Paying for Prestige: Compensating Differentials in Faculty Job Choice

Alex Bell and Todd R. Jones*

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Abstract

We quantify in dollar terms how faculty trade off salary and job amenities, particularly the prestige of their departments. To overcome the typical problems of the hedonic literature, we use the anti-instrumental variable approach. While compensating differential theory predicts such trade-offs, standard regression techniques fail to account for unobserved variation in faculty offer sets, leading to intuitively wrong-signed estimates. Our approach addresses this challenge by leveraging the relationship between a faculty member's PhD-granting university rank, current institution salary, and current university rank to better identify the salary-prestige tradeoff. Using de-identified data on over 220,000 faculty-field pairs in 341 U.S. universities across 107 fields, we find strong evidence that faculty are willing to forgo substantial earnings for positions at more prestigious institutions. While exact magnitudes vary with how one operationalizes "prestige," we consistently find the average faculty member must *give up* on the order of $1,500 in pay to move to the next-most-prestigious school. These findings contribute to a broader understanding of labor market dynamics in high-skilled professions, where non-monetary factors play a critical role in job selection. Our methodological approach offers new insights into the pricing of job amenities and how institutions compete for talent beyond academia.

*Bell: Georgia State University. *ambell@gsu.edu*. Jones: Mississippi State University, CESifo, and IZA. *trj234@msstate.edu*. We thank Daniel Larremore for sharing and helping us understand the data.

1 Introduction

Do faculty "pay" for prestige? Economists dating back to Smith (1776) have long theorized that workers forego earnings for other desirable facets of a job, but empirical evidence in favor of that view is scarce. This paper applies new methods in labor economics to granular data on U.S. faculty rosters and backgrounds to document and explore the trade-off faculty face when choosing to work at more prestigious schools versus schools that pay better.

This paper contributes to our understanding of incentives in labor markets for high-skilled workers. As evidenced by Stern (2004), scientists and researchers often exhibit non-financial motivations for their work beyond pay, but the extent of this preference variation was not previously documented across the broader academic labor market. This paper builds on a broad literature pricing job amenities in various contexts (Ashenfelter and Greenstone, 2004; Greenstone et al., 2015; Lavetti, 2015; Cook et al., 2018). This paper also complements surveys indicating that workers have preference over job attributes by showing a salient case in which worker preferences can actually translate to labor market factor prices (Mas and Pallais, 2017; Maestas et al., 2018; Wiswall and Zafar, 2018; He et al., 2019).

While evidence is growing that non-wage attributes are important facets of the labor market, little is known about the role of job amenities in high-skilled markets. On one hand, by focusing solely on the academic labor market, we are already considering a very specialized type of job. Relative to other jobs, US faculty jobs offer autonomy, flexible schedules, and the potential for long-term job security through tenure. Faculty also benefit from intellectual freedom, access to research funding, campus amenities, and perks like tuition benefits and sabbaticals. However, faculty salaries often lag behind industry, and the workload—especially before tenure—can be intense.

As unique as the academic career path may be, variation in job types still exists within the academic job market. For instance, the investigation of faculty hiring practices by

Goolsbee and Syverson (2023) concluded that faculty view "jobs at prestigious schools as meaningfully differentiated from alternative positions." Other ways to classify or differentiate academic jobs exist; research universities tend to offer more funding and lighter teaching loads, whereas liberal arts colleges emphasize student engagement. Geographic locations of universities, such as rural versus urban, also shape how prospective faculty evaluate the utility conferred by a job offer. Although we find some evidence that these other amenities matter for faculty, our analysis suggests that the salary versus prestige trade-off is surprisingly distinct and robust to controlling for other amenity measures.

Our analysis reveals that across US colleges and universities, the average price for prestige is about $1,500. More precisely, the average professor wishing to move to a marginally one-rank-better school can expect a pay cut of $1,500 to be associated with that move.

We use data collected by Academic Analytics Research Center (AARC), which were then cleaned and made publicly available by Wapman et al. (2022). These data include the university and field a faculty member works at, as well as the university at which he or she received his or her Ph.D. Our sample consists of over 220,000 faculty-field pairs in 341 U.S. universities across 107 fields. To arrive at our estimates, we first need a measure of university prestige. Our preferred specification uses SpringRank, which operationalizes the notion that the most prestigious schools are those that hire from the most prestigious PhD programs De Bacco et al. (2018). Appendix Figure A.1 plots distributions of this measure of prestige. Faculty in the sample tend to work at universities with higher SpringRank scores (Panel A). Strikingly, faculty disproportionately received their PhDs at highly-ranked universities (Panel B).

Still, even with a state-of-the-art measure of school prestige, traditional economic analysis fails to accord with intuition. Panel C of Figure 1 shows the raw relationship between average salary at a school and the job's rank (as measured by SpringRank). Following the theory of compensating differentials, if faculty trade off between pay and prestige, a

downward-sloping relationship should emerge here. Instead, the relationship is strongly upward-sloping. One hypothesis for the wrong-signed result is that some jobs are just better than others—in terms of both pay and prestige—but we lack an adequate measure of worker ability for which to control. In Panel D, we test the "ability bias" hypothesis by including the prestige measure of the PhD granting institution for each faculty member. The resulting relationship is still upward-sloping, but slightly less so, which is evidence consistent with ability being a confounding factor in the relationship in Panel C, but we do not observe the full set of ability-relevant controls.

The approach we apply in this paper is to treat the rank of each faculty member's PhD not as a control but instead as an anti-instrument for their job rank (Bell, 2020). As with other recent literature, the anti-IV methodology adequately controls for the latent index, and reveals the expected downward-sloping market tradeoff between pay and prestige (Folke and Rickne, 2022; Burbano et al., 2023; Ferreira et al., 2024; De Schouwer and Kesternich, 2024; Bell et al., 2024).

The details of that empirical strategy are the subject of the next section. Subsequently, we discuss our data on faculty and their PhD-granting institutions, interpret our results, and conclude with a discussion of open questions in this literature.

2 Empirical Strategy

2.1 The Anti-IV Approach

The key confounding factor when studying job choice among academics is that the market does not operate such that a given worker has access to all jobs. Instead, following Bell (2020), we assume the market is segmented vertically such that some workers have access to better jobs than other workers, both in terms of pay and prestige.

The ideal experiment in this case would be to observe two workers who could have chosen among the same sets of jobs, but differing preferences for pay versus prestige led

to different choices. If we could observe and condition on the sets of jobs available to all workers in academia, this variation in preferences would trace out the trade-off workers face when choosing between jobs with greater pay versus prestige. While surveys of job applicants like that of Stern (2004) among biology post-docs are helpful for studying the behavior of small groups of individuals, we seek to study the broader academic labor market in the US.

Following Bell (2020), we use observed qualifications of workers as anti-instruments for the quality of their offer sets. The intuition for the anti-instrumental variable approach is similar to the typical approach of controlling for qualifications in hedonic regressions, but it differs in that the assumptions are weaker: Instead of needing to observe all productivity-relevant attributes of the worker, we only need to observe one. In our preferred specification, we take the ranking of the program from which the worker received their PhD as the anti-instrument for the quality of their offer set.

Implementing this approach requires 1) regressing the anti-instrumental variable (PhD rank) on the dependent variable (average salary) and amenity (job rank); 2) creating predicted values; and then 3) regressing the dependent variable on the amenity, while controlling for the predicted values. The coefficient on the amenity is the coefficient of interest.

This approach estimates the wage-amenity frontier commonly attributed to Rosen (1986). The intuitive interpretation of the frontier is the price of the amenity that arises from a perfectly competitive frictionless sorting equilibrium between workers and firms. It is an equilibrium price in the sense that if an additional worker were added to the market, the price dictates the schedule of wage-amenity combinations that the worker would be able to choose from. Our approach differs from the literal textbook model of compensating differentials only in that we allow for a single, partially latent index of vertical job rank (whereas the textbook model assumes no such vertical differentiation of jobs or workers).

Figure 2 demonstrates the problem that has so consistently plagued the hedonics literature, using economics rankings.[1] More prestigious schools pay higher salaries, which suggests if anything that prestige appears to be a disamenity. But we augment that thinking to suppose that the labor market for faculty has a notion of vertical constraints to it. Intuitively, it is not reasonable to suspect that faculty who hold positions at state schools like Arizona State or Penn State had turned down more prestigious and higher-paying schools like Harvard and MIT. Instead, our data and estimation approach will indicate that a more realistic counterfactual would have been a higher paying but slightly less prestigious private institution, like SMU, Georgetown, or Rice.

While the anti-IV approach removes the need for the researcher to observe and condition on the full set of productivity-relevant attributes, a remaining limitation (as with the traditional hedonic approach) is that the researcher still needs to observe the set of job attributes that generate utility for the worker. At present, we primarily model the worker's decision problem as trading off only between pay and prestige because we feel this is an interesting and under-explored dimension of job choice. Still, future work should explore robustness to incorporating additional workplace amenities into the job choice model.

2.2 Approach to Aggregation

Although the quality of one's PhD granting institution is measured at the individual-level, other key variables are observed only at more aggregated levels. The primary job attribute of interest, job rank (prestige), is measured at the level of the school-by-field. We also measure pay at the school level from IPEDS. We therefore conduct the analysis at the individual level, and cluster our standard errors at the school-by-field level. In additional analysis that estimates the price of prestige within a field, we cluster our standard errors at the school level. We also explore robustness of our estimates to estimating the price of

[1] We show similar plots for economics using REPEC and US News & World Report Rankings in Appendix Figure A.2, and National Research Council (both survey-based and regression-based rankings) in Appendix Figure A.3.

prestige on datasets that are collapsed to the school-by-field (or school) level.

2.3 Ranking Schools

Following a growing wave of recent applied work in labor economics, we use the network of worker flows across universities as a revealed-preference indicator for university prestige. The specific algorithm used to rank universities is called SpringRank (De Bacco et al., 2018).[2] While the exact details of the implementation differ slightly from PageRank (Sorkin, 2018) or "poaching rank" (Bagger and Lentz, 2019), it is also recursive in nature in that departments are ranked higher if their graduates place at higher-ranked universities. Moreover, recent research in network sciences has found SpringRank to be more robust than alternatives such as PageRank in a variety of real-world and simulated datasets, particularly when the underlying data imply a natural hierarchy (De Bacco et al., 2018).

3 Data

3.1 Faculty Data

Our baseline data on a faculty's current university (which we refer to as job) and the university at which they received their PhD come from Wapman et al. (2022) (hereafter, WZCL) as part of their publicly available replication package.[3] WZCL obtained their original data from Academic Analytics Research Center. These original data, for each year between 2011 and 2020, included a census of the tenure or tenure-track faculty at the 392 US universities that grant PhD degrees. The data include the institution at which the faculty received their PhD (or other terminal degree). WZCL conducted an extensive

[2]The algorithm is named after an analogy to a physical system in which universities (i.e., the nodes of the graph) are connected by springs. The resting lengths of these springs (i.e., the edges of the graph) are determined by hiring patterns across the universities. The algorithm then finds the ordering of universities that minimizes the resting energy of the system.

[3]We downloaded data from `https://github.com/LarremoreLab/us-faculty-hiring-networks`. Accessed January 17, 2025.

data cleaning process, which we summarize in the Data Appendix (and which is outlined in more detail in the Methods section of their paper). Several technical aspects of our data are worth highlighting. First, our unit of observation is the individual-field. This is because WZCL allowed a person to appear in multiple fields; for instance, someone in a department of economics and finance would appear in both fields. Second, a field-job contains all relevant departments. For instance, if a university contained both a department of economics and a department of business economics, then faculty from each would be grouped together. Third, these data include only those with a PhD (excluding those whose highest degree is, for example, a Master's). Finally, the data do not always include information on faculty in all fields that a given university has.[4] This is due to combination of AARC not collecting data on all fields and due to other university-fields being dropped in the preprocessing steps used to create the WZCL sample.

3.2 Job and PhD Ranking Metrics

For our primary ranking metric, we use SpringRank.[5] The data contain two versions: the raw SpringRank variable and an ordinal rank of SpringRank; we use the latter. We reverse the ranking of ordinal SpringRank such that higher numbers are better (more prestigious) and call it 'SpringRank,' which ranges from 1 to N, where N is the highest number within a field, noting that the N varies widely across fields, as depicted in Appendix Figure A.4. We also construct 'SpringRank (normalized to 0-100 within field)' by scaling 'SpringRank' by the number of ranked schools, N, which ranges from 0 to 100 in each field regardless of the field's size. This formulation has the advantage of placing all fields on a common scale, which is especially useful for graphing. We match the job (university) and PhD for each faculty member to SpringRank. We refer to a job's SpringRank as 'job rank' and a PhD's SpringRank as 'PhD rank.'

[4]For instance, Boise State University has only three fields.

[5]For this variable and the PhD production rank variable (discussed later), we use an updated version provided to us directly by Daniel Larremore.

We use two additional measures of prestige: PhD production and undergraduate acceptance. Production is an ordinal ranking of how many PhDs a given university-field produced that are among the faculty-field pairs in the sample. In addition, we use the undergraduate acceptance rate at the university.[6] We convert this to an ordinal rank and do so within field, using only the universities that appear in the final sample.[7]

In Appendix Tables A.1, A.2, and A.3, we present examples for three disciplines—economics, history, and computer science—of the top 30 ranked SpringRank universities. For comparison, we include the PhD production rank, the USNWR rank (which we have for only these three disciplines), and the undergraduate acceptance rate. For ease of interpretation, we present the rankings such that 1 is the top-ranked school, and we use the raw undergraduate acceptance rate.

3.3 Salary Data

We use salary data from IPEDS. A main limitation of our paper is that because we do not have individual-level faculty salary data, we rely on average salary data at the university level (i.e., the data are not reported separately by field). We use the average salary for assistant professors for the 2020-2021 school year. We test robustness by using the average salary for associate professors, also for 2020-2021.

3.4 Sample Selections and Summary Statistics

We exclude observations that are missing data on salary, school rank, and/or PhD rank. We are unable to match a small number of schools to the average salary data in IPEDS. As stated above, we rely on the same SpringRank ranking for a given school, whether it serves as the faculty member's current job or school at which they received

[6] We access the variables in IPEDS used to construct this variable, as well as various other variables such as salary data, using the educationdata Stata package (Urban Institute, 2024).

[7] Thus, the N for this variable is the same as the number of universities (jobs) or PhD universities in the field as opposed to the number of universities in the raw acceptance rate data.

their PhD. This means that some individuals will be missing either their job rank and/or PhD rank. We find that 1.4% of individuals are missing average salary, .01% are missing school rank, and 29.1% are missing PhD rank. As Appendix Table A.4 shows, we begin with 317,009 observations; after sequentially dropping those missing salary data and school ranking, our sample falls to 312,426 and 312,391 observations, respectively. When we drop those missing PhD rank because the PhD is clearly not in the US, the sample falls to 275,487 observations. Finally, the sample falls to 221,199 observations after we drop remaining individuals who are missing PhD rank. In this last step, many are dropped because the faculty member works in a given field, but the school at which he/she received his/her PhD does not appear in our sample as having a program in this same same field, leading to the PhD school not receiving a rank in this field. For example, we drop 259 observations of faculty who work in the field of computer engineering, but who received their PhD at MIT. MIT is not, in the data, ranked in computer engineering. It is likely that many of these students instead obtained their PhD in a related field at MIT, such as computer science.[8] Appendix Table A.5 lists the number of observations for each academic field after sample selection.[9] We show the number of fields per school in Appendix Figure A.5.

4 Results

In Table 1, we compare naive regressions to the anti-IV approach. We begin by regressing income on job rank in Column 1 of Table 1. Contrary to what theory would predict, we find a positive coefficient, which suggests that faculty accept $193 to go to a

[8]The next most common PhD-fields that are missing PhD rankings (with N in parentheses) are: Stanford-Computer Engineering (218); Berkeley-Computer Engineering (210); Cornell-Biological Sciences (179); Berkeley-Biochemistry (176); Wisconsin-Biological Sciences (161); Michigan-Biological Sciences (151); UC Davis-Biological Sciences (146); Michigan-Management (127); MIT-Biochemistry (124); MIT-Business Administration (120); Chicago-Finance (120).

[9]The fields are grouped into domains, following WZCL.

one higher-ranked job.[10] In Column 2, we control for PhD rank. Doing so decreases the coefficient on job rank slightly, but it remains positive.[11] We then implement the anti-IV approach, using PhD rank as the anti-instrument.[12] In Column 3, we find a trade-off of $1,668 to move to a school ranked one rank higher.

To help visualize the result, we proceed to conduct a nonparametric analysis in Figure 3, which shows the nonparametric analogue of our preferred specification. Within quantile bins of salary and rank (constructed within field), we calculate the mean PhD rank (using the normalized within field version), the levels of which are depicted by different colors. The result is a downward-sloping relationship between salary and school rank, revealing that the market imposes a tradeoff between these two forms of compensation. However, we do find some evidence that the price of prestige is higher at more elite universities. Panel A of Appendix Table A.8 reports this result in regression format. In particular, we estimate a trade-off of -$1,318 at below median (less prestigious) universities, compared to -$2,144 at above median universities. When we split by quartile, we find a much larger trade-off for the fourth (most prestigious) quartile than the second and third quartiles.[13] However, we also find a larger trade-off for the first quartile than for the second and third quartiles, which is in contrast to our prior.

4.1 Robustness and Evaluation of Alternative Explanations

We test robustness in several different ways. First, in Appendix Table A.9, we collapse the data to the field-school level. We find similar results (noting that the drop-off in the

[10] Column 1 of Appendix Table A.6 shows this same regression using the full sample, excluding only observations missing salary and job rank, but including those missing PhD rank. The estimate, $200, is similar to the baseline estimate of $193 (Column 2).

[11] In Appendix Table A.7, we present versions of Columns 1 and 2 using different measures of job rank. Coefficients in the analogues to Column 1 (2) range from $175 to $330 ($155 to $313).

[12] To do so, we use the `aivreg` Stata package, available at https://github.com/ZhongShusheng/aivreg_stata_package.

[13] We construct the quartiles in sample. If we create the quartiles out of sample (which leads to the fewest (most) observations in the first (fourth) quartile, before constructing the sample, we obtain estimates of -$3,676 for the first quartile, and -$1,194, -$1,192, and -$3,023 for the second, third, and fourth quartiles, respectively.

school rank coefficient between Columns 1 and 2 is larger than in Table 1).

Second, we investigate whether residential amenities confound our estimation of the pay-prestige tradeoff (as might arise, for instance, in a Rosen-Roback model). In Table 2, we present the results, with Column 1 reproducing our baseline estimate for comparison. In column 2, we add several amenities: mean January temperature, public school rankings, urbanicity (all corresponding to the county of the university, borrowing from the geographic amenities collected by Bell et al. (2024)), and the Carnegie ranking of the university.[14] We find a large coefficient on urbanicity (which ranges between 4 and 12, with larger numbers being more urban), indicating a strong preference to live in cities. We find a positive coefficient for January temperature (standardized, where higher is warmer) and for Carnegie rank, both of which are contrary to our expectation, though understanding how geographic amenities are priced is beyond the scope of this paper. In column 3, we add county PageRank (standardized, also from Bell et al. (2024)), a proxy for how desirable a county is. Importantly to the results of this paper, the coefficient on job rank is robust to the addition of these additional geographic control variables. In addition, we probe the robustness of our baseline specification to adjusting the salary measure for cost of living at the county-level U.S. Department of Commerce (2024).[15] In Appendix Table A.10, we find that if anything, this magnifies our baseline results; the coefficient (in Column 2) rises by about 50%. We therefore conclude that, to the extent that geographic amenities may also influence professors' job searches, prestige still remains a strong and significant independent channel.

Third, we compare our baseline assistant professor salary measure to using associate professor salary in Appendix Table A.11. Results are similar, with a somewhat larger

[14]We use the 2018 Carnegie classification (observed in the 2020-21 IPEDS directory file), and code this variable as follows: 6: Doctoral universities: Very high research activity; 5: Doctoral universities: High research activity; 4: Doctoral/professional universities; 3: Master's colleges & universities: Large programs, Master's colleges & universities: Medium programs, or Master's colleges & universities: Small programs; 2: Baccalaureate colleges: Arts & sciences focus or Baccalaureate colleges: Diverse fields; 1) Baccalaureate/associate's colleges: Mixed baccalaureate/associate's.

[15]McMahon (2024) describes this data.

estimate when using associate professor salary of -$1,875 in Column 2 compared to the baseline estimate of -$1,668 in Column 1.

Fourth, in Table 3 we probe robustness of our preferred specification to different choices of anti-instruments as an intuitive test of over-identification. Reassuringly, all anti-instruments that we investigate yield a negative sign, indicating (in contrast to hedonic approaches) that a trade-off exists between pay and prestige. The exact magnitude changes somewhat between -$800 to -$1,700 in the first three columns, which use different parameterizations of PhD rank as measured by SpringRank or the number of PhD's produced in the PhD-granting institution.[16] While the signs of all estimates align with theoretical expectations, the trade-off appears notably smaller when using the undergraduate acceptance rate of the PhD-granting institution as the anti-instrument. Appendix Figure A.6 shows the non-parametric version, with a noticeably flatter slope. We suspect this occurs because undergraduate acceptance rates are not perfect anti-instruments for PhD rank, but may instead be contaminated by preferences for pay vs prestige themselves. Notably, as shown in Appendix Tables A.1–A.3, schools with higher acceptance rates (relative to other prestige measures) tend to be state schools. Since state schools typically charge lower tuition, they may attract students who prioritize financial considerations over prestige. Following Bell (2020), the bias in our second-stage estimate corresponds to the coefficient in a hypothetical regression of salary on the undergraduate acceptance rate of one's PhD-granting school, controlling for true PhD program rank. Given that state schools tend to have both higher acceptance rates and graduates more focused on salary over prestige, this coefficient is likely positive. Thus, it is unsurprising that this specification yields a more positive estimate. For this reason, we mainly stick to our preferred specification using SpringRank as the anti-instrument, but still include undergraduate acceptance rates as a reasonable alternative one might a priori consider as relevant. Fifth, Table 4 evaluates ro-

[16] Appendix Table A.16 shows the version where we use SpringRank (normalized to 0–100 within field) as the measure of job rank. The magnitude of the second column is larger compared to the second column of Table 3.

bustness of our estimates to how we measure the prestige amenity. We consider prestige as measured by SpringRank, ProductionRank, or undergraduate acceptance rates. There is variation in the estimated tradeoff depending on which prestige measure we use, although all prestige measures consistently reveal trade-offs associated with them when priced using the anti-IV framework. Sixth, we test robustness to using an alternate measure of job rank and PhD ranking: the 2010 National Research Council (NRC) doctoral program ranking; the data are in regards to the 2005-06 academic year, which predates our sample period. In Table 5, we consider the fields that appear in both datasets. We show results using both the NRC survey-based rankings and the NRC regression-based rankings. The survey-based rankings are obtained by asking faculty in a field about the importance of each of 20 factors[17] in the ranking of departments. The responses are translated into weights, which are then used in regressions to determine rankings. For the regression-based rankings, faculty in a field are presented with a list of 15 departments, with their characteristics and rank them. Weights are inferred based on these rankings and then applied to the entire set of departments in the field in order to obtain rankings.[18] To increase comparability, we include only individuals for whom we observe both SpringRank and NRC and re-rank each variable such that the maximum number of universities (N) for a given ranking (SpringRank and NRC) is the same for job rank as well as for PhD rank. We then vary the measure of job rank and the anti-instrument. When we use NRC rank as the measure of job rank, we find estimates that are on the order of -$550 to -$1100, which are negative, but smaller in magnitude that our main estimates.

We conduct a similar exercise in Table A.12 using three fields—economics, history, and computer science—for which we have US News & World Report data.[19] We find

[17]These include characteristics of faculty, such as publications; characteristics of students, such as median GRE scores of entering students; and program characteristics, such as average number of graduates over the last five years).

[18]Ostriker et al. (2011) provides details used in this paragraph. Additional statistical techniques are applied to account for uncertainty, etc. The data are presented at the 5th and 95th percentile ranges. We take the mean value and then rank them. We provide additional data cleaning details in the Data Appendix.

[19]Clauset et al. (2015) collected the USNWR data for history and computer science, and Jones and Sloan (2024) collected the USNWR data for economics. We do not consider departments that USNWR classifies

that the results are similar for each of the four combinations of job rank variable and AIV variable.[20]

Sixth, we test the hypothesis that the results of our analysis are driven by differences in the field composition across schools. As stated above, we observe salary at the institution level, not the institution -by- field level. One might be concerned that the analysis is therefore confounded by the differences in the field mix of faculty.[21] We find if anything the opposite: That accounting for field differences across schools magnifies the results. To operationalize this, we replace average salary with residuals from a regression of average salary by bachelor's degree shares by field of study. We focus on the number of 2020–2021[22] Bachelor's degree recipients (using first major) by field of study using the 2-digit CIP code from the IPEDS Completions Survey. We take degree recipients to be a rough proxy for the number of faculty by field. This approach allows us to separate a university's average salary into an additively separable school component and a field component. We do this by regressing average salary on the share of Bachelor's degrees for each field code. We obtain the residuals and call this the school component. In Appendix Table A.14, we show the results, with Column 1 as the baseline as reference. In Column 2, we obtain the residuals after using all 1,738 universities with salary data and degree recipient data in the regression. The estimate, -$2,234 is larger in magnitude than the baseline. In Column 3, we do the same, but obtain the residuals using only the 321 uni-

at 'Unranked.'

[20]In Appendix Table A.15, we consider only economics and consider SpringRank, NRC (Survey), and NRC (Regression) measures of job rank, using SpringRank as the AIV in each case. Keeping in mind the small sample size, we find a statistically insignificant estimate for SpringRank, and negative, but smaller-in-magnitude estimates for the two different NRC variables. We do not show results using USNWR or REPEC rankings as no standard error is estimated.

[21]For instance, suppose that University 1 consists of 90% English professors and 10% accounting professors. University 2 consists of 10% English professors and 90% accounting professors. Assume that accounting professors get paid more than English professors. If both universities pay the same salary to their English professors and the same salary to their accounting professors, then the average salary that University 1 pays to all of their professors will be lower than that of University 2. To our knowledge, IPEDS does not report the share of faculty by field, but it does report the number of degree recipients by field in the Completions Survey. We considered using the fields in the WZCL data, but not all disciplines for a given school always appear in the data.

[22]We choose this academic year to be consistent with the academic year we use for our salary data, noting that the Covid pandemic may have affected the number of degree recipients.

versities[23] that appear in the estimating sample. Surprisingly, the estimate is even larger in magnitude (-$5,093), noting that the standard error is also an order of magnitude larger.

4.2 Heterogeneity

How does the price of prestige vary across disciplines? To explore this question, we separately consider the eight individual domains, Applied Sciences; Education; Engineering; Humanities; Mathematics and Computing; Medicine and Health; Natural Sciences; and Social Sciences.[24] We first subset to a given domain, and then conduct the anti-IV approach, using field fixed effects and clustering at the field-school level. In Panel A Figure 4, we present the results. Based on the size of the confidence intervals, many of the fields are indistinguishable from each other, the exception being that medicine and health does not overlap with several of the fields, and there is no overlap between applied sciences and natural sciences. We also present in Panel B the results when using job rank, normalized to 0–100 within field. There is more variation, though the interpretation of the coefficients is harder to compare across fields based on having differing numbers of jobs in the fields in each domain.

We repeat the above exercise in Figure 5, but instead subset to each individual field. We show the baseline results in Panel A and the results using the job rank normalized within field in Panel B. The samples are relatively small at this point, contributing to, in some cases, small partial F-statistics. As such, we present results only for those fields with a value of at least 10.[25] For the most part, in both panels, the fields are not statistically

[23] 20 out of the 341 schools in the sample do not have degree completion data. To give a sense of what the adjustment does, in Appendix Table A.13, we show the fifteen schools with the highest salary (Panel A), the fifteen highest residuals using the full sample of salary data to obtain the residuals (Panel B), and the fifteen schools with the highest residuals using only the estimating sample to obtain the residuals (Panel C).

[24] A mapping between domains and fields is found in The Data Appendix.

[25] We also truncate the lower bounds at -7,000 for the graph. We present a version of these figures in Appendix Figure A.7 that does not impose the partial F-statistic of 10 restriction, instead showing all fields for which a finite confidence interval was estimated; for ease of interpretability, we truncate the lower bounds for these plots at -10,000.

different from each other, limiting the conclusions we can make about individual fields.

5 Conclusion

This paper provides new evidence on the trade-off between salary and prestige in faculty job choices, using a novel anti-IV approach to correct for unobserved heterogeneity in offer sets. We find that faculty are willing to forgo on the order of $1,500 of earnings for the opportunity to work at a more prestigious institution. Our results challenge the assumption that salary is the dominant factor in academic job decisions and highlight the role of non-monetary job amenities in shaping career trajectories.

By leveraging anti-instruments, our methodology overcomes key limitations of standard hedonic regression approaches, offering a more robust estimate of compensating differentials in academia. While the results of stated choice surveys like that run by Janger and Nowotny (2016) have suggested that faculty value non-pecuniary aspects of their jobs, the extent to which markets prices these features has not previously been documented. This has broader implications for understanding labor market sorting in high-skilled professions, where prestige, mission alignment, or job security may be as valuable as pay.

Despite the strengths of our approach, some limitations remain. While our sample is very large, it covers only faculty members at U.S. PhD-granting institutions; we are further limited in that we can only consider a portion of these faculty based on needing to observe data on both a faculty member's job rank and PhD rank. Our reliance on university-level salary data constrains our ability to measure individual wage variation (and matching offers, etc.), and our model primarily focuses on pay and prestige, omitting other key job attributes. We prioritize prestige in our framework because it is an especially salient factor in academic job choice, often considered a central motivation for faculty decisions, and because its measurement benefits from greater consistency across

institutions. Future work could extend this framework by incorporating more detailed salary data, exploring alternative measures of prestige, and applying the anti-IV approach to other professional labor markets.

Overall, our findings contribute to a broader understanding of how highly skilled labor markets function, particularly in academia, where non-monetary job attributes play a significant role in career decisions. Researchers often prioritize factors such as research autonomy and mission alignment, willingly accepting lower salaries in exchange for positions that offer greater academic freedom and prestige. By refining estimates of the pay-prestige tradeoff, this paper provides new evidence for how preferences for institutional prestige and career incentives shape labor market outcomes across different high-skilled professions. More directly, our estimates will be useful for universities wishing to tailor their recruitment and retention incentives by understanding the prices the academic labor market imposes on prestige.

The results also have implications for tax policy, particularly as it relates to tax competition across government entities. For instance, while Akcigit et al. (2016) find that "superstar" inventors are highly mobile and exhibit large migration responses to changes in top income tax rates, our results suggest that among academic-affiliated researchers, university prestige may be an often-overlooked mechanism of job location decisions that is unaffected by top income tax rates.

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Table 1: Comparison of Naive and AIV Approaches

	(1)	(2)	(3)
Job Rank	192.58***	182.60***	-1668.31***
	(3.67)	(3.67)	(86.03)
PhD Rank		34.23***	
		(1.63)	
Constant	73841.14***	70475.02***	
	(300.03)	(338.90)	
Observations	222199	222199	222199
AIV	No	No	PhD Rank

Notes: Column 1 shows a regression of average salary on job rank, measured by the department's SpringRank, where higher numbers indicate more prestige. Column 2 adds PhD rank, defined as the SpringRank of the faculty's PhD-granting school. Column 3 regresses average salary on job rank, with PhD rank as the anti-instrument. All regressions include field fixed effects. We cluster at the school-field level for all columns and use Anderson-Rubin standard errors for column 3. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table 2: Adding Additional Amenities

	(1)	(2)	(3)
Job Rank	-1668.31***	-1408.62***	-1727.55***
	(86.03)	(75.52)	(94.07)
Mean January Temperature		3121.77***	
		(607.07)	
Public School Ranking		-1939.11***	
		(645.14)	
Urbanicity		-2451.72***	
		(370.90)	
County PageRank			-602.16***
			(202.39)
Observations	222199	198871	222199

Notes: Each column includes a regression of average salary on job rank, measured by the department's SpringRank, where higher numbers indicate more prestige, with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-IV. Column 2 also includes mean January temperature, public school ranking, urbanicity (all at the county-level), and Carnegie classification for the job. Column 3 instead adds the county's PageRank control as a summary measure of place rank (Bell et al., 2024). All regressions include field fixed effects. We cluster at the school-field level and use Anderson-Rubin standard errors. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table 3: Comparison of Different Anti-IV Variables

	(1)	(2)	(3)	(4)
Job Rank	-1668.31***	-810.24***	-1710.71***	-456.89***
	(86.03)	(42.69)	(109.50)	(20.82)
Observations	222199	222199	222199	222199
AIV	PhD Rank	PhD Rank (Normalized within Field)	Production	UG Acceptance at PhD
Mean of AIV	123.6	78.6	107.6	83.5
SD of AIV	66.0	21.3	53.0	53.1

Notes: This table shows a regression of average salary on job rank (SpringRank). We vary the anti-IV we use across columns: we use PhD rank (SpringRank of the faculty's PhD-granting school) in column 1, PhD rank (SpringRank, normalized to 0–100 within each field) in column 2, PhD production (ranking of the number of PhDs one's PhD school produced that are in the sample) in column 3, and the rank of the undergraduate acceptance rate at one's PhD school in column 4. The means and standard deviations of the anti-IVs are presented at the bottom of the the tables. All regressions include field fixed effects. We cluster at the school-field level and use Anderson-Rubin standard errors. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table 4: Comparison of Different Measures of Prestige

	(1)	(2)	(3)	(4)
Job Rank	-1668.31***			
	(86.03)			
Job Rank (Normalized within Field)		-2009.62***		
		(101.75)		
PhD Production at Job			-392.74***	
			(19.66)	
Rank of UG Acceptance Rate at Job				-159.01***
				(16.69)
Observations	222199	222199	222199	222199
Mean of Job Rank Variable	86.7	54.9	75.2	75.7
SD of Job Rank Variable	61.7	28.1	52.8	56.4

Notes: This table shows a regression of average salary on job rank, with PhD rank (SpringRank of the PhD-granting school) as the anti-instrument. It varies the definition of job rank, with our preferred measure (SpringRank) in column A, SpringRank normalized to 0–100 within each field in column B, the PhD production (ranking of the number of PhDs one's PhD-granting school produced that are in the sample) in column 3, and the undergraduate acceptance rate at the job in column 4. All regressions include field fixed effects. The mean and standard deviation of the relevant measure of job rank are presented at the bottom of the table. We cluster at the school-field level for all columns and use Anderson-Rubin standard errors for column 3. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table 5: Comparison of SpringRank and NRC Rankings

Panel A: NRC (Survey-based Ranking)

	(1)	(2)	(3)	(4)
Job Rank	-2763.78***	-1923.02***		
	(249.65)	(178.48)		
NRC			-550.19***	-863.42***
			(40.34)	(59.39)
Observations	91624	91624	91624	91624
AIV	SpringRank	NRC	SpringRank	NRC

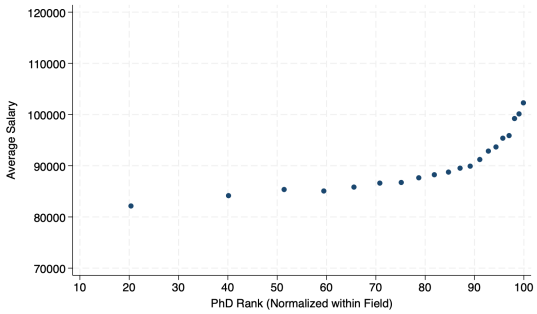
Panel B: NRC (Regression-based Ranking)

	(1)	(2)	(3)	(4)
Job Rank	-2763.78***	-2347.56***		
	(249.65)	(230.91)		
NRC			-750.47***	-1126.12***
			(50.36)	(79.41)
Observations	91624	91624	91624	91624
AIV	SpringRank	NRC	SpringRank	NRC

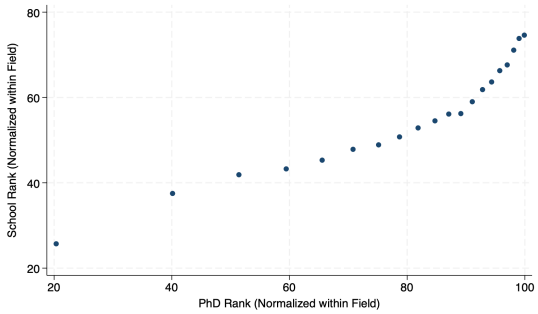
Notes: This table shows a regression of average salary on job rank, with PhD rank as the anti-instrument. The measure of job rank is our preferred measure: SpringRank in columns 1 and 2, and NRC in columns 3 and 4. We vary the anti-IVs, with PhD rank defined as SpringRank of the faculty's PhD-granting school in columns 1 and 3, and as the NRC rank of the faculty's PhD-granting school in columns 2 and 4. To increase comparability across datasets, we use only observations that have non-missing observations for each of the variables mentioned above. We also re-rank each variable so that N is the same for SpringRank and NRC, separately for job rank rank and AIV rank. Panel A (Measure 1) shows the survey-basd NRC rankings, while Panel B (Measure 2) shows the regression-based NRC rankings. All regressions include field fixed effects. We cluster at the school-field level and use Anderson-Rubin standard errors. Standard error in parentheses. * 0.10; ** 0.05; *** 0.01.

Figure 1: Binscatters of Salary, Job Rank, and PhD Rank

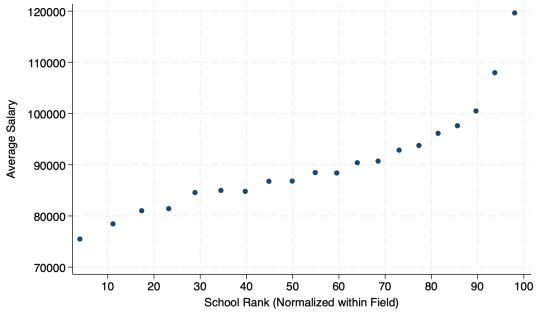
(a) Salary on PhD Rank



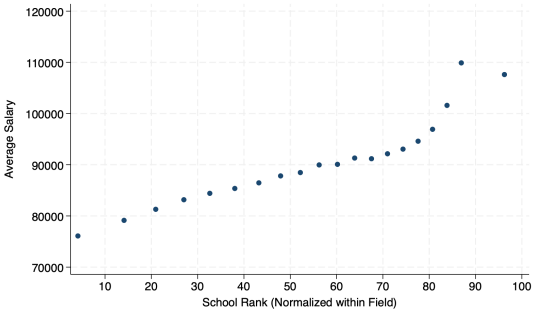
(b) Job Rank on PhD Rank



(c) Salary on Job Rank

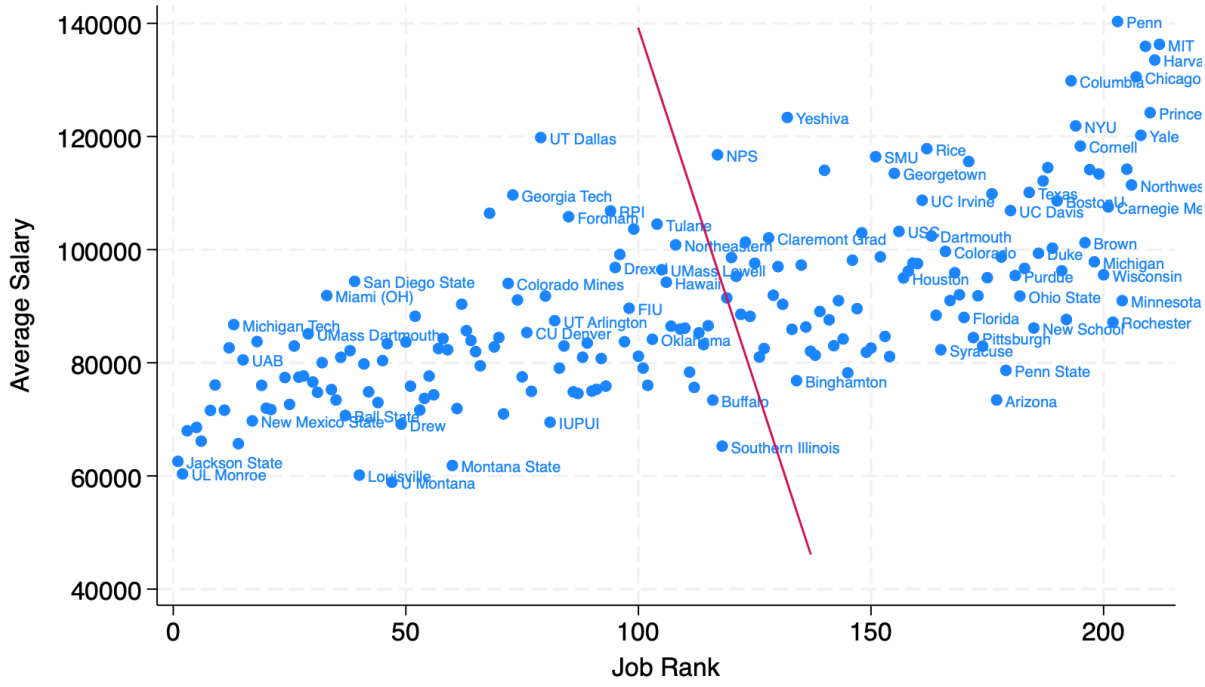


(d) Salary on Job Rank, Residualize on PhD Rank



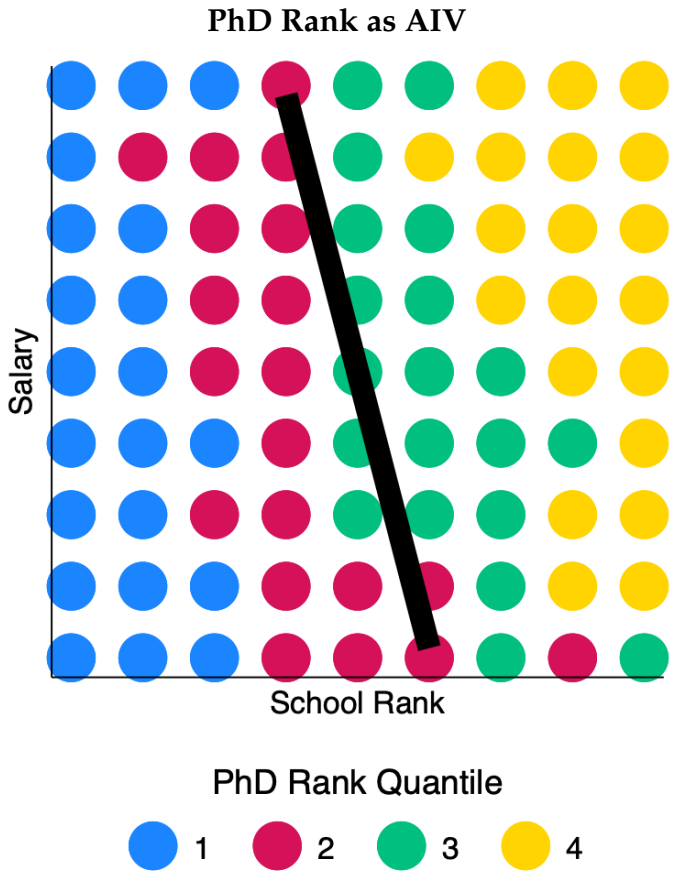
Notes: Each panel includes a binscatter: Panel A) average salary on PhD rank (SpringRank of the school where the faculty obtained their PhD); Panel B) job rank (SpringRank) on PhD rank (SpringRank of the PhD-granting school); Panel C) average salary on job rank (SpringRank); and Panel D) average salary on job rank (SpringRank), residualizing on PhD rank (SpringRank of PhD-granting school). For this figure, all measures of SpringRank are normalized 0-100 within field.

Figure 2: Illustration of Approach, Economics



Notes: This graph plots average salary versus job rank for economics. Each dot corresponds to a university. Some labels are omitted to decrease the degree of overlapping labels. The slope of the red line is obtained from the AIV approach, limited to economics. In particular, it is obtained after regressing average salary on job rank (SpringRank of the employer), with PhD rank (SpringRank of the employee's PhD-granting school) as the anti-instrument. However, we note that this estimate is statistically insignificant.

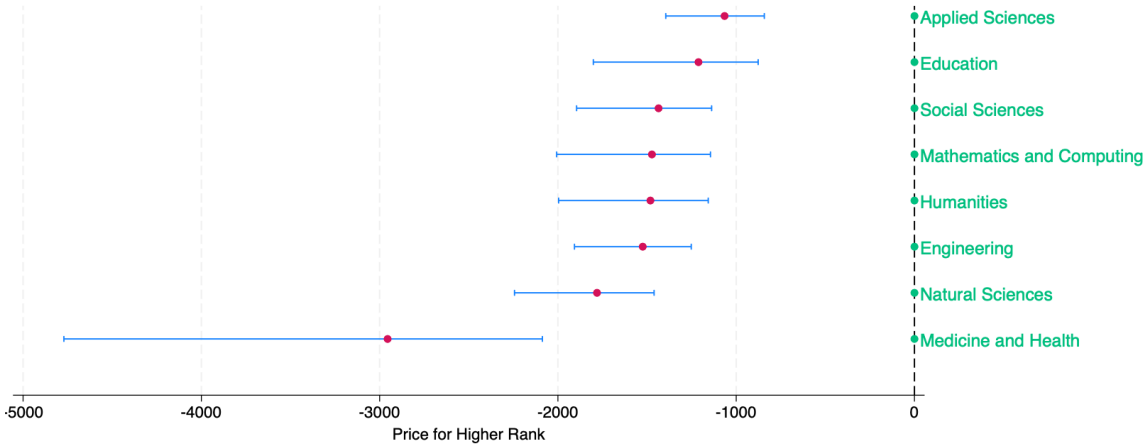
Figure 3: Nonparametric



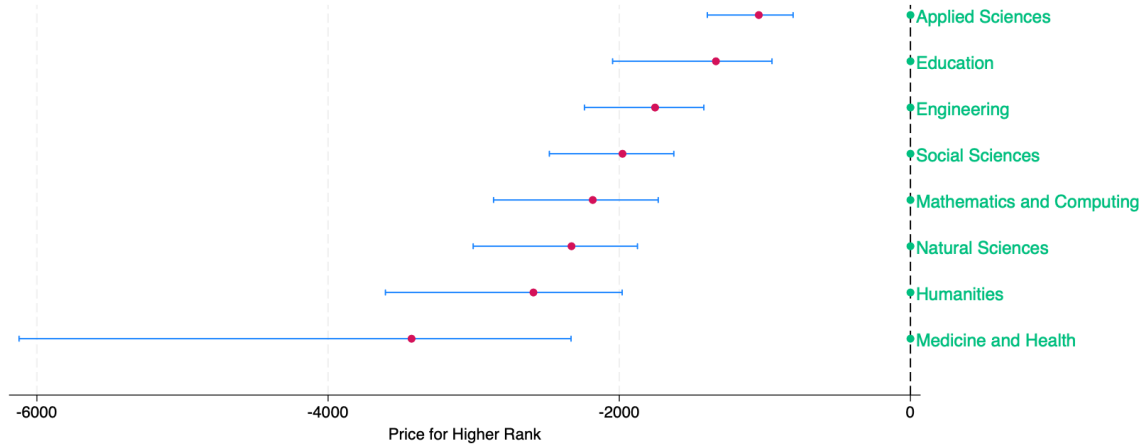
Notes: To create this figure, we take the following steps: 1) Within field, create quantiles of job rank (SpringRank of the faculty's job) and PhD rank (SpringRank of the faculty's PhD-granting school). 2) Collapse the data to the average salary quantile -by- job rank quantile level, computing means for average salary, job rank, and PhD rank (the version that is normalized to 0–100 within field). 3) Create quantiles (4 categories) of PhD rank. 5) Graph, where we assign each average salary quantile -by- job rank quantile level to its corresponding PhD rank quantile, shading them blue, red, green, and yellow, from lowest to highest. Finally, we show a line obtained from a applying the anti-IV method to the data (after constructing the quantiles, not the raw data)

Figure 4: By Domain

Panel A: SpringRank



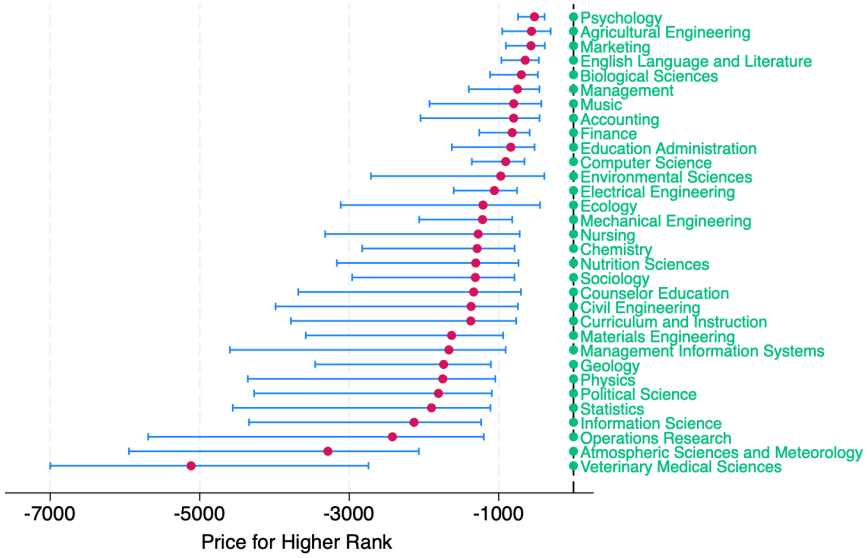
Panel B: SpringRank, Normalized to 0–100 Within Field



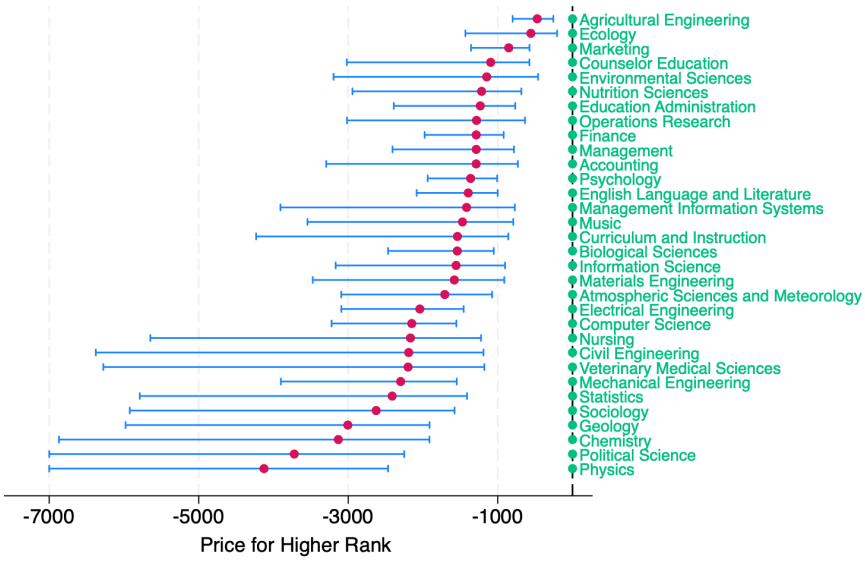
Notes: For each domain, we subset to fields within that domain and use the anti-IV approach of average salary on job rank (SpringRank), with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-instrument. In Panel A (B), we use baseline SpringRank (SpringRank, normalized within field to 0–100) as our measure of job rank. We cluster at the field-school level and use Anderson-Rubin standard errors. The dots are the point estimates, with the blue lines representing the confidence intervals.

Figure 5: By Field

Panel A: SpringRank



Panel B: SpringRank, normalized to 0–100 within each field



Notes: For each field, we subset to that field and use the anti-IV approach of average salary on job rank, with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-instrument. In Panel A (B), we use baseline SpringRank (SpringRank, normalized to 0–100 within each field) as our measure of job rank. The dots are the point estimates, with the blue lines representing the confidence intervals. We present only fields that have a partial F statistic of at least 10. We also truncate confidence intervals at -7,000 where applicable.

A Appendix Figures and Tables

Table A.1: Comparison of Measures of Prestige, Economics

	Spring	Production	USNWR	Accept Rate
Massachusetts Institute of Technology	1	2	1	7.3
Harvard University	2	1	1	5.0
Princeton University	3	7	1	5.6
Stanford University	4	5	1	5.2
Yale University	5	6	1	6.5
University of Chicago	6	3	7	7.3
Northwestern University	7	7	7	9.3
University of California-Berkeley	8	4	1	17.5
University of Minnesota-Twin Cities	9	11	16	69.6
University of Pennsylvania	10	10	10	9.0
University of Rochester	11	18	21	35.4
Carnegie Mellon University	12	37	20	17.3
University of Wisconsin-Madison	13	9	12	57.2
University of California-Los Angeles	14	14	12	14.3
University of Michigan-Ann Arbor	15	11	12	26.1
University of California-San Diego	16	22	12	36.6
Brown University	17	28	19	7.7
Cornell University	18	13	16	10.7
New York University	19	21	11	21.1
Columbia University in the City of New York	20	15	9	6.7
University of Iowa	21	36	42	84.3
University of Illinois Urbana-Champaign	22	17	29	63.3
Boston University	23	42	23	20.1
University of Maryland-College Park	24	24	21	51.0
Washington University in St Louis	25	34	27	16.0
Johns Hopkins University	26	35	23	11.1
Duke University	27	16	16	7.7
The New School	28	65		69.1
The University of Texas at Austin	29	23	27	32.0
University of Virginia-Main Campus	30	30	29	22.6

Notes: This table compares measures of prestige for 30 top-ranked universities in economics. It is sorted by SpringRank, and the top 30 universities along this measure are included. We also present US News & World Report rankings, PhD production rankings (how many PhDs a university produced in the sample that are in economics), and the undergraduate acceptance rate (which has not been converted to a rank in this table). One school in the list is not ranked in the USNWR rankings.

Table A.2: Comparison of Measures of Prestige, History

	Spring	Production	USNWR	Accept Rate
Harvard University	1	1	5	5.0
Stanford University	2	10	1	5.2
University of California-Berkeley	3	3	1	17.5
Yale University	4	2	1	6.5
Columbia University in the City of New York	5	4	7	6.7
Princeton University	6	6	1	5.6
University of Chicago	7	5	5	7.3
University of Michigan-Ann Arbor	8	8	7	26.1
Brandeis University	9	31	36	33.4
University of Pennsylvania	10	11	9	9.0
Johns Hopkins University	11	12	9	11.1
University of Wisconsin-Madison	12	7	14	57.2
University of California-Los Angeles	13	9	9	14.3
New York University	14	14	17	21.1
Brown University	15	21	17	7.7
Northwestern University	16	20	14	9.3
Cornell University	17	16	12	10.7
Massachusetts Institute of Technology	18	47	28	7.3
University of North Carolina at Chapel Hill	19	17	12	25.0
University of Minnesota-Twin Cities	20	23	24	69.6
University of Rochester	21	39	64	35.4
University of California-San Diego	22	28	33	36.6
Rutgers University-New Brunswick	23	19	20	66.9
University of Virginia-Main Campus	24	15	20	22.6
University of Washington-Seattle Campus	25	30	26	55.9
The University of Texas at Austin	26	13	17	32.0
University of Illinois Urbana-Champaign	27	25	22	63.3
Georgetown University	28	35	36	16.8
University of California-Davis	29	36	28	46.4
Indiana University-Bloomington	30	18	22	80.4

Notes: This table compares measures of prestige for 30 top-ranked universities in history. It is sorted by SpringRank, and the top 30 universities along this measure are included. We also present US News & World Report rankings, PhD production rankings (how many PhDs a university produced in the sample that are in history), and the undergraduate acceptance rate (which has not been converted to a rank in this table).

Table A.3: Comparison of Measures of Prestige, Computer Science

	Spring	Production	USNWR	Accept Rate
Stanford University	1	4	1	5.2
Massachusetts Institute of Technology	2	1	1	7.3
University of California-Berkeley	3	2	1	17.5
Carnegie Mellon University	4	5	1	17.3
Harvard University	5	17	17	5.0
California Institute of Technology	6	39	11	6.7
Cornell University	7	9	5	10.7
Princeton University	8	10	8	5.6
University of California-Los Angeles	9	14	14	14.3
The University of Texas at Austin	10	8	8	32.0
University of Illinois Urbana-Champaign	11	3	5	63.3
University of Wisconsin-Madison	12	15	11	57.2
University of Pennsylvania	13	13	17	9.0
University of Washington-Seattle Campus	14	16	7	55.9
University of Rochester	15	55	47	35.4
Yale University	16	37	20	6.5
Rice University	17	39	20	10.9
Georgia Institute of Technology-Main Campus	18	7	10	21.3
Columbia University in the City of New York	19	24	17	6.7
Brown University	20	30	20	7.7
University of Michigan-Ann Arbor	21	11	13	26.1
University of Maryland-College Park	22	12	14	51.0
University of Cincinnati-Main Campus	23	82	99	76.4
University of California-San Diego	24	26	14	36.6
University of Massachusetts-Amherst	25	18	20	65.3
University of North Carolina at Chapel Hill	26	23	20	25.0
University of California-Santa Barbara	27	26	35	36.7
Johns Hopkins University	28	50	28	11.1
University of Minnesota-Twin Cities	29	20	35	69.6
Duke University	30	50	27	7.7

Notes: This table compares measures of prestige for 30 top-ranked universities in computer science. It is sorted by SpringRank, and the top 30 universities along this measure are included. We also present US News & World Report rankings, PhD production rankings (how many PhDs a university produced in the sample that are in computer science), and the undergraduate acceptance rate (which has not been converted to a rank in this table).

Table A.4: Sample Restrictions

Step	N Dropped	N Remaining
Full sample	-	317,009
Drop if missing salary	4,583	312,426
Drop if missing job rank	35	312,391
Drop if PhD not clearly in the US	36,904	275,487
Drop remainder missing PhD rank	53,288	222,199

Notes: This table shows how many observations are dropped during ours sample restrictions. The first row shows the full sample, before restrictions. The 'N Dropped' column shows how many observations are dropped at each step, and the 'N Remaining' column shows how many observations are remaining.

Table A.5: Observations by Field

Applied Sciences	
Urban and Regional Planning	745
Agronomy	739
Horticulture	596
Management Information Systems	887
Accounting	2221
Soil Science	745
Finance	2041
Management	4017
Architecture	853
Marketing	1859
Business Administration	1219
Food Science	947
Animal Sciences	1590
Education	
Curriculum and Instruction	2458
Special Education	779
Education Administration	2328
Education	1535
Counselor Education	868
Engineering	
Electrical Engineering	6133
Chemical Engineering	2533
Civil Engineering	3775
Operations Research	556
Industrial Engineering	1214
Materials Engineering	1737
Aerospace Engineering	1668
Mechanical Engineering	5255
Agricultural Engineering	1811
Biomedical Engineering	1501
Environmental Engineering	2907
Systems Engineering	636
Humanities	
Near and Middle Eastern Languages and Cultures	392
French Language and Literature	512
Germanic Languages and Literatures	566
Theatre Literature, History and Criticism	499
Religious Studies	1243
Classics and Classical Languages	1290
Asian Studies	645
Art History and Criticism	1446
Slavic Languages and Literatures	413
English Language and Literature	7364
History	6559
Music	3865
Linguistics	960
Spanish Language and Literature	787
Asian Languages	465
Philosophy	3138
Theological Studies	1171
Comparative Literature	467
Mathematics and Computing	
Computer Engineering	4179
Information Science	958
Information Technology	564
Mathematics	6985
Statistics	2411
Computer Science	6799

Medicine and Health	
Pharmaceutical Sciences	1043
Epidemiology	1781
Communication Disorders and Sciences	665
Nursing	5542
Pathology	2982
Anatomy	652
Human Development and Family Sciences	1350
Physiology	1734
Pharmacology	1526
Health, Physical Education, Recreation	764
Environmental Health Sciences	568
Veterinary Medical Sciences	2519
Genetics	321
Immunology	1416
Exercise Science, Kinesiology, Rehab, Health	4062
Pharmacy	1268
Speech and Hearing Sciences	507
Public Health	3837
Natural Sciences	
Cell Biology	2111
Atmospheric Sciences and Meteorology	885
Biological Sciences	4943
Biophysics	386
Chemistry	5570
Entomology	792
Forestry and Forest Resources	854
Biostatistics	1361
Plant Sciences	738
Plant Pathology	754
Marine Sciences	605
Environmental Sciences	1715
Evolutionary Biology	425
Ecology	679
Physics	5654
Nutrition Sciences	1503
Microbiology	2442
Geology	3487
Astronomy	2093
Biochemistry	3850
Molecular Biology	1734
Natural Resources	918
Neuroscience	1582
Social Sciences	
Agricultural Economics	815
Anthropology	3485
Psychology	7978
Educational Psychology	1008
Gender Studies	355
International Affairs	502
Economics	5498
Political Science	5301
Social Work	2927
Sociology	4442
Criminal Justice and Criminology	858
Geography	1581

Notes: This table shows the number of observations by field, organized by domain.

Table A.6: Naive Regression, Full Sample and Estimating Sample

	(1)	(2)
Job Rank	199.98***	192.58***
	(3.69)	(3.67)
Constant	74576.61***	73841.14***
	(291.77)	(300.03)
Observations	312391	222199
AIV	No	No

Notes: Column 1 shows a regression of average salary on job rank (SpringRank) using the full sample (excluding only observations missing salary). Column 2 shows the same, but limits to the estimating sample, as in Column 1 of Table 1. All regressions include field fixed effects. We cluster at the school-field level. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table A.7: Comparison of Different Measures of Job Rank, Naive Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Job Rank	192.58***	182.60***						
	(3.67)	(3.67)						
Job Rank (Normalized within Field)			330.42***	312.88***				
			(5.86)	(5.76)				
PhD Production at Job					174.59***	155.03***		
					(4.38)	(4.20)		
Rank of UG Acceptance Rate at Job							205.67***	191.47***
							(3.92)	(3.78)
PhD Rank		34.23***		39.10***		87.60***		83.49***
		(1.63)		(1.83)		(2.44)		(2.73)
Constant	73841.14***	70475.02***	72378.41***	68507.64***	77401.95***	68043.26***	74967.21***	65719.84***
	(300.03)	(338.90)	(302.47)	(356.21)	(295.36)	(392.49)	(272.87)	(396.07)
Observations	222199	222199	222199	222199	222199	222199	222199	222199

Notes: This table varies the definition of job rank, with our preferred measure (SpringRank) in columns 1 and 2; SpringRank, normalized to 0–100 within each field in columns 3 and 4; PhD production (ranking of the number of PhDs one's employer produced that are in the sample) in columns 5 and 6; and the undergraduate acceptance rate at the job in columns 7 and 8. The odd-numbered columns show a regression of average salary on the relevant measure of job rank. The even-numbered columns add PhD rank (SpringRank of the faculty's PhD-granting school). All regressions include field fixed effects. We cluster at the school-field level for all columns. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table A.8: Below and Above Median, and Quartiles of Job Ranking

Panel A: Below (Less Prestigious) and Above Median

	(1)	(2)
Job Rank	-1317.77***	-2143.74***
	(102.45)	(159.52)
Observations	109471	112728
Sample	Below Median	Above Median

Panel B: Quartiles

	(1)	(2)	(3)	(4)
Job Rank	-2104.60***	-984.10***	-1354.96***	-4799.58***
	(260.48)	(131.66)	(145.82)	(706.65)
Observations	56954	55372	56063	53810
Quartile	1	2	3	4

Notes: This table shows a regression of average salary on job rank (SpringRank), with PhD rank (SpringRank of the PhD-granting school) as the anti-instrument. In Panel A, we split by being below or above the median quartile of job rank, where above is more prestigious. In Panel B, we run each quartile separately. Quartile 4 is the most prestigious. Column 1 (2) considers only professors in at or below (above) median ranked-jobs. Both columns regress average salary on job rank (SpringRank), with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-instrument. Both regressions include field fixed effects. We cluster at the school-field level for all columns and use Anderson-Rubin standard errors. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table A.9: Comparison of Naive and AIV Approaches, Data Are Collapsed

	(1)	(2)	(3)
Job Rank	197.88***	113.30***	-1787.47***
	(2.98)	(4.86)	(92.04)
PhD Rank		288.38***	
		(13.27)	
Constant	74537.94***	48515.28***	
	(216.85)	(1215.80)	
Observations	10280	10280	10280
AIV	No	No	PhD Rank

Notes: The data are collapsed to the school-field level. Column 1 shows a regression of average salary on job rank (SpringRank). Column 2 adds PhD rank (SpringRank of the faculty's PhD-granting school). Column 3 regresses average salary on job rank (SpringRank), with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-instrument. All regressions include field fixed effects and are unweighted. We cluster at the school-field level for all columns and use Anderson-Rubin standard errors for column 3. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table A.10: Using Cost of Living-Adjusted Average Salary

	(1)	(2)
	Avg. Salary	Avg. Salary Adjusted for Cost of Living
Job Rank	-1668.31***	-2652.93***
	(86.03)	(232.29)
Observations	222199	222199
AIV	PhD Rank	PhD Rank

Notes: Column 1 regresses average salary on job rank (SpringRank), with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-instrument. Column 2 does the same, but adjusts average salary for cost of living. Both regressions include field fixed effects. We cluster at the school-field level for all columns and use Anderson-Rubin standard errors for column 3. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table A.11: Using Associate Salary

	(1)	(2)
	Avg. Assistant Salary	Avg. Associate Salary
Job Rank	-1668.31***	-1875.22***
	(86.03)	(96.23)
Observations	222199	222199
AIV	PhD Rank	PhD Rank

Notes: Column 1 regresses average assistant professor salary on job rank (SpringRank), with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-instrument. Column 2 does the same, but instead uses average associate professor salary. We cluster at the school-field level for all columns and use Anderson-Rubin standard errors for column 3. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table A.12: Comparison of SpringRank and USNWR Rank for Three Fields

	(1)	(2)	(3)	(4)
Job Rank	-2063.89***	-1868.44***		
	(477.89)	(440.34)		
Job Rank, USNWR			-1816.67***	-2131.75***
			(440.19)	(578.83)
Observations	13861	13861	13861	13861
AIV	PhD Rank	USNWR Rank	PhD Rank	USNWR Rank

Notes: This table shows a regression of average salary on job rank (SpringRank), with PhD rank as the anti-instrument. The dependent variable in each column is average salary. The measure of job rank is our preferred measure (SpringRank) in columns 1 and 2, and USNWR rank in columns 3 and 4. We vary the anti-IVs, with PhD rank defined as SpringRank of the faculty's PhD-granting school in columns 1 and 3, and as USNWR rank of the faculty's PhD-granting school in columns 2 and 4. This table considers the fields of economics, history, and computer science. To increase comparability across datasets, we use only observations that have non-missing observations for each of the variables mentioned above. We also re-rank each variable within field so that they are on the same scale. All regressions include field fixed effects. We cluster at the school-field level and use Anderson-Rubin standard errors. Standard error in parentheses. * 0.10; ** 0.05; *** 0.01.

Table A.13: Highest Paying Schools and Schools with Highest Residuals

Panel A: Salaries

1	University of Pennsylvania	140320
2	California Institute of Technology	136444
3	Massachusetts Institute of Technology	136294
4	Stanford University	135936
5	Harvard University	133516
6	University of Chicago	130526
7	Columbia University	129837
8	Bentley University	128319
9	Princeton University	124204
10	Yeshiva University	123357
11	Stevens Institute of Technology	123329
12	New York University	121863
13	Yale University	120212
14	The University of Texas at Dallas	119802
15	Cornell University	118308

Panel B: Residuals based on full sample

1	Bentley University	67218.41
2	University of Pennsylvania	60069.52
3	Yeshiva University	56059.63
4	Jewish Theological Seminary of America	46997.78
5	The University of Texas at Dallas	44681.39
6	Princeton University	42260.80
7	New York University	41217.69
8	Stanford University	40203.11
9	Columbia University	38486.61
10	Rutgers University-Newark	38271.22
11	California Institute of Technology	36890.30
12	Rosalind Franklin University	36098.33
13	Boston College	35931.03
14	Cornell University	35247.82
15	Long Island University	34421.74

Panel C: Residuals based on estimating sample

1	University of Pennsylvania	38303.25
2	Yeshiva University	32800.01
3	Princeton University	27104.65
4	Bentley University	26089.07
5	New York University	25417.92
6	Stanford University	24492.17
7	Long Island University	22384.91
8	Boston College	19579.11
9	Columbia University	19439.57
10	Palo Alto University	18686.10
11	University of Arkansas for Medical Sciences	18525.00
12	Rutgers University-Newark	18426.81
13	Adelphi University	18004.02
14	Cornell University	17790.29
15	University of Virginia	17738.79

Notes: This table shows the fifteen schools with the highest average salary (Panel A), residuals based on the full sample (Panel B), and residuals based on the estimating sample (Panel C). To obtain the estimates in Panels B and C, we regress average salary on the share of bachelor degree recipients by field (two-digit CIP). In Panel B, we obtain the residuals after using all 1,738 universities with salary data and degree recipient data in the regression. In Panel C, we use only the 321 universities that have salary data and degree recipient data that also appear in the estimating sample.

Table A.14: Using 'School Portion' of Salary

	(1)	(2)	(3)
	Avg. Salary	School Component, Approach 1	School Component, Approach 2
Job Rank	-1668.31***	-2237.27***	-5093.20***
	(86.03)	(161.60)	(1071.74)
Observations	222199	219417	219417
AIV	PhD Rank	PhD Rank	PhD Rank

Notes: Column 1 regresses average salary on job rank (SpringRank), with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-instrument. Columns 2 and 3 do the same, but use the residual after regressing average salary on the share of bachelor degree recipients by field (two-digit CIP). In column 2 we obtain the residuals after using all 1,738 universities with salary data and degree recipient data in the regression. In column 3, we use only the 321 universities that have salary data and degree recipient data that also appear in the estimating sample. All regressions include field fixed effects. We cluster at the school-field level for all columns and use Anderson-Rubin standard errors for column 3. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Table A.15: Comparison of SpringRank and NRC for Economics

	(1)	(2)	(3)
Job Rank (Preferred)	-2509.10		
	(5591.44)		
NRC (Survey)		-301.89**	
		(148.04)	
NRC (Regression)			-788.24**
			(378.41)
Observations	5498	3460	3460

Notes: Column 1 regresses average salary on job rank (SpringRank), with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-instrument. Columns 2 and 3 do the same, but use NRC (Survey) and NRC (Regression) for the measure of job rank. We cluster at the school level for all columns and use Anderson-Rubin standard errors. We do not show results for the USNWR and REPEC rankings as no standard error is estimated. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

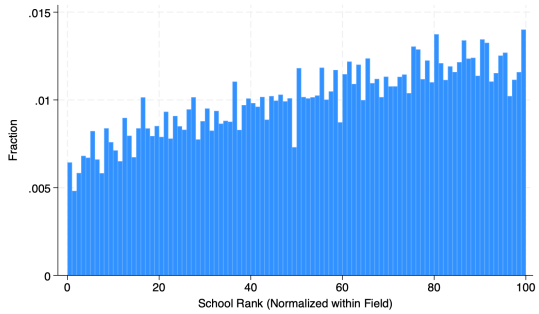
Table A.16: Comparison of Different Anti-IV Variables, Using SpringRank, Normalized Within Field

	(1)	(2)	(3)	(4)
Job Rank (Normalized within Field)	-2009.62***	-2638.42***	-1857.26***	-454.17***
	(101.75)	(152.67)	(113.70)	(22.58)
Observations	222199	222199	222199	222199
AIV	PhD Rank	PhD Rank (Normalized within Field)	Production	UG Acceptance
Mean of AIV	123.6	78.6	107.6	83.5
SD of AIV	66.0	21.3	53.0	53.1

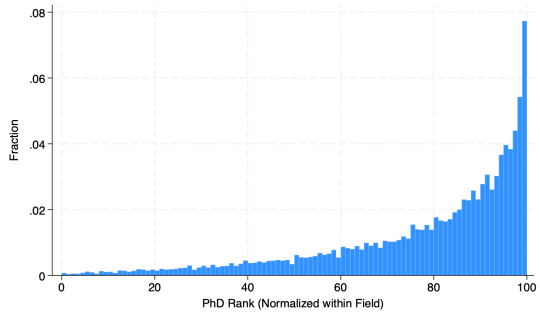
Notes: This table shows a regression of average salary on job rank, where we use SpringRank normalized to 0–100 within each field. We vary the anti-IV we use across columns: we use PhD rank (SpringRank of the faculty's PhD-granting school) in column 1, PhD rank (SpringRank of the faculty's PhD-granting school, normalized to 0–100 within each field) in column 2, PhD production (ranking of the number of PhDs one's PhD-granting school produced that are in the sample) in column 3, and the rank of the undergraduate acceptance rate at one's PhD-granting school in column 4. The means and standard deviations of the anti-IVs are presented at the bottom of the the tables. All regressions include field fixed effects. We cluster at the school-field level and use Anderson-Rubin standard errors. Standard errors in parentheses. * 0.10; ** 0.05; *** 0.01.

Figure A.1: Distribution of SpringRank for Job; SpringRank for PhD-granting School, and Undergraduate Acceptance Rate at PhD-granting School

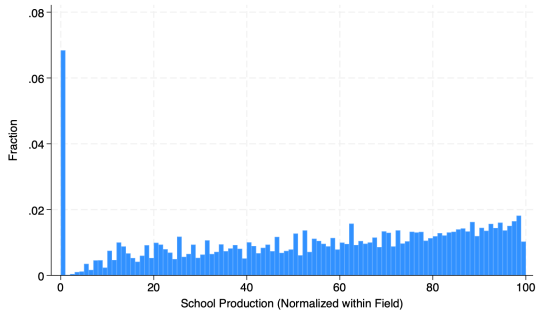
(a) Job Rank



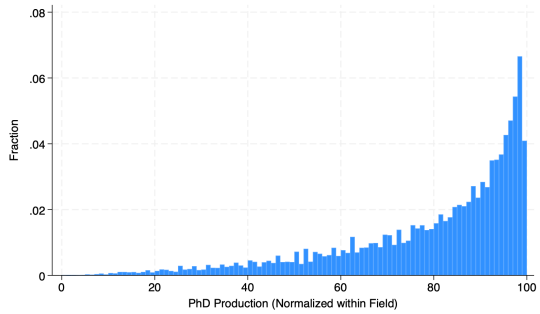
(b) PhD Rank



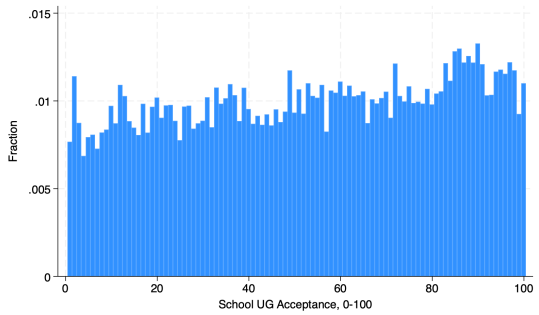
(c) PhD Production Rank of Job



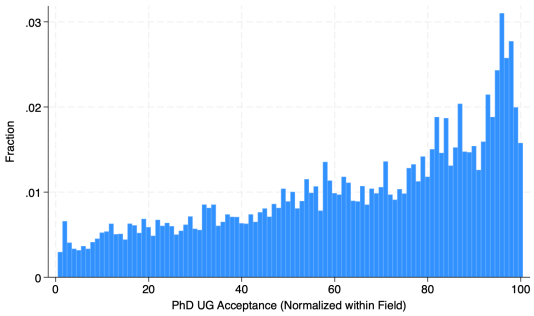
(d) PhD Production Rank of PhD-granting School



(e) Undergraduate Acceptance Rank at job



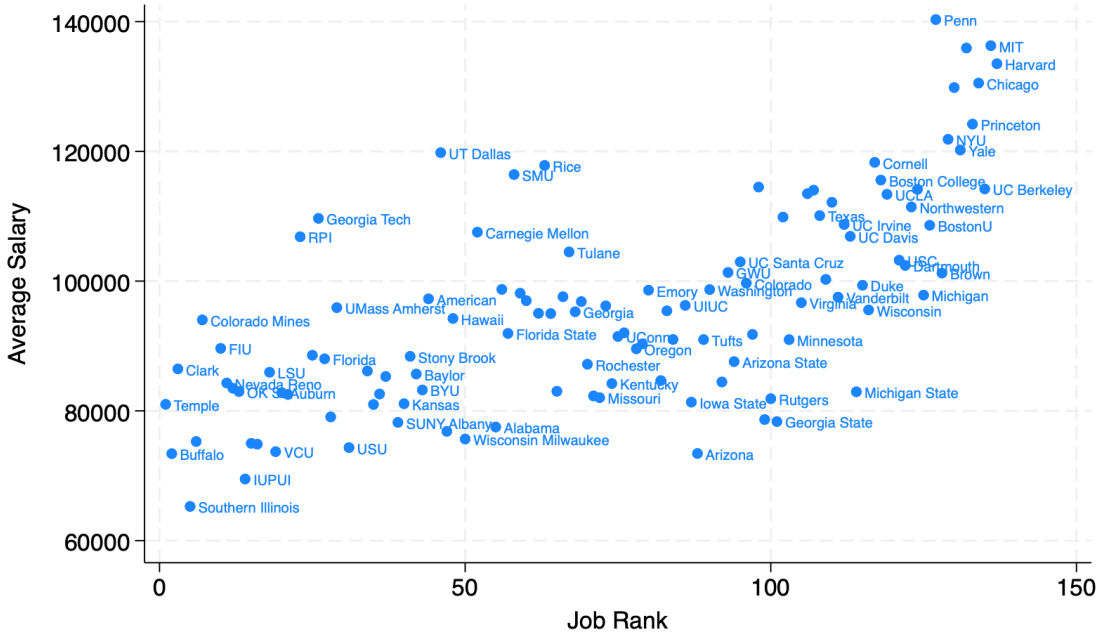
(f) Undergraduate Acceptance Rank of PhD-granting School



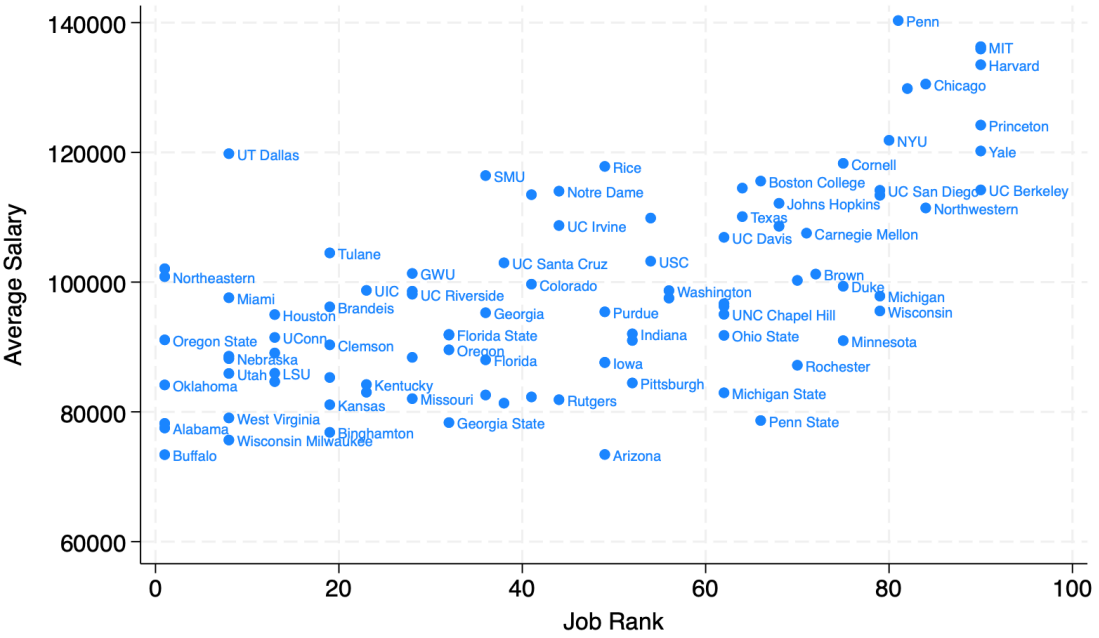
Notes: These figures are histograms of SpringRank at a faculty member's job (Panel A) and PhD-granting school (Panel B); PhD production rank at a faculty member's job (Panel C) and PhD-granting school (Panel D); and undergraduate acceptance rate at a faculty member's job (Panel E) and rank of the PhD-granting school (Panel F). Each measure is normalized to 0–100 within each field.

Figure A.2: Illustration of Approach, REPEC and USNWR Rankings

(a) Salary vs. REPEC Rankings



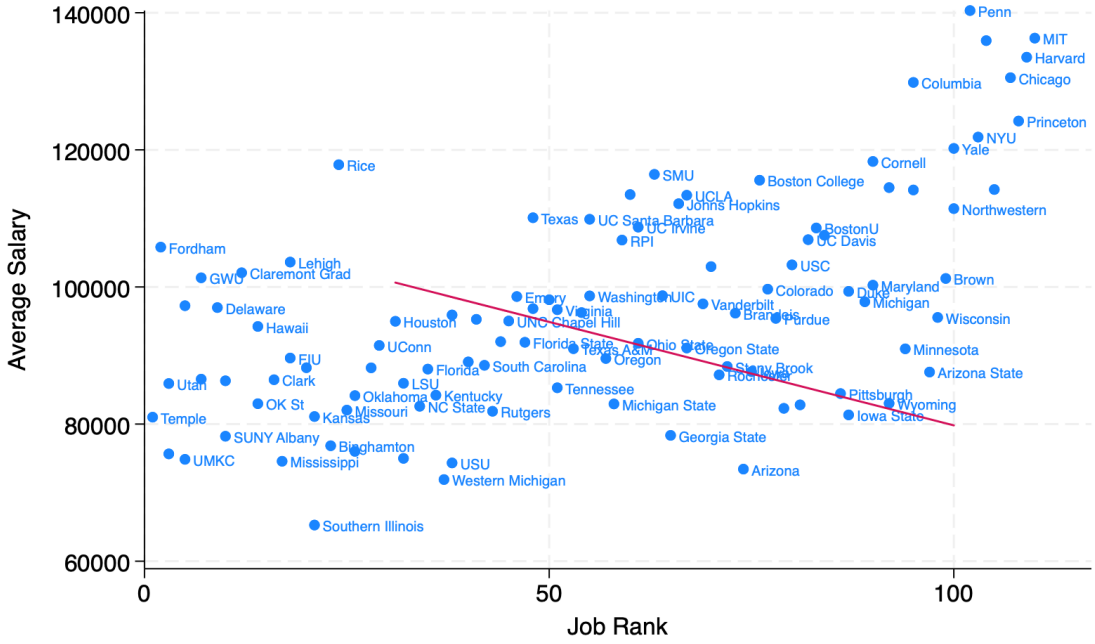
(b) Salary vs. USNWR Rankings



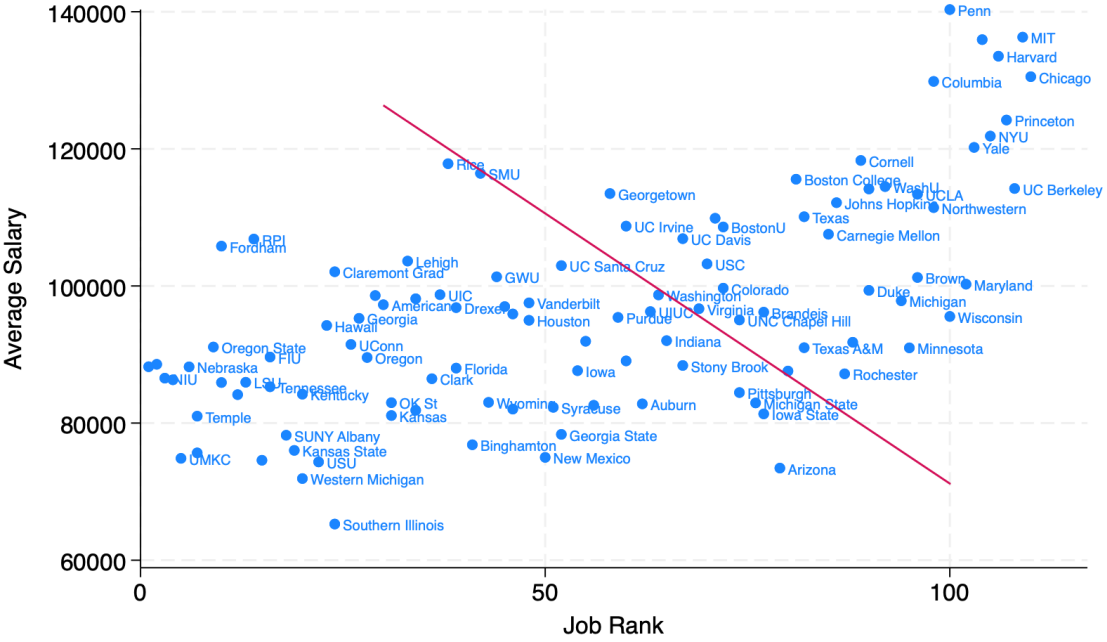
Notes: This graph plots average salary versus job rank for economics. Panel A uses the REPEC rankings as the measure of prestige, while Panel B uses the USWNR rankings. Each dot corresponds to a university. Some labels are omitted to decrease the degree of overlapping labels. We do not display the slope estimate as no standard errors are estimated. We do not restrict the sample to the universities that appear in the estimating sample.

Figure A.3: Illustration of Approach, NRC Rankings

(a) Salary vs. NRC (Survey) Rankings

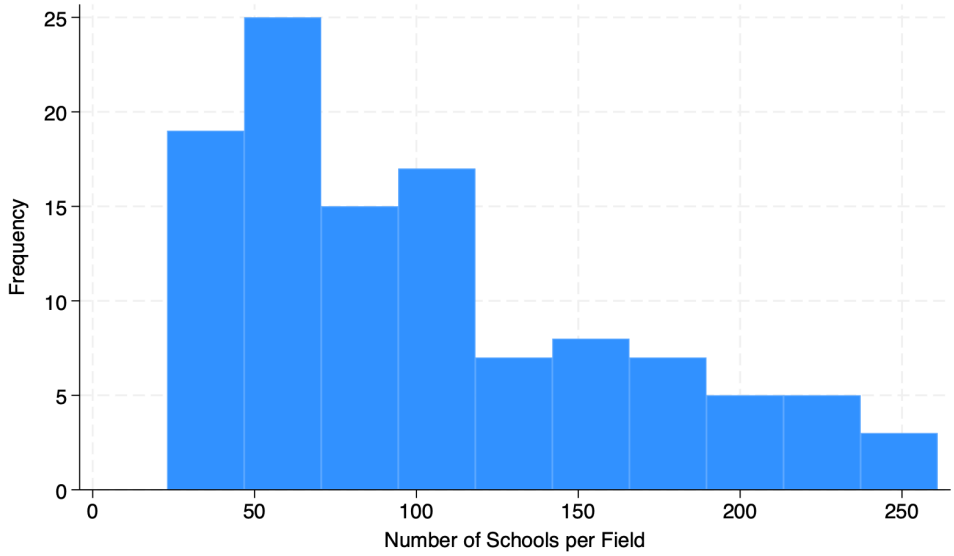


(b) Salary vs. NRC (Regression) Rankings



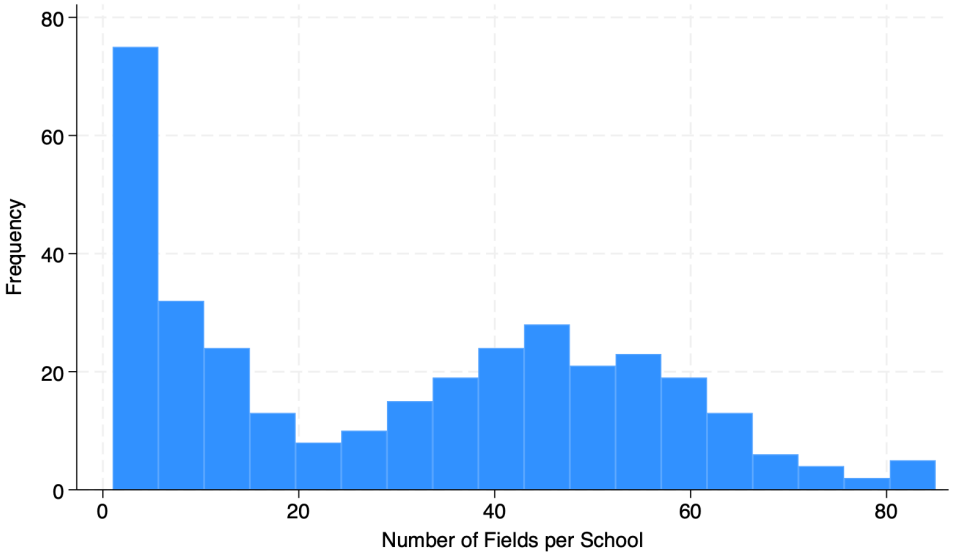
Notes: This graph plots average salary versus job rank for economics. Panel A uses the NRC (Survey) rankings as the measure of prestige, while Panel B uses the NRC (Regression) rankings. Each dot corresponds to a university. Some labels are omitted to decrease the degree of overlapping labels. The slope of the red line is obtained from the AIV approach, limited to economics. In particular, it is obtained after regressing average salary on job rank (NRC (Survey) or NRC (Regression)), with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-instrument. We do not restrict the sample to the universities that appear in the estimating sample.

Figure A.4: Number of Schools per Field



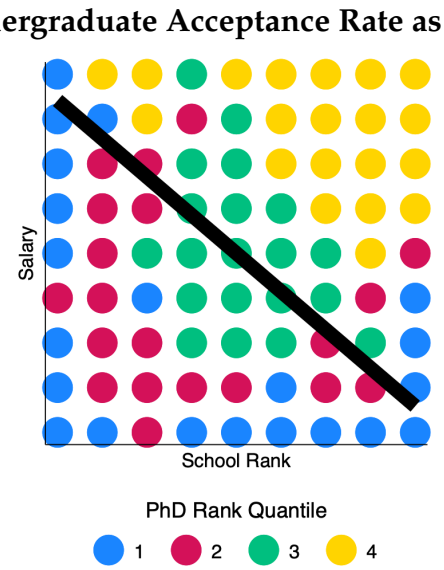
Notes: This figure shows the number of universities per field, before sample restrictions.

Figure A.5: Number of Fields per University



Notes: This figure shows the number of fields per university, after sample restrictions.

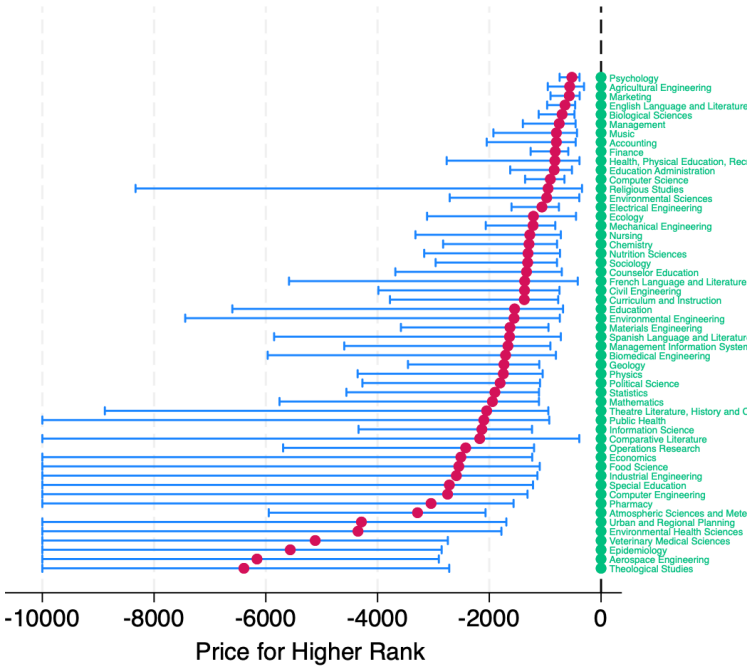
Figure A.6: Nonparametric, Undergraduate Acceptance Rate as AIV



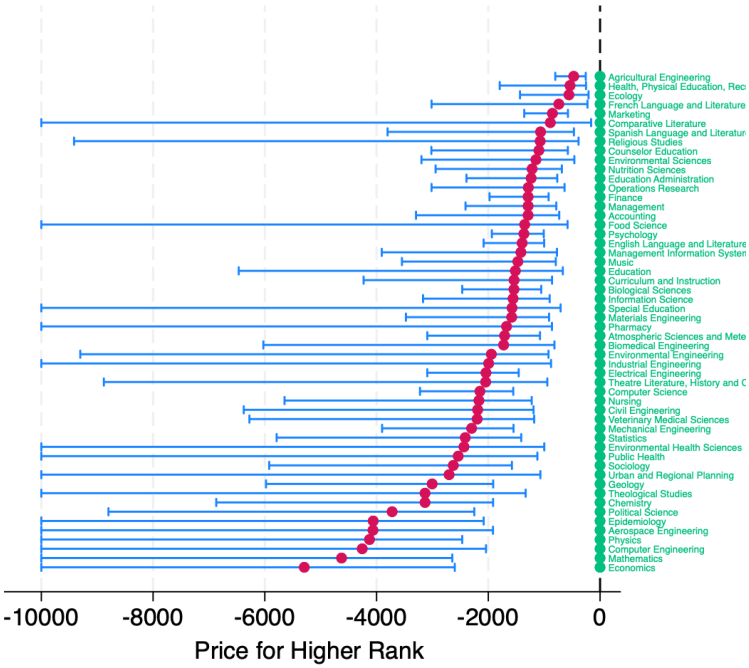
Notes: To create the figure in Panel A, we take the following steps: 1) By field, de-mean average salary, job rank (SpringRank), and the rank of the undergraduate acceptance rate at the PhD-granting school. 2) Create quantiles (9 categories) for average salary and for job rank. 3) Collapse the data to the average salary quantile -by- job rank quantile level, computing means for average salary, job rank, and undergraduate acceptance rate at the PhD university. 4) Create quantiles (4 categories) of undergraduate acceptance rate at the PhD-granting school. 5) Graph, where we assign each average salary quantile -by- job rank quantile level to its corresponding undergraduate acceptance rate at the PhD university quantile, shading them blue, red, green, and yellow, from lowest to highest. Finally, we show a line obtained from a applying the anti-IV method to the data (after constructing the quantiles, not the raw data).

Figure A.7: By Field

Panel A: SpringRank



Panel B: SpringRank (normalized)



Notes: For each field, we subset to that field and use the anti-IV approach of average salary on job rank (SpringRank), with PhD rank (SpringRank of the faculty's PhD-granting school) as the anti-instrument. We cluster at the field level and use Anderson-Rubin standard errors. The dots are the point estimates, with the blue lines representing the confidence intervals. We present all fields with a non-infinite confidence interval. We truncate confidence intervals at -10,000 where applicable. Panel A shows results for the baseline job rank (SpringRank), and Panel B shows results for SpringRank of job, normalized to 0–100 within each field.

B Data Appendix

B.1 Additional Details on WZCL Data

Here, we summarizing part of WZCL's data appendix to detail how they cleaned their data. First, standardized the names of the PhD-granting universities, necessary because sometimes a single university appeared under different names. Second, they cleaned the terminal degree. Third, they de-duplicated departments, combining a department that is coded as having different names in different years. Fourth, they mapped departments to the more granular field-level, such as physics and astronomy, and to the less-granular domain, such as natural sciences.[26] Each department gets mapped to one field, or, in some cases, to more than one field—for instance a department of physics and astronomy would get mapped to both physics and astronomy (both in the natural sciences). For this reason, the unit of observation is a person-field (or person-domain), entailing that a person can appear multiple times in the dataset. If a university has multiple departments for a given field, then all of these departments are considered. For instance, if there is a department of economics and a department of business economics, then both would be considered as economics. Fifth, they cleaned cases in which a faculty member appeared to be employed by two universities in a given year, due to mid-career moves. Sixth, they addressed cases where a faculty member disappears in a year(s) from the data, only to re-appear later. Seventh, they attempted to identify a faculty member's primary appointment and discarded other appointments (such as courtesy appointments). They do not consider faculty (1.2%) for which they cannot determine the primary appointment in their analysis (other than when considering academia as whole). Eighth, they assign a professor to the university at which they were most recently employed (relevant if faculty switch universities mid-sample). Ninth, they removed departments that did not appear in most of the sample years. In addition, they employed several steps to identify the gender of faculty, and were able to do so for 85% of the sample.

We make use of a file that has been collapsed (separately) to the field-job-PhD level, to the domain-job-PhD level, and to the academia-job-PhD level, where job is the university of the professor and PhD is the university at which they earned their terminal degree.[27] We focus only on field level. Each row contains the total number of faculty for each field-job-PhD. We then expand the data to be at the individual level (as opposed to the total level), resulting in 317,009 observations, which is higher than if we were to do this at the domain or academia levels. A key reason why there are more observations at finer levels of taxonomy is that, as mentioned above, an individual can appear in multiple fields and in multiple domains. Another complication in comparing across levels is that some fields are excluded from the domain and academia levels (due to being too small), and two domains are excluded from academia.

We use the university as defined by WZCL. In rare cases, entities that constitute one university appear separately, for instance Columbia University and Teacher's College Columbia. We treat the entities separately.

As stated in the main body of text, not all fields are represented for all universities in

[26] A field maps into only one domain.

[27] The data do not include the departments of the schools and PhDs, only the universities.

the original WZCL file. For instance, Boise State has only three fields in these data.

B.2 Additional Details on NRC Data

We use the 2010 NRC data. We consider two rankings, the 'S' ranking and the 'R' ranking. The 'S' ranking is obtained based on faculty members ranking departments. The 'R' rankings are based on a weighted average of a number of different characteristics of PhD programs, where the weights are obtained from faculty members reporting the relative importance of each factor. In the data, both the 'S' and 'R' rankings are reported in 5th and 95th percentile bands, which correspond to ordinal rankings. For instance, one department might receive a range of 1 and 8, where 1 is the very best department in the field. We take the mean of the 5th and 95th percentile values, separately for the 'S' and 'R' rankings. We then rank them based on these values. One thing that differs between the NRC data and the main WZCL data is that the NRC data come at the department level, while the WZCL data come at the university level. To account for this, in the NRC data, we construct ranks based on the number of core and new faculty as appears in the NRC data; this is the number of core (not courtesy faculty) who have been dissertation committee members in the past five years or are currently a member of the graduate admissions committee or curriculum committee. Thus, if a university has two departments in a field, we construct its raw rank based on this weighted average. After doing this, we re-rank ordinally. After doing the above, we drop departments at universities that we cannot match to the IPEDS data, including a number of collaborations between universities, such as 'San Diego State University-University Of California San Diego'. We do not consider departments that are unranked.

We map NRC fields to WZCL fields. In many cases, there is a 1:1 match, but not always.[28] We identified only one case in which two NRC fields map onto two WZCL fields: mathematics and applied mathematics. In this case, we drop applied mathematics. It is more common that one NRC field maps onto two or three Nature fields. The mappings are not always perfect, but this is how we did them:

- NRC: Ecology and Evolutionary Biology. WZCL: 1) Ecology; 2) Evolutionary Biology
- NRC: Electrical and Computer Engineering. WZCL: 1) Electrical Engineering; 2) Computer Engineering
- NRC: Civil and Environmental Engineering. WZCL: 1) Civil Engineering; 2) Environmental Engineering
- NRC: Cell and Developmental Biology. WZCL: 1) Cell Biology; 2) Molecular Biology
- NRC: Pharmacology, Toxicology and Environmental Health. WZCL: 1) Pharmacology; 2) Environmental Health Sciences

[28] One example is that one data includes "Spanish" and the other contains "Spanish and Portuguese." We match these together.

- NRC: Operations Research, Systems Engineering and Industrial Engineering. WZCL: 1) Operations Research; 2) Systems Engineering; 3) Industrial Engineering

In these cases, we still cluster our standard errors at the school -by- field level, which may not be quite correct, but the estimates are highly statistically significant, so this will not make a difference in practice.

We do not consider the following NRC fields given that there did not seem to be a good match in the WZCL data: 1) American Studies; 2) Biochemistry, Biophysics, and Structural Biology; 3) Communication; 4) Earth Sciences; 5) Languages, Societies and Cultures; 5) Public Affairs, Public Policy and Public Administration.

B.3 Additional Details on REPEC Data

We obtain our REPEC data from https://ideas.repec.org/top/top.usecondept.html and use the March 2025 Top 25% of US economics departments rankings. Because this focuses on economics departments, it does not include things like Chicago Booth. In some cases, a university has multiple departments. In these cases, we consider only the top-ranked department.