, as rankings are often tied across many departments. We focused on the top PhD-granting departments since we wanted to prioritize respondents who had experience with PhD students going on the academic job market for research-intensive and highly-ranked schools, and tenure-track faculty in research-intensive and highly-ranked schools typically come from highly-ranked PhD programs (see e.g. Jones and Sloan, 2022).

[56] We fielded pilot surveys to 4 departments, and the main survey to the remaining 47 departments.

Disciplinary survey was fielded during April and May 2025.[57] Participants were contacted with an email to their university email address, with a request to take a survey about "the role of socioeconomic background in academic careers". For the Economics survey we received 558 responses, a 21.6% response rate. For the Multi-Disciplinary Survey, we received 1,668 responses, a 10.6% response rate. When combining across the two surveys, we **received 2,226 responses, for a final response rate of 12.1%**.[58] We show summary statistics on respondents in Table E2.

E.2 Class background: different measures

As discussed in section 2 of the main paper, ideally we would be able to use a range of proxies for class background. In this survey, we asked parental education, and also asked three further measures: (i) self-identified status as a first-gen college grad, (ii) self-identified status as having grown up in a low-income family, (with additional questions about eligibility for income-restricted programs), and (iii) self-identified class position (on the rungs of a 10-rung ladder "representing where people stand... in terms of income or wealth, education, or respected or prestigious jobs").[59] This gave us the opportunity to analyze our data based on not only parental education but also other markers of socioeconomic background; it also enabled us to cross-check how these different measures of class background related to each other in our target population of US academics. As Figure E1 shows, these three measures are closely related: those self-reporting being either first-gen and/or low-income are much more likely to place themselves growing up on the lower rungs of the ladder, and parental education levels also correspond cleanly to different self-reported rungs on the ladder. This

[57] There were some wording changes (i) part-way through the fielding of the Economics survey and (ii) between the Economics and Multi-Disciplinary survey to reflect feedback on clarity of the questions.

[58] The survey was administered via an anonymous link using the Qualtrics survey platform. All responses were anonymous unless a respondent voluntarily provided their email address.

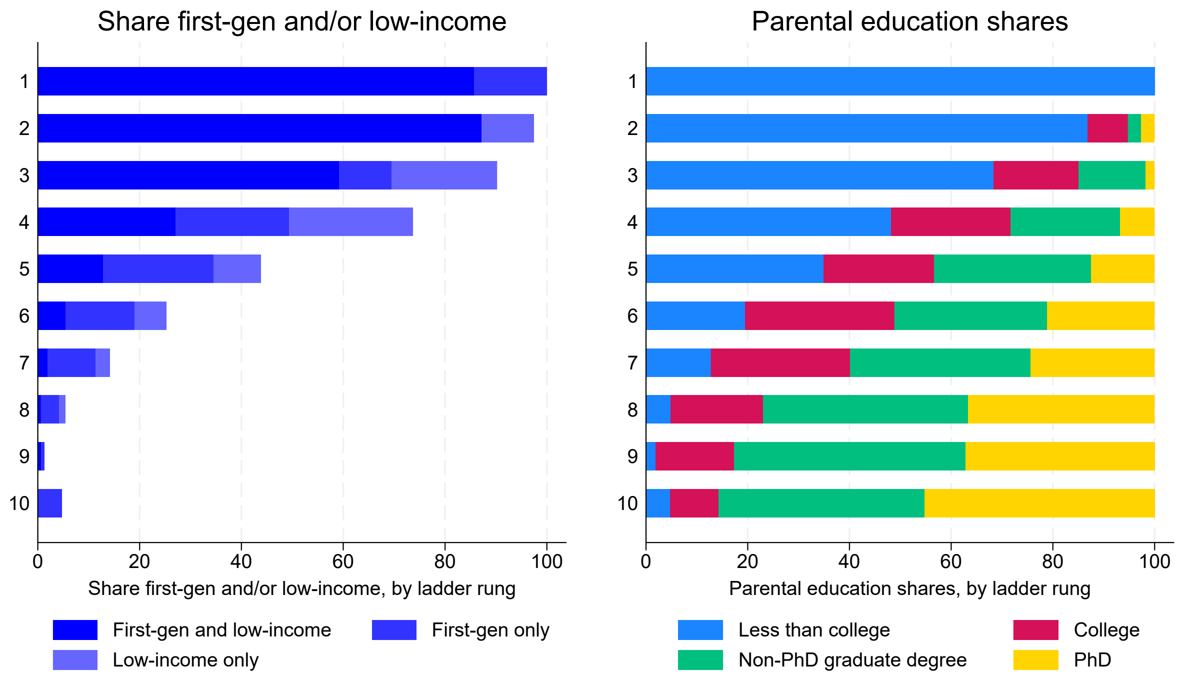
[59] The ladder question was: "Think of this ladder as representing where people stand in your home country. At the top of the ladder are the people who are the best off – in terms of income or wealth, education, or respected or prestigious jobs. At the bottom are the people who are the worst off – in terms of income or wealth, education, or the least respected or prestigious jobs, or no job. Consider your family when you were growing up. Where would you have placed your family on this ladder if the bottom rung is equal to 1 and the top rung is equal to 10?"

Table E2: Survey Respondents: Summary Statistics

	All	Not L.I. or First Gen	L.I. or First Gen
Nb. Obs.	2,226	1,570	656
Low-Income	22.8		
Low-Income or First-Gen	29.5		
Highest Level of Parental Education:			
Less than College	26.0		
College Only	21.8		
Non-PhD Graduate Degree	31.4		
PhD	20.8		
Female	31.7	34.2	26.6
Race/Ethnicity:			
White	83.9	84.2	83.1
Asian	9.8	10.7	8.2
Black	2.6	1.7	4.5
Hispanic	6.6	6.2	7.4
Native American	0.7	0.2	1.4
Native Hawaiian/Pacific Islander	0.2	0.2	0.2
Other	3.7	3.7	3.7
Familial Background:			
Grew Up in the U.S.	69.3	73.2	61.9
Average Rung on Ladder	6.1	7.0	4.4
Current Field:			
Economics	25.1	26.7	21.3
Political Science	9.7	9.6	10.1
Sociology	7.6	7.6	7.6
Biology	7.9	7.1	9.8
Physics	8.6	8.9	7.9
Computer Science	10.6	10.6	10.8
Mathematics	6.4	6.9	5.0
Engineering	19.0	17.8	21.6
Other	5.0	4.7	5.8
Faculty Level:			
Tenured	52.7	52.5	52.9
Tenure-Track	23.9	24.3	22.9
Non-Tenure-Track/Teaching	18.4	18.7	17.7
Emeritus	6.8	6.1	8.3

Source: Survey of academics at US institutions, fielded Spring 2025 *Notes:* This table reports summary statistics for the full sample of survey respondents as well as by self-reported background: those who are not low-income (L.I.) or first-generation (First Gen), and those who are either low-income or first-generation. Faculty level categories are mutually exclusive. Race and ethnicity categories are not mutually exclusive; respondents could select multiple categories. "Average Rung on Ladder" refers to the mean response to the question: "Imagine a ladder representing where people stand in society...", where respondents report their childhood household position on a scale from 1 (lowest) to 10 (highest). All other statistics are percentages.

Figure E1: Comparison of self-reported socioeconomic background ("rung" on a ladder) against parental education and low-income status



Source: Authors' survey (Multidisciplinary and Econ). *Notes:* This figure shows the relationship among our survey respondents between different proxies for socioeconomic background. The numbers 1 through 10 on the y axes of each figure reflect the "rungs" on a ladder, with 1 the lowest and 10 the highest. For each rung, the figure shows the share of respondents who identified as first-gen and/or low-income (left panel), or the share with each parental education level (right panel).

gives further confidence that parental education – our only measure available in the main paper – is a good proxy for socioeconomic background.

Our survey also enabled us to get more information on what kinds of graduate degrees the parents of academics tend to hold.[60] This matters because the income levels associated with some non-PhD graduate degrees (e.g. medical, law, business, or science degrees) are higher than those of other non-PhD graduate degrees (e.g. education, social work). We show the breakdown of degree types in Table E3. Relative to the non-PhD graduate degree holders in the US population, shown in Appendix Table A1, people with with education, psychology,

[60] In our survey, there were 769 respondents with at least one parent with a non-PhD graduate degree. 554 individuals reported the non-PhD graduate degree type (for 706 parents, since some people have two parents with a non-PhD graduate degree).

or social work degrees are very underrepresented among parents of academics (8% vs. 32%), people with business, law, or medical degrees are a little overrepresented (43% vs. 38%), and people with masters degrees are highly overrepresented (48% vs 32%).

Table E3: Degree types among parents with a non-PhD graduate degree

Degree type	Share
Masters	48%
...of which MA	12%
...of which MS	12%
...of which unspecified	23%
Medical Doctor (MD and others)	18%
Law (JD and others)	12%
Business (MBA and others)	9%
Education	6%
Other Medical (e.g. Nursing, Pharmacy)	3%
Psychology or Social Work	2%
Other	2%

Source: Authors' survey (Multidisciplinary and Econ). *Notes:* This table shows the shares, by degree type, of the non-PhD graduate degrees of parents of academic respondents to our study.

E.3 Multiple choice responses

We asked a question intended to elicit respondents' priors about our core "intensive margin" result in this paper: "Imagine you had data on the academic placements of all *[your discipline]* PhD students, and were interested in comparing the academic placement outcomes of students from the same PhD program, by demographic group. On average, which groups do you think the data would show went to better academic placements? Remember, these are comparisons among people from the same PhD program." The possible responses were: Much better, slightly better, about the same, slightly worse, much worse, don't know. We asked this question for women vs. men, URM vs non-URM PhD students, non-US vs. US students, and first-gen college graduates vs. non first-gen college graduates.

Of our sample, 47% reported that they would expect first-gen college grads to go to placements that were slightly worse or much worse than their non-first-gen PhD classmates, 4% reported expecting better placements, and 33% reported expecting about the same placements (the remainder selected "Don't know" or did not answer).[61] Because of selection into taking the survey, we see this as an upper bound of the share of academics who think that first-gen college grads go to worse placements: since the email requesting survey participation described the survey as about the "role of socioeconomic background in academic careers", those who chose to take the survey were more likely to be people who believed socioeconomic background was important in academic career progression.

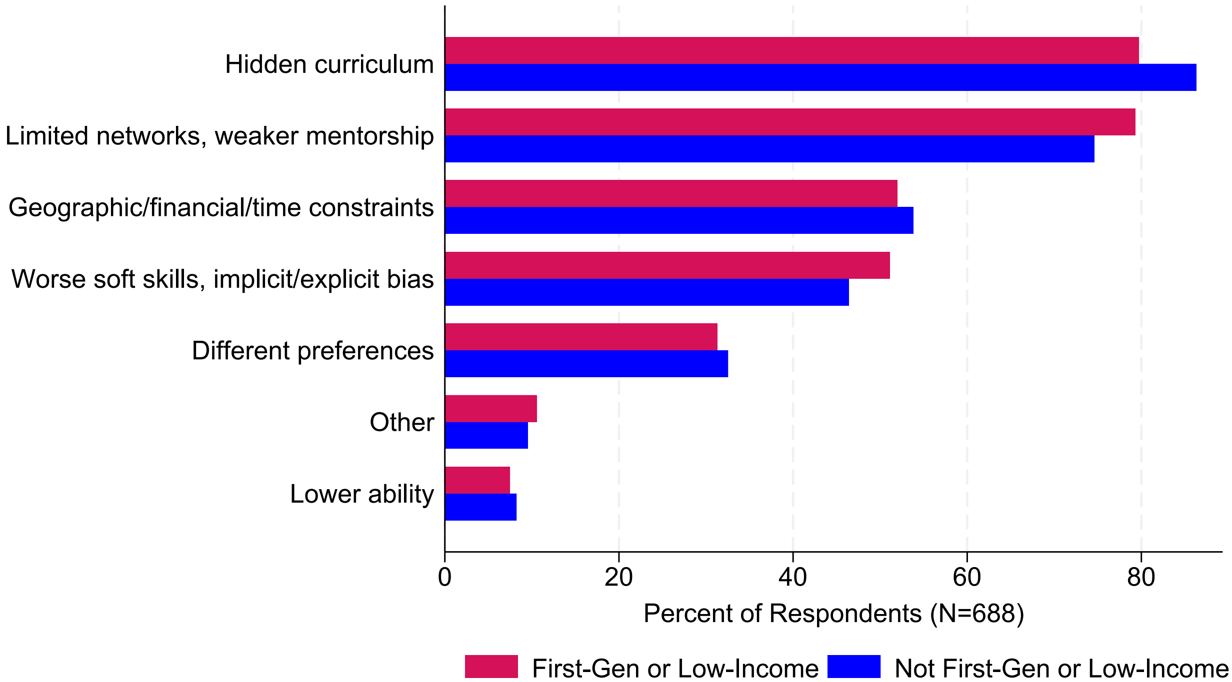
For all respondents who answered that they expect first-gen college grads to place worse, we followed up with a multiple choice question asking why they think this is the case: "You answered that first-generation college graduates go to worse placements on average than their PhD classmates. Which of these factors, if any, do you think are driving this?". Respondents could check as many options as they thought were important and/or write in their own. We see this as less subject to the sample selection concerns above: it is reasonable to expect that those who chose to take the survey are more likely to be believe socioeconomic background matters (compared to those who chose not to take the survey), but there is no particular reason to think that among those who believe socioeconomic background matters, there was selection into taking the survey by the *mechanism* they think is most important.

Figure E2 visualizes the results.[62] Two factors stood out as particularly important: the hidden curriculum and more limited professional relationships. Worse soft skills and implicit/explicit bias, and geographic, financial and time constraints, were also selected by roughly half of respondents. Few respondents thought the main drivers of the class gap in post-PhD job placement were preferences (that first-gen college grads were more likely

[61] The sample size for this question is 1,669 individuals. Notably, the share reporting that women or URM PhD students would go to better placements was substantially higher than the share reporting that first-gen college grads would go to better placements (28% for women and 27% for URM PhD students). In the open-ended responses, a large number of respondents mentioned that in recent years they have observed affirmative action toward women or racial/ethnic minority candidates, but *not* toward people based on socioeconomic background.

[62] The results presented in the figure group together some of the response categories for easier interpretation. We show results only from the 688 respondents from the Multi-Disciplinary Survey who answered that first-generation college graduates place worse. We do not show the Econ Only results here because we added extra multiple choice options to this question in the Multi-Disciplinary survey in response to the open-ended answers we received in the Econ Only survey.

Figure E2: Why first-gen college grads get worse academic placements than their PhD classmates: Survey respondents' perceptions

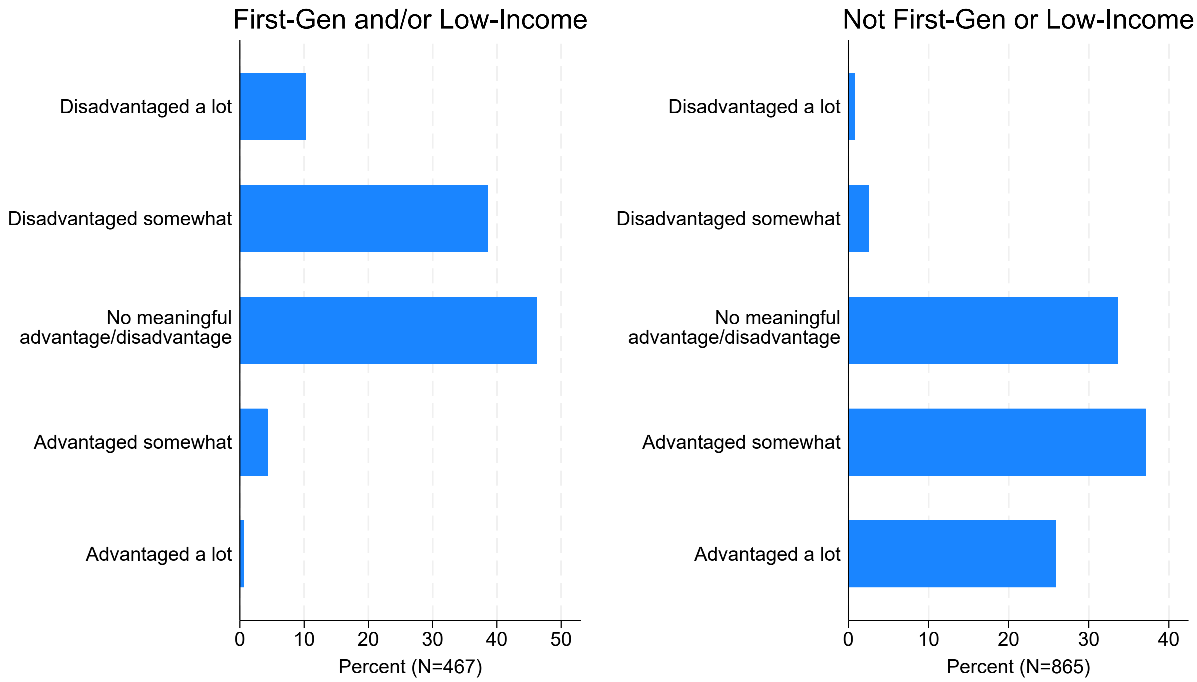


Source: Authors' survey (Multidisciplinary only). *Notes:* Red bars show the percent of FGLI respondents who select each mechanism; blue bars show the percent of non-FGLI respondents who select each mechanism. Respondents could select multiple mechanisms. "FGLI" = First-Gen college grad or from a Low-Income background.

to actively choose lower-ranked placements), and very few thought a key driver was lower academic ability (e.g. because of affirmative action toward first-gen college grads in PhD admissions). There was very little variation across fields in these responses, and also almost no variation in perceived importance of different factors for first-gen or low-income respondents, vs. non-first-gen non-low-income respondents.

We also asked questions about respondents' own perception of how their family background had affected their career progression. Specifically, we asked respondents who identified as first-gen college grads or from low-income backgrounds ("FGLI") "Do you believe that being from a low income family and/or being a first-generation college student disadvantaged you or advantaged you in your academic career outcomes during and/or after your PhD, relative to peers from more socioeconomically advantaged backgrounds? This includes your initial placement after graduation, the type of institution you joined, research produc-

Figure E3: Perceived impact of own socioeconomic background on academic career outcomes during and/or after PhD



Source: Authors' survey (Multidisciplinary & Econ Surveys).

tivity, grant and fellowship opportunities, and long-term career trajectory (e.g. tenure-track / receiving tenure)." We asked the converse question to those who were not FGLI. 46% of FGLI respondents and 34% of non-FGLI respondents thought that their socioeconomic background brought no meaningful advantage or disadvantage in their PhD or post-PhD careers. 48% of FGLI respondents believed their socioeconomic disadvantaged them at least somewhat relative to non-FGLI peers, and 63% of non-FGLI respondents believed their socioeconomic background advantaged them at least somewhat relative to FGLI peers (Figure E3).[63]

To respondents who believed that their socioeconomic background advantaged or disadvantaged them, we then asked about mechanisms. In Figure E4 we show the multiple choice

[63]Those in the social sciences were slightly more likely to believe that their socioeconomic background had mattered for their own career progression, as compared to those in the hard sciences. FGLI respondents who got their PhD in more recent years were more likely to believe that their background had disadvantaged them, which may reflect the fact that the composition of the academic profession has become substantially more socioeconomically elite over time.

responses for FGLI respondents who believed their background disadvantaged them, and for non-FGLI respondents who believed their background advantaged them. For FGLI respondents, the two most dominant factors were (i) cultural capital – as reflected by unfamiliarity with academic norms, imposter syndrome, and others' bias or negative perceptions: 92% of FGLI respondents chose at least one of these three factors – and (ii) the hidden curriculum, selected by 72% of respondents. Limited professional networks and limited access to mentorship, which may reflect the difficulties of limited cultural capital, were also prominent, as were financial constraints and low familial/social support.[64] For non-FGLI respondents, financial and social support featured prominently, as well as awareness of cultural capital advantages (which may be thought of as proxied by soft skills or norms and values).

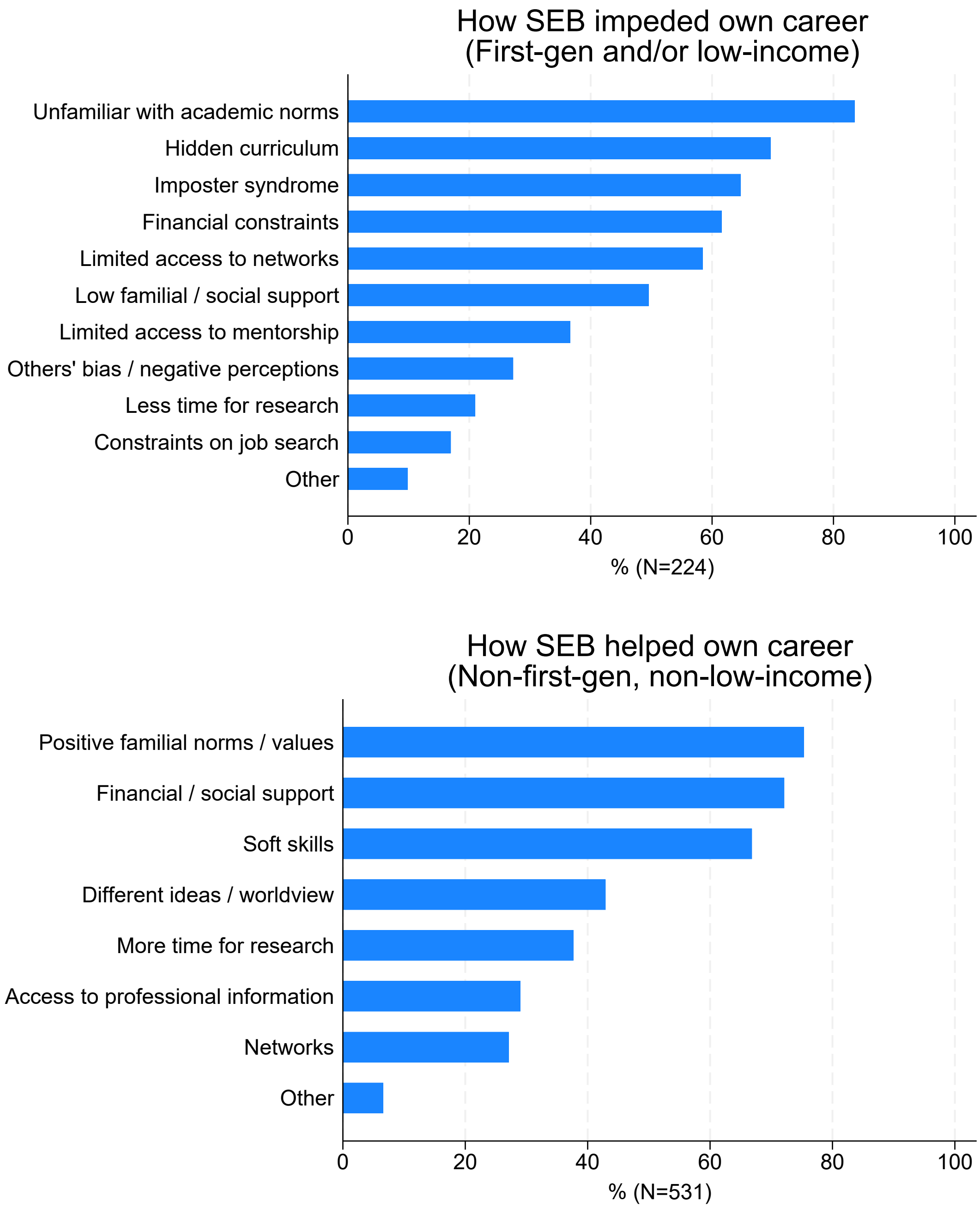
E.4 Open-ended questions: key themes

In the main paper we discuss the two overwhelming themes that emerged from the open-ended responses: cultural capital and social capital. Here, we discuss other themes which emerged from the open-ended responses.

Cultural capital: geography. In the main text we discuss cultural capital manifesting in two ways: different norms about speech, dress, and behavior, and different prior cultural experiences. Beyond class background, *geography* which was frequently emphasized as a factor in cultural capital. For example, a biologist who was not first-gen explained that "I grew up in a rural and poor part of the country, West Virginia. I made an effort in college to speak without an accent, as I have seen how people in academia respond to those of us from regions like this. While I had financial and racial advantages, I did not know how to play the academic game or how to network among wealthy and city-savvy/sophisticated/private-school-educated people who dominate academia." Similarly, an economist who was not first-gen wrote "I have a perceptible Ozarkian accent and 'hillbilly' kind of drawl. I think these

[64] There were few field differences in ranking of which factors were considered most important. One notable exception is that FGLI respondents in the social sciences rated financial constraints as having been very important during and after the PhD, while FGLI respondents in the hard sciences were less likely to rate this as having been important.

Figure E4: Perceived impact of own socioeconomic background on academic career outcomes during and/or after PhD



Source: Authors' survey (Multidisciplinary & Econ Surveys). *Note:* The top panel shows, of the FGLI respondents who said that their socioeconomic background impeded their career during or after their PhD, the shares who selected each mechanism as important. The bottom panel shows, of the non-FGLI respondents who said that their socioeconomic background helped their career during or after their PhD, the shares who selected each mechanism as important. Respondents could select multiple mechanisms.

things are often associated with 'lower class' familial backgrounds... I think the rural/urban divide is just as important (maybe even more important) than class". The intersection of class and geography was sometimes particularly difficult, as noted by one political scientist: "Being from the Midwest and a low-income family meant I had no knowledge of elite East Coast norms".

Financial constraints. Financial constraints during the PhD and in the immediate years after were heavily emphasized as a factor for people from low-income or financially precarious backgrounds. Many respondents discussed being in serious debt from student loans and/or credit cards, particularly during graduate school and the early post-PhD years. Some also needed to support family financially. While few people said that they needed to take extra jobs during their PhD to finance themselves (unlike in college, where this was common), financial constraints played a role in limiting professional risk-taking, by limiting the ability to take on risky research projects, or reducing the ability to take longer to graduate or take on postdocs before a secure position. Several respondents also said that their financial situation limited their ability to take advantage of professional opportunities (like conferences) during graduate school: a public policy scholar from a low-income background, for example, said that "international trips, summer methods workshops, or any action that would have added a year to my schedule was not remotely considered". Finally, many people emphasized the stress of strained finances (or the converse): for example a first-gen biologist from a low-income background wrote that "Every reimbursement that is months late, every meeting with hidden costs, cause a huge amount of stress". Conversely, people from middle-class backgrounds and more advantaged backgrounds frequently noted financial stability – in particular, the presence of a "safety net" – as a substantial advantage during their PhD and immediate post-PhD years. Women who had children during the PhD or postdocs also raised financial constraints as particularly relevant: those with family resources mentioned having financial support for childcare, for example.

Family expectations and support. A very frequently raised issue in the open-ended responses was one of family expectations, understanding, and (non-material) support. Several respondents from advantaged backgrounds emphasized the support of their family for their pursuit of graduate education, and their family's understanding of why an academic career might be desirable and what it would entail. Many FGLI respondents also emphasized their family's strong support for education. Some FGLI respondents, however, wrote about a lack of family support or understanding as a major factor that disadvantaged them in their careers. This included a lack of family understanding of academia, or family concerns that the respondent was pursuing an unstable or low-paid career path. This was described by one respondent as a "psychological burden". Another respondent said that the lack of her family's support "contributed to the feeling that I was on my own and didn't really belong to the academic community". Several respondents discussed how going into academia has to some extent alienated them from the communities that they grew up in, with one emphasizing the "serious relational and emotional toll" this caused.

Pre-PhD preparation. Some respondents emphasized that lower-SEB academics often have worse prior academic preparation when coming into their PhD program. This means that they start behind, and need to spend time catching up during the PhD, which can leave them at a disadvantage in terms of producing research, gaining mentors, and then getting a good post-PhD job. A first-gen mathematician from a low-income background, for example, wrote that he "knew less technical knowledge than my peers" coming into his PhD, and a computer scientist from a low-income background wrote that because she had to work full-time during her undergraduate degree, she had less time during that degree to acquire relevant skills, meaning during her PhD "I had to take time from research to fill those gaps". A physicist with parents with graduate degrees similarly wrote that he came in with better writing ability than others in his PhD, meaning that "when it came time to write papers, I could proceed much more rapidly than my labmates".

Values. Many respondents discussed their family's values as important in how their family background had affected their journey into academia. Consistently across all backgrounds, people discussed two values prominently: first, their family's emphasis on the value of education and knowledge, and second, their family's emphasis on the value of hard work. (This is perhaps not surprising, given that both of these values are effectively prerequisites to end up in an academic career.) Differences by socioeconomic background were rarely clearly apparent in discussions of values: people from less advantaged backgrounds frequently emphasized having an extremely strong work ethic as a result of their family's experiences, but people from more advantaged backgrounds frequently did the same. One intersection was around class and immigration status. Many children of immigrants identified their overwhelming values as stemming from this background: a physicist, for example, wrote that "Almost as important as my father's occupation, I think, is that my parents were children of immigrants. I was taught to work hard and not always to expect success. I think the generational connection to immigration will give you a bigger signal than a family's socioeconomic status."

No Post PhD effect. A meaningful share of respondents in our multiple choice questions responded that their socioeconomic background gave them no meaningful advantage or disadvantage in their PhD and post-PhD careers. While most of these respondents did not follow up with open-ended text responses, some did. The clear theme among these responses was that these individuals thought their socioeconomic background had mattered in terms of their undergraduate education, and perhaps the decision to do a PhD and where they got into the PhD, but that after that, success was based on academic merit and hard work. An economist, for example, wrote that "In the US, education is a great equalizer. SES is [an] important element in access to high[er] education, but conditional on access, most differences wash out." A mathematician wrote that "My sense is that socioeconomic background makes a difference up until one enters a PhD program (and in particular, whether one goes on to a PhD program). Once one is in such a program, it seems to me that there is little further effect of a person's socioeconomic background, compared with other students in the same program at the same university."