Market Forces in Academia: Returns to Education and Faculty Pay*

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Abstract

We study long-term trends in the compensation of faculty and its drivers in the U.S. and Canada, using a panel dataset covering most research institutions. We document three stylized facts across academic disciplines. First, the dispersion of faculty pay has widened significantly over the past 50 years, with economics, business, and especially finance exhibiting a large and growing premium. Second, faculty wages correlate strongly with their student returns to college education, both in levels and in the time-series. Third, high paying fields display higher students per faculty ratios and a lower supply of PhD students relative to faculty. Using granular data on students' future earnings at the university-field level, we estimate the elasticity of faculty pay to returns to college education to be in the [0.4-0.7] range. However, this elasticity varies significantly across disciplines: it is higher in fields with larger student-to-faculty ratios and lower PhD supply. This heterogeneity in elasticity explains, for example, the sizable wage premium of finance over computer science faculty, despite similar student future earnings in both fields. Our findings suggest that faculty wages are increasingly shaped by inter-university competition within fields, driven by student demand responding to varying returns to university education across disciplines. In contrast, industry outside options for faculty appear to play only a limited role.

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1 Introduction

While returns to postsecondary education are high and have increased significantly since the 1970s (Goldin and Katz 2008), these returns vary greatly across fields of study. Earning differentials persist even after controlling for institution type, selection, and peer quality (Kirkeboen et al. 2016), are often larger than the earnings gap between high school and college graduates (Altonji et al. 2012), and have grown over time (Altonji et al. 2014).[1] As a result, the choice of college major has become a crucial determinant of the level, profile, and risk of future earnings.[2]

Although a growing literature investigates the influence of heterogeneous returns to education across fields on student educational, career and financial choices, little is known about its effects on the supply side of education, especially on faculty wage.[3] Beyond tuitions and university costs, faculty wages may also affect the quality of education, the allocation of talent across fields, research productivity, and innovation.[4] Prior research provides suggestive evidence of increasing dispersion in faculty wages across academic disciplines (e.g., Courant and Turner (2019)), but a comprehensive assessment is lacking. How are academic wages distributed across faculty, and how has this distribution evolved over recent decades? To what extent does cross-field wage dispersion reflect differences in student labor market outcomes? Is the relationship between student post-graduation earnings and faculty pay homogeneous across disciplines, or are there systematic differences? If so, what mechanisms drive these differences?

This paper documents rising heterogeneity in faculty pay across fields since the 1970s, driven not only by increasing dispersion in student post-graduation earnings, but also by growing variation in the *elasticity* of faculty wages with

[1] See Altonji et al. (2016) and Lovenheim and Smith (2023) for a review of the literature on returns to college majors.

[2] The literature investigating the labour market outcomes of college major choices includes Arcidiacono (2004); Hamermesh and Donald (2008); Altonji et al. (2012); Hastings et al. (2013); Andrews et al. (2017); Andrews and Stange (2019); Hampole (2023); Andrews et al. (2024).

[3] Recent studies on the effects of earning differentials across majors on the supply side of education, such as Conzelmann et al. (2023) and Light (2024), explore impacts on course offerings and the number of degrees awarded.

[4] In 2022, faculty salaries accounted for an average of 62% of instructional expenditures at four-year postsecondary institutions, according to the Integrated Postsecondary Education Data System (IPEDS).

respect to these student earnings across disciplines. Our empirical findings suggest that faculty compensation is increasingly shaped by inter-university competition within fields, where competitive pressures reflect differences in student demand that are themselves shaped by heterogeneous returns to university education. In contrast, industry outside options for faculty appear to play only a limited role in academic wage heterogeneity.

To conduct our empirical investigation, we first assemble a longitudinal dataset of individual-level faculty pay across most universities in the U.S. and Canada.[5] This dataset includes over 320,000 faculty from 1,500 universities and 20 fields, spanning 1993–2023, and is augmented with historical survey data at the university–field level dating back to 1974. We collect faculty compensation data available through public record requests in accordance with the freedom of information laws for most U.S. and Canada public four-year institutions. To extend coverage to private universities and additional public universities, we complement this dataset with green card and H1B application data, leveraging the significant share of non-U.S. citizens employed in academia. We identify faculty academic fields using textual analysis of department names when available (60% of the data), results from Google searches using names and affiliations collected through an API (30%), and academic field directories (10%). Our faculty pay dataset includes over 1.4 million individual observations with information on academic field, rank, base salary and/or total compensation, and university affiliation over the 1974-2023 period.

We then merge this faculty pay dataset with a yearly panel of student post-graduation earnings constructed using the Post-Secondary Employment Outcomes (PSEO) data. Produced by the U.S. Census Bureau, the PSEO dataset links individual-level graduation records from post-secondary institutions with data from the Longitudinal Employer-Household Dynamics program to report earnings one, five, and ten years after graduation, along with their industry and geographical placement. Our faculty salary dataset covers 76% of the 488 four-year institutions included in the PSEO. The resulting merged panel includes 76,000 observations

[5]We define "universities" as four-year postsecondary institutions that award bachelor degrees.

on faculty compensation and student post-graduation outcomes, spanning 366 universities and approximately 5,000 degree majors per year. Finally, we link faculty pay to additional institutional characteristics using IPEDS data, capturing information on the number of degrees awarded and tuition levels by field, university, and year.

We establish three stylized facts using this comprehensive dataset. First, we document a growing dispersion in faculty pay across fields since the 1970s, primarily driven by finance, business, law, and economics. Over the past five decades, the wage premium for finance professors relative to the average across all fields has increased from approximately 5% in the 1970s to over 60% in the 2020s. The current wage differential between finance and philosophy professors exceeds 100%, a gap comparable to that between humanities faculty and kindergarten teachers.[6] In economics and business, faculty wage premiums have also risen, from less than 10% in the 1970s to around 30% and 40%, respectively, by the 2020s. By contrast, the premium in computer science and engineering emerges earlier, and peaks in the late 1990s and early 2000s, at 10 and 20%. At the lower end of the spectrum, humanities professors, who earned about 10% less than the average faculty member in the 1970s, now face a 20% wage discount. Similarly, while mathematics faculty once enjoyed a wage premium in the 1970s, they now earn approximately 5% less than the average in the 2020s. These trends are observed across all faculty ranks and institutional types, but the growing gaps are even more pronounced at research-intensive universities.

Our second stylized fact is that faculty pay is positively correlated with student post-graduation earnings, both in the aggregate and in the cross section of academic fields. Specifically, the average faculty wage premium by field, measured after controlling for rank, year, and affiliation, is strongly related to the average wage premium earned by students post-graduation across majors, controlling for socio-demographic characteristics. Compensation in higher education is thus partially aligned with labor market outcomes for graduates, a linkage largely absent in

[6] Annual wages in May 2022: kindergarten teachers - \$60,490, elementary teachers - \$61,690, high school teachers - \$62,360. Data source: Bureau of Labor Statistics, U.S. Department of Labor, Occupational Outlook Handbook.

secondary education. However, the ratio of faculty wage premia to student earnings premiums varies widely across disciplines, suggesting significant heterogeneity in the elasticity of faculty pay with respect to student labor market returns.

Our third stylized fact is that high paying academic fields tend to exhibit higher students-to-faculty ratios, and lower PhD candidates-to-faculty ratios. In top-paying fields, faculty compensation is positively associated with the number of undergraduate students per professor, and negatively associated with the number of PhD students per professor. This pattern may reflect discipline-specific imbalances between student demand and faculty supply, leading to variation in competitive pressures that shape wages.[7]

Having established these three stylized facts, we turn to precisely measuring the elasticity of faculty pay to post-graduation earnings and its heterogeneity across fields, to make progress towards a causal interpretation of this relationship and uncover the mechanism at play.

We begin by estimating a panel model at the university-field-year-rank level regressing faculty pay on student post-graduation earnings. The specification includes either university-by-year-by-rank fixed effects (when estimating within-university elasticities across fields) or field-by-year-by-rank fixed effects (when estimating within-field elasticities across universities). Across all specifications, we find that academic wages are strongly related to undergraduate student wages, with elasticities in the range of 0.4 to 0.6. The magnitude is remarkably consistent whether measured within universities across fields or within fields across universities. We validate these findings using Scorecard data on median student earnings one year after graduation, which confirms the robustness of our results.

We next develop an empirical setting akin to a shift-share instrument for student future earnings, based on persistent program placement patterns. Our identification strategy aims at addressing concerns over measurement error, which is plausible given the IPEDS data characteristics, reverse causality –well paid academics might deliver higher value education that is recognized as so in the labor market– and more generally unobserved variable bias. We construct a synthetic

[7]An alternative hypothesis is that faculty wages are largely exogenous, and the number of students adjusts accordingly to fit institutional budget constraints Courant and Turner (2019).

wage index at the university times field level, based on the industries and geographical areas where the university has historically placed students from that field, combined with the wage evolution for those industries and areas. The intuition behind the instrument is that, all else being equal, universities that historically place students in regions and industries where wages increase more than in other areas and industries experience a rise in student wages plausibly exogenous to the quality of education they offer.

We show that a plausibly exogenous increase in post-graduation wages of students from a given field at a given university leads to significantly higher wages for their faculty. The elasticity measured through this instrumental variable analysis is of a similar magnitude as the one from the OLS regressions. Hence, the widening dispersion over the past decades in student future earnings across industries contributes to the growing heterogeneity in faculty pay across disciplines.

However, the increasing dispersion of academic wages result primarily from a pronounced heterogeneity in the elasticity of faculty pay to their student future earnings, and to a lesser extent from the increasing dispersion of student future earnings. Measuring elasticities *within field* over time or across universities reveals for instance that the elasticity of faculty pay to student earnings in finance is two to three times higher than in the humanities. This higher elasticity, combined with the substantial increase in wages within the finance industry, thus explains the majority of the growth in the finance faculty wage premium over the same period.

We next investigate the drivers of the heterogeneity in faculty pay elasticity to student future earnings across fields and find that it relates to the number of students per faculty, a proxy for university revenues, and to the supply of phd students into the academic field.

Higher student future earnings in a given field predict an increase in the number of students per faculty, particularly in fields that are more scalable. Conversely, the ratio of PhD students to faculty declines as undergraduate and master student future earnings rise, creating frictions in the faculty supply. Additionally, universities at the top of the revenue distribution capture a greater share of total revenues

in high-earning fields through increased tuition and donations. Together, these factors shape competition forces that vary significantly across fields, contributing to the observed heterogeneity in faculty pay elasticity and the growing dispersion in academic wages.

Finally, we argue that this heterogeneity is unlikely to be primarily driven by professors outside options – such as joining the industry at the end of PhD or later transitions to industry –. First, fields with high academic wages and high elasticity to student future earnings exhibit a low share of non-academic placement for PhDs. Second, conditional on working in the industry, the returns to phd education (vs. having a master) are also lower in these fields. Last, the fields exhibiting pronounced right tails in compensation for PhD working in the industry do not exhibit particularly high academic wages.

Our work relates to the literature on wage differentials across skills and majors and their broader implications. Several studies show how earnings levels (Arcidiacono 2004; Wiswall and Zafar 2014, 2015), trajectories (Hampole 2023), and risks (Nielsen and Vissing-Jorgensen 2006; Bonin et al. 2007; Dillon 2018; Saks and Shore 2005) affect occupational and education choices. Differences in wage returns to majors can also explain long-term changes in inequality and earnings differences across gender and race (Grogger and Eide 1995; Brown and Corcoran 1997; Weinberger 1998; Gemici and Wiswall 2014) and the "collegiate degrissivity" documented in Bleemer and Quincy (2025). This paper illustrates how wage differentials across industries can have long-reaching effects by influencing the wages of academic faculty, which in turn might affect talent allocation, learning, and innovation in the economy.

Second, our study contributes to the literature on the determinants of academic wages, such as publications (Katz 1973; Tuckman and Leahey 1975; Swidler and Goldreyer 1998; Garfinkel et al. 2024), citations (Katz 1973; Hamermesh 2018), department performance (De Fraja et al. 2020), seniority (Ransom 1993; Moore et al. 1998; Hilmer and Hilmer 2011), university monopsony power (Ransom 1993; Goolsbee and Syverson 2019), university rank (Kim et al. 2009) and attributes such as race or gender (Gordon et al. 1974; Hoffman 1976), including a more

recent focus on finance within business schools (Sherman and Tookes 2022). By focusing on the growing field differentials, this paper proposes a novel mechanism: we show how market forces can account for a wage spillover from the industry to academia. Our findings also provide evidence consistent with the rationale behind the field differentials documented since the mid-1980s by studies such as Bowen and Schuster (1986), Hearn (1999), and Bellas (1997).

Third, we add to the growing literature on productivity in higher education by documenting heterogeneous labour costs across fields. Middaugh et al. (2003) and Johnson (2009) provide evidence that instructional costs vary across fields and tend to be higher for STEM courses, as well as courses in education, art, and nursing. Altonji and Zimmerman (2019) estimate net returns to college majors by considering heterogeneous student earnings and costs. Our findings suggest that higher wage returns to some majors may be partly offset by increased tuition costs and faculty salaries.

More generally, our study informs the ongoing debate on the role of universities and their relationship with markets and societies. The literature has documented a shift from the traditional model of public good knowledge production to a framework where universities compete in a market for knowledge through their research and instruction (Slaughter and Rhoades 2004). Our study provides additional evidence of the interconnectedness between universities and market dynamics. This ties into a longstanding debate about whether universities should be insulated institutions focused mostly on producing knowledge for its own sake or whether they should focus on producing marketable skills.

The paper is organized as follows. Section 5.1 provides institutional context on faculty pay. Section 2 describes the faculty and student wage data we collected across U.S. and Canadian universities over 50 years. Section 3 provides stylized facts on faculty pay. Section 4 investigates the causal relationship between student earnings and faculty pay. Section 5 explores the potential channels at play. Section 6 considers the potential role of industry outside options in the previous results. Section 7 concludes.

2 Data Sources and Methodology

This section describes the construction of the dataset that combines individual-level faculty salaries with student post-graduation earnings. Throughout our analysis, we define "universities" as four-year post-secondary institutions that offer bachelor's or graduate degrees.[8]

2.1 Faculty Wages: Sources

We build a dataset of individual-level faculty salaries using data from two primary sources: Freedom of Information Acts (FOIA) requests and H-1B or green card applications. We extend this dataset back to 1974 using field-year-rank level data from historical archives.

Figure 1 summarizes the university coverage of our dataset over time in Panel A and by state if Panel B. In total, our individual-level faculty salary dataset covers around 1,500 universities across all U.S. states.[9] These institutions grant over 85% of the bachelor degrees conferred by four-year colleges in the U.S. as of 2019 and employ over 85% of tenure-track professors at such institutions in the same academic year.[10]

INSERT FIGURE 1 HERE

2.1.1 Public Record Requests

We collect faculty wages at public universities by submitting public record requests across U.S. states and Canadian provinces, or by extracting information directly from university or state agency websites when publicly available. In the U.S., state-level Freedom of Information laws guarantee access to records maintained by state agencies. We direct our requests to states where (1) postsecondary institutions are not exempt from disclosure requirements, and (2) access rights are granted to all

[8] Accordingly, we exclude community colleges, which typically offer two-year programs.

[9] According to the U.S. Department of Education, there were 2,679 four-year post-secondary institutions in 2019-2020 in the U.S. `https://nces.ed.gov/programs/digest/d20/tables/dt20_317.10.asp?current=yes`

[10] We use data from the Integrated Postsecondary Education Data System (IPEDS) on enrolled students and professors across universities and degrees.

individuals, not just state residents. Depending on the legal framework, we submit requests to state agencies, university systems, or individual universities and seek data over the longest available period.

While our dataset includes data from all 50 U.S states and the federal district, data coverage varies by state and institution, as described in Table A1 in the Internet Appendix. Some states or universities provide information on all university employees, including teaching-track faculty, while others restrict disclosure to research tenure-track faculty. Similarly, some report only base salary, while others include total compensation, department affiliation, or additional demographic variables such as gender or race.

Our final dataset compiled from public record requests covers approximately 330 universities across all U.S. states. These institutions represent 45% of all U.S. public four-year colleges and account for 90% of all bachelor's degrees conferred by U.S. public universities in 2019.[11] The dataset spans the period from 1993 to 2023.

For each university and year, we extract and standardize data on each individual's first and last name, base salary and/or total compensation, academic rank, and university affiliation. Base salary typically refers to the 9-month academic-year wage, while total compensation includes summer stipends, grant-funded salary supplements, and other variable payments. We retain only full time positions, teaching or research faculty, and identify academic rank (assistant, associate, or full professor) when available. Where reported, we also extract and standardize departmental affiliation. When an explicit full-time indicator is unavailable, we exclude observations with base salary or total compensation below a minimum threshold.[12] The resulting public records dataset includes over 2 million observations and 460,000 unique combinations of first name, last name, and university, which we screen and classify across academic fields.

[11]There were 772 four-year public institutions in the U.S. in 2019-2020.`https://nces.ed.gov/programs/digest/d20/tables/dt20_317.10.asp?current=yes`.

[12]We exclude observations with annual earnings below $40,000 when the dataset does not specify whether the position is full time. This helps eliminate part-time or adjunct positions that may otherwise be misclassified.

2.1.2 Green Card and H-1B Application Data

We complement our dataset from public record requests with data on green card and H-1B applications, enabling broader coverage across universities, including private institutions, and an extended time period. According to the National Study of Postsecondary Faculty, 17% of tenure track (but not yet tenured) faculty are not U.S. citizens. The U.S. Department of Labor provides public access to permanent residence and H-1B application data through its Employment and Training Administration.[13]

We use green card applications from 2005-2024 and H-1B applications from 2010-2024. These records include anonymized information on wages, employer, occupation, and position. We identify academic employees as those working at universities, based on employer names, and further classify faculty and their academic fields using job titles and U.S. Bureau of Labor Statistics occupation codes that identify postsecondary professors and their field of study.

We arrive at an anonymized wage dataset of around 82,000 faculty over the 2005-2024 period working across 1,460 universities, which we append to our public record request dataset.

2.1.3 Faculty Survey Data from 1974

We extend the sample back to 1974 using data collected from a survey of public universities available in the Oklahoma State University historical archives. For over five decades, the National Association of State Universities and Land-Grant Colleges (NASULGC) has conducted yearly surveys on faculty pay across fields, compiled by the Office of Institutional Research at Oklahoma State University.[14] Each survey includes information on average salaries and the number of professors across faculty rank, fields, and university categories, covering an average of 80 public universities.

We digitize and analyze the surveys available in the Oklahoma State University archives to collect data on academic wages across fields for the 1974-2000 period.

[13] Data available at `https://www.flcdatacenter.com/`.

[14] See, for example, Scott and Bereman (1992)

Using OCR and machine learning techniques, we convert the digitized PDF files into tables, extracting both average salaries and the number of professors by academic discipline, university categories, and faculty ranks.

2.2 Classifying Faculty into Academic Fields

A significant challenge to our analysis is to accurately determine each faculty's academic fields. To do so, we proceed in three steps. First, if the original data collected through public record requests or green card/H1B applications includes the department information, we map it to its corresponding academic field using keywords. Second, we leverage academic directories to classify faculty across academic fields based on their name and university affiliation. Last, for the faculty not yet classified, we run automated google search queries and run a textual algorithm to map them to their fields.

2.2.1 Field Classification

We single out 18 academic fields and two departments following the Classification of Instructional Program (CIP) from the U.S. Department of Education's National Center for Education Statistics. Introduced in 1980 and periodically revised to reflect changes in academic disciplines, the CIP assigns a six-digit code to each instructional program. We use the first two digits to define broad *academic fields* and the first four digits to identify *departments*, which correspond to subgroups of programs with similar content and objectives.

We retain all academic fields that (i) offer graduate programs and (ii) represent more than 1% of our sample, with the exception of medicine. We exclude medicine because wage data in that field often reflect compensation for clinical practice, making it less comparable to other academic disciplines. In addition, we single out two departments: finance/accounting, which we we refer to as *Finance* throughout the study, and economics, whose average faculty wages are more than 20% above their parent field averages (Business and Social Sciences, respectively). These departments exhibit wage patterns that diverge significantly from those of their broader academic fields.

Table A2 in the Internet Appendix lists all retained academic fields, the departments they encompass, their CIP code, and the keyword strings used to classify faculty into fields and departments.[15] 65% of all observations in our dataset, corresponding to 72% of all individual faculty, are directly mapped into academic fields using original department information.

We construct counts of faculty by university, field, year, and academic rank using data from institutions with complete public records, defined as those that report all faculty members without applying a minimum salary or employment threshold and that retain the original departmental affiliation information. This subset comprises approximately 170 distinct public universities located across 30 U.S. states.

2.2.2 Field Directories

Second, we use existing field directories, augmented where necessary with participant lists from conference programs, to identify departments and academic fields.

For *Economics*, we rely on several sources: membership lists from the American Economic Association (AEA) for the years 1990 to 1997; the dataset constructed by Brogaard et al. (2018), which covers individuals affiliated with the top 50 economics departments from 1996 to 2014; and participant lists from the AEA annual meetings in 2005, 2015, and 2020.

For *Business* and *Finance*, we use James Hasselback's faculty directories from 1993 to 2023.[16] These directories compile information on faculty members in Accounting, Finance, Marketing, Economics, and Management departments across roughly 500 U.S. public and private institutions. For each entry, the directory provides the faculty member's field, institutional affiliation, and position.

[15]For example, the department "Electrical, Electronics and Communications Engineering," with CIP code 1410, included in the "Engineering" field, is described as "A program that prepares individuals to apply mathematical and scientific principles to the design, development and operational evaluation of electrical and electronic systems and their components, including electrical power generation systems; and the analysis of problems such as superconductor, wave propagation, energy storage and retrieval, and reception and amplification." We map this department with the following strings of key words "Electrical Engineering," "Electronics," or "Communications Engineering," "Electronic Systems," "Power generation," "Superconductor," "Energy Storage."

[16]http://www.jrhasselback.com/FacDir.html

For *Computer Science*, we use CSRankings as of June 2025. CSRankings is a metrics-based global ranking of computer science departments, listing faculty based on their publication records at all ranked institutions in the U.S. and Canada.

Finally, for all other academic fields, we construct field-specific directories by collecting and cleaning participant lists from the most prominent conference in each field for three benchmark years.

2.2.3 Automated Google Searches and Textual Analysis

Finally, we conduct automated Google searches for all unique combinations of first name, last name, and university in our dataset. For each query, structured as "first name + last name + university + 'professor of,' " we retrieve the top four search results and extract the first three lines of text from each. We then use a textual analysis algorithm to identify the faculty member's department.

Our textual analysis algorithm is optimized for accuracy rather than coverage, as our primary objective is to ensure precise cross-field wage comparisons. We validate the algorithm's performance by comparing its output to known field classifications for the subset of observations with available department information, adjusting the design iteratively to maximize precision. The final version achieves 95% accuracy at a 26% coverage rate.

To identify departments, the algorithm scans each search result for predefined word sequences such as "professor of," "professor in," or "in the department of," and extracts the associated terms. To minimize false positives, the algorithm processes only search snippets that include faculty-related keywords such as "professor," "research," or "publication." For lower-ranked search results and less precise phrasings, it requires that both the first and last names appear in the snippet. To improve coverage while maintaining accuracy, we supplement the Google search results with entries from the RateMyProfessors website.

Table 1 presents summary statistics for our final faculty salary dataset, which includes only observations with identified academic fields. The table reports faculty wages, both base salary and total compensation, by teaching or research stream,

and for research faculty, further disaggregates by academic field, rank, university classification, and data source. The final dataset includes over 1.2 million faculty-year observations, representing approximately 300,000 unique professors employed at around 1,500 universities, spanning 20 academic fields over the 1993-2023 period.

INSERT TABLE 1 HERE

2.3 Student Post-Graduation Earnings

We construct a panel dataset on student post-graduation earnings by university, degree major, and year for the 2002-2022 period, which we match with our faculty salary dataset, using the U.S. Census Bureau's Post-Secondary Employment Outcomes (PSEO) dataset.[17] The panel focuses on four-year institutions and includes data from both undergraduate and graduate programs. Figure 2 summarizes the coverage of the panel across university-degree major combinations and its overlap with our faculty salary data. The PSEO provides post-graduation earnings and employment outcomes for roughly 7,700 academic programs per year in the field we study at the baccalaureate and master's levels across 480 four-year institutions, representing about 50% of major U.S. public institutions over the 2002-2022 period. Our faculty salary dataset matches a substantial portion of this information, covering up to 70% of the academic programs included in the panel.

INSERT FIGURE 2 HERE

2.3.1 Panel Data Source and Construction Methodology

The Longitudinal Employer-Household Dynamics program (LEHD) at the U.S. Census Bureau produces the PSEO dataset by collecting graduation records from post-secondary institutions. This records include information on student identity, degree type, academic major, and graduation date. Post-graduation earnings are

[17] To confirm the robustness of our results, we replicate our analysis using Scorecard data. While the scorecard data covers more universities, the university-field dataset starts only in 2015, it does not include the placement information we need for our instrument, and it only includes salaries one year after graduation, and only the median.

then obtained by matching each graduate to the LEHD census database, which covers more than 96% of U.S. employment.

The PSEO reports earnings outcomes by university, degree major, and graduation year as follows. It retains only graduates with earnings data for at least three quarters of the reference year and with annual earnings at or above the full-time federal minimum wage. For confidentiality, earnings are aggregated into three-year graduation cohorts for undergraduates and five-year cohorts for graduate students. For each cohort, the PSEO provides median annual earnings one, five, and ten years after graduation (when available), along with the 25th and 75th percentiles and the number of graduates in each university-degree major cell.

We construct a yearly panel of student post-graduation earnings by university and degree major at both the baccalaureate and master's levels over 2002-2022 as follows. We restrict the sample to four-year institutions and students earning a bachelor's or master's degree. We keep only academic programs corresponding to the 20 academic fields we study. To create an annual panel, we infer the survey years and assign each three-year undergraduate cohort or five-year graduate cohort to the corresponding number of survey years, repeating identical earnings data for each year within the cohort. We approximate annual enrollment using the number of graduates in each cell, dividing by the cohort length and multiplying by the program length (four years for undergraduate programs, two years for graduate programs).[18] All earnings data are converted to current dollars for consistency with our faculty salary dataset.

The final panel comprises 160,000 degree major-year observations, an average of 7,700 degree majors per year, across 480 universities in 31 states. Of these observations, 81% are at the undergraduate/baccalaureate level and 19% at the graduate level. Earnings information is available for 90%, 60%, and 40% of observations one, five, and ten years after graduation, respectively.

[18]For example, if a three-year undergraduate cohort has 300 graduates, we impute 100 graduates per year and, assuming a four-year program, approximate 400 enrolled students per year.

2.3.2 Matching Methodology and Summary Statistics

To link the faculty pay dataset to the university-degree major-year panel on student post-graduation earnings, we aggregate the faculty data by computing the average salary at the *rank* × *field* × *university* × *year* level. Each resulting cell represents the mean of approximately five individual observations.[19] We then map each PSEO degree major to one of our 20 academic fields using its CIP code, and expand it to match the faculty pay panel across the three academic ranks. The final matched panel is structured at the *degree major* × *university* × *year* × *rank* level. All empirical specifications include academic rank fixed effects.

Table 2 provides summary statistics on student post-graduation earnings in our final panel after collapsing academic academic rank. The resulting panel includes 76,000 observations across 366 universities, with around 5,000 degree majors per year over the 2002-2022 period.

INSERT TABLE 2 HERE

In addition, we use the PSEO placement data, which reports the number of employed graduates by industry and region for each cohort, university, and field, to construct our instrument. The region classification follows the nine Census divisions, each covering several states. The dataset also reports the number of graduates residing in the university's state and those living outside the state but within the same Census division.

3 Three Facts on Faculty Pay, Student Outcomes, and Enrollment across Fields

This section documents three stylized facts regarding heterogeneity and long-term trends across academic fields. First, there is substantial heterogeneity in faculty pay, which has emerged and widened significantly in recent decades. Second, faculty wages are positively correlated with the post-graduation earnings of their students. Third, high-paying fields have experienced growing enrollment, exhibit

[19] We restrict the sample to tenure-track research faculty for this analysis.

higher student-to-faculty ratios, and have a relatively lower supply of PhD graduates per faculty member.

3.1 Faculty Pay: Field-Level Variation and Trends

3.1.1 Faculty Pay Heterogeneity

Table 1 provides summary statistics of faculty wages by field, position, rank, and university classification across different time periods. Unconditionally, we observe higher average pay in Law, Finance, Business and Economics, and in universities with high and very high research activity, especially during the most recent period (2015-2024).

To assess these wage differentials across fields while accounting for observable characteristics and potential composition effects, we estimate the following specification for the 2015-2024 period, using Languages as the reference field:

$$\ln(w_{i,t}) = \sum_{f=1}^{n} \beta_{field_f} \mu_{field_f} + \mu_{u,t} + \mu_{rank_i,t} + \mu_{tc,t} + \mu_{source,t} + \epsilon_{i,t}, \qquad (1)$$

where $w_{i,t}$ is the salary of faculty i in year t, μ_{field_f} are field dummies for all fields except Languages. $\mu_{u,t}$ are university $\times$ year fixed effects and $\mu_{rank_i,t}$ are academic rank $\times$ year fixed effects, i.e., assistant, associate, or full professor, accounting respectively for 32%, 27% and 37% of our observations after 2015.[20] Finally, $\mu_{tc,t}$ and $\mu_{source,t}$ are fixed effects for pay format, base salary vs. total compensation, and data source, i.e. public records vs. H1B/green card applications. Standard errors are clustered at the university level.

Figure 3 plots the estimated β_{field} coefficients in percent and their 95% confidence intervals for research tenure-track faculty in Panel A and teaching faculty in Panel B.

Among research faculty, Finance stands out as the highest-paying field, with a wage premium of 70% relative to Languages, the lowest-paying field in the sample. The Finance premium is significantly larger than that observed for closely related fields such as Business and Economics. Other fields with comparatively high wages

[20] 3% of observations lack information on academic rank after 2015.

include Law, Computer Science, and Engineering, each offering premiums exceeding 30% relative to Languages.

Wage premia and heterogeneity are similar in magnitude among teaching faculty though slightly more compressed in magnitude.

INSERT FIGURE 3

Table 3 reports regression coefficients from the same specification across a range of sub-samples to examine how wage differentials vary across faculty levels, ranks, and faculty types. We find that field-level wage premia persist even among top scholars, defined as those ranked in the top 2,000 of their field, with Finance consistently offering the highest premium. Across ranks, wage premia are more pronounced at the assistant (Column 3) and associate professor (Column 4) levels than among full professors (Column 5). Comparing across university types, wage premia are similar between private and public institutions (Columns 6 and 7), but significantly larger in universities classified as having very high research activity according to the Carnegie Classification (Column 8). In these institutions, the within-university and within-year wage premium for Finance relative to Languages approaches 90%, implying that Finance professors earn nearly twice as much as their counterparts in Languages. Finally, we examine premia across data sources used to identify fields, and find that the observed differentials remain robust across classifications.

INSERT TABLE 3

The Finance-academia wage premium we identify is economically large: the wage gap between Finance versus Languages faculty at top universities is of the same magnitude, at around 100%, as the wage gap between Language faculty and kindergarten teachers. We obtain data on kindergarten teacher wages from the Bureau of Labor Statistics, U.S. Department of Labor. In May 2022, the average wage of a kindergarten teacher amounts to $60,490, while the average wage of a Humanities professor in our dataset is $138,000 and Finance faculty's one is $275,000. Compared to what we observe in other high-skill service professions like

consulting, banking, or auditing, the impact of field-specific expertise on wages seems considerably more pronounced in academia.

3.1.2 Growing Differentials across Fields

We now investigate the evolution of field-level wage differentials over the longest time period possible. To do so, we utilize the dataset we have built from the OSU faculty surveys. For almost all years over the 1974-2023 period, we have information on salaries and faculty count by field, university category, and faculty rank.

Panel A of Figure 4 displays the growing wage heterogeneity across eight broad groups of academic fields: *Humanities*, comprising Philosophy, English, Communication, History and Languages, *Social Sciences*, *Natural Sciences*, including Biology, Agriculture, and Physics, *Mathematics*, *Economics*, *Computer Sciences and Engineering*, *Business*, and *Finance*. The lines plot the estimated β_{field} coefficient when regressing the log of the yearly salary separately on each field dummy within each year with university category times academic rank fixed effects for each year, the reference being the mean salary across fields. Regressions are weighted by the number of faculty in each university category x field x rank cell.

INSERT FIGURE 4

Panel B of Figure 4 presents similar trends from our individual-level dataset over the 1996-2023 period. We estimate the following model separately for each year and field f:

$$\ln(w_i) = \beta_f \mu_f + \mu_u + \mu_{rank} + \mu_{source} + \epsilon_i, \tag{2}$$

where w_i denotes the annual wage of professor i, and μ_f is a field indicator. We include university fixed effects μ_u, academic rank fixed effects μ_{rank}, and data source fixed effects μ_{source} (e.g., public records vs. visa applications). The coefficient β_f captures the wage premium for field f relative to the average across all fields in that year.

Finally, Figure 5 illustrates the growing dispersion in faculty wages across the full set of 20 academic fields, grouped into three panels: Social Sciences (Panel A), Formal and Natural Sciences (Panel B), and Humanities (Panel C).

INSERT FIGURE 5

3.2 Faculty Pay and Student Post-Graduation Earnings across Fields

We document a strong positive correlation between faculty pay and students' post graduation earnings across fields.

First, Table 2 reports summary statistics of post-graduation earnings by field. The highest-paying fields for faculty also tend to yield the highest earnings for graduates, although the ranking is not identical. For example, graduates in Computer Science earned the highest wages in 2016-2021, even though this field does not top the faculty pay rankings.

Second, Figure 6 plots faculty and post-graduation earnings premia across fields, estimated from wage regressions with field fixed effects. Two key patterns emerge: (1) faculty and student earnings premia are strongly correlated, with a correlation coefficient of 0.70; and (2) the ratio of faculty to student earnings premia varies substantially across fields. In some disciplines, such as Business, Finance, and Economics, faculty enjoy higher relative premia than their students, while in others, such as Mathematics, Computer Science, and Engineering, the reverse holds. This variation suggests that the link between student earnings and faculty pay is heterogeneous across fields, a question we examine further in Section 4. Consistent with these findings, Figure A2 in the Internet Appendix shows a similar pattern when comparing expected lifetime earnings of faculty and graduates across fields.

INSERT FIGURE 6

3.3 Enrollment and Number of Students per Faculty

Out dataset allows us to document patterns in how resources are allocated across fiels, looking at the number of students per professor. We focus on universities in which we have department affiliations for all professors from the public record requests, and on the information on the number of professors from the OSU survey.

Using data from IPEDs, we first document heterogenous trends in enrolled students across academic fields.

Second, we find large heterogeneity in the number of students per professors, and in the number of PhD candidates, potentially shaping faculty salary across fields.

INSERT FIGURE 7 HERE

4 Elasticity of Faculty Pay to Post-Graduation Earnings

We estimate the elasticity of faculty pay to students' post-graduation earnings, using both OLS and an instrumental variable based on graduates' industry and geographic placements. We find that this elasticity is large, varies substantially across fields, and has increased over time.

4.1 Identification Strategy

4.1.1 OLS

We begin by estimating the following specification, using our annual panel of post-graduation earnings and faculty pay at the university-field-degree-faculty rank level:

$$\ln(w_{f,u,y,r}) = \beta \ln(\omega_{d,f,u,y}) + Rank_{r,y} + Level_{d,y} + \mu_{f/u,y,r} + \epsilon_{f,u,y,r}, \qquad (3)$$

where $w_{f,u,y,r}$ denotes the average salary of tenure-track faculty in field f, university u, year y, and rank r (assistant, associate, or full professor), and $\omega_{d,f,u,y}$

measures student earnings one or five years after graduation by degree major d, field f, university u, and year y, at the 25^{th}, 50^{th}, or 75^{th} percentiles. The terms $Rank_{r,y}$ and $Level_{d,y}$ are fixed effects for academic rank-by-year and degree level (baccalaureate or master)-by-year, respectively. The specification includes either university-by-year-by-rank fixed effects (when estimating within-university elasticities across fields) or field-by-year-by-rank fixed effects (when estimating within-field elasticities across universities). Standard errors are clustered at the university level.

4.1.2 Instrumental Variable Approach

A natural question is to what extent causality drives the elasticity we measure in the OLS specification. It may be driven by omitted variable bias, with latent factors such as university prestige or general labor market trends influencing both variables. Reverse causality is also possible: higher faculty pay may improve the quality of teaching through selection and incentives, thereby enhancing student skills and future earning potential. Finally, there may be concerns about measurement error in the PSEO, as coverage and representativeness vary across years and degree majors, with response rates sometimes falling well below 50%.

To address these concerns, we construct a synthetic post-graduation earnings index at the university × field × year level to instrument observed post-graduation earnings.

The intuition behind the instrument is similar to the Bartik approach (Bartik 1991): all else equal, institutions that place students in industries and regions experiencing higher wage growth in their field will, mechanically, see higher predicted student earnings. We exploit the historical geographic and sectoral *placement* of students in each university-field combination and interact these patterns with wage trends by industry and location. Specifically, we compute:

$$Z_{f,u,t} = \sum_{g} \sum_{n} s_{f,u,g,n} \ln \varpi_{g,n,t}, \tag{4}$$

where $s_{f,u,g,n}$ is the average share of graduates from field f and university u em-

ployed in Census division g and 2-digit NAICS industry n over the PSEO sample, and $\varpi_{g,n,t}$ is the average wage of workers residing in region g and employed in industry n in year t, measured using the American Community Survey.

This instrument addresses key limitations of the PSEO, potentially reducing measurement error. First, by collapsing placement patterns over a full decade, we improve representativeness and reduce sampling noise from small PSEO cells. Second, it allows us to generate a complete time series for all universities and fields with at least one year of PSEO coverage, enabling the estimation of within-field-university elasticities across years. Third, because the variation comes from industry-region wage shocks external to a given institution, the instrument plausibly isolates exogenous shifts in predicted graduate earnings.

Our approach also has limitations, which we address in robustness checks. Placement information is available only at the 2-digit industry level (around 4,500 university-field observations), while student post-graduation earnings are observed at the more granular 4-digit CIP level (roughly 10,000 degrees). The PSEO also lacks placement data for Finance and Economics; we therefore proxy Finance placements with Business at both undergraduate and graduate levels, and Economics placements with Social Sciences at the undergraduate level. Finally, the index does not capture within-industry wage heterogeneity across the earnings distribution, and the geographic and sectoral aggregation (nine Census divisions and 20 industries) may limit granularity.

4.1.3 Instrumental Variable Specifications

We use our instruments in two different specifications.

The first one instruments student post-graduation earnings in the cross section by instrumenting post-graduation earnings in Equation (**??**).

The instrument allows to bring the identification one step further by instrumenting university-field specific shock in the following specification:

$$\ln(w_{f,u,y,r}) = \beta \widehat{\ln(\omega_{d,f,u,y})} + Rank_{r,f} + Level_{d,f} + \mu_{f,u} + \eta_{u,y} + \epsilon_{f,u,y,r}, \qquad (5)$$

where $w_{f,u,y,r}$ denotes the average salary of tenure-track faculty in field f, university u, year y, and rank r (assistant, associate, or full professor), and $\omega_{d,f,u,y}$ measures student earnings one or five years after graduation by degree major d, field f, university u, and year y, at the 25^{th}, 50^{th}, or 75^{th} percentiles. The terms $Rank_{r,f}$ and $Level_{d,f}$ are fixed effects for academic rank-by-field and degree level (baccalaureate or master)-by-field, respectively.

This specification gets us closer to identifying a causal link between student post-graduation earnings and faculty pay by including both university times field and year fixed effects. It hence measure the within field-university changes in faculty pay correlation with within field-university changes in post graduation earnings instrumented by local shocks to our wage index.

4.2 Results

4.2.1 Faculty Pay to Post-graduation Earnings Elasticities

Table 4 reports the estimated coefficients β, which capture the elasticity of faculty pay with respect to student post-graduation earnings. Across all specifications, we find that academic wages are strongly related to undergraduate student wages, with elasticities in the range of 0.4 to 0.6. The magnitude is remarkably consistent whether measured within universities across fields (Columns 1-6) or within fields across universities (Columns 7-12). Estimates are robust to alternative measures of student earnings, including the median, 25th, and 75th percentiles, and are larger when based on student earnings five years after graduation relative to one year. Finally, we validate these findings using Scorecard data on median student earnings one year after graduation (Table XX in the Internet Appendix), which confirms the robustness of our results.

INSERT TABLE 4

Table 5 confirms the magnitude and robustness of the elasticity using our instrument for student post-graduation earnings.

INSERT TABLE 5

4.2.2 Heterogeneity across Fields

We investigate how this within field across universities elasticity varies across fields, by estimating Equation (3) within each field. Figure 8 plots the estimated coefficients. We find that while on average faculty pay elasticity to student post-graduation earnings is high, it varies significantly across fields. This elasticity amounts to 120% in Finance and is more than three times higher than the elasticity in Computer Science or Engineering (around 40%).

INSERT FIGURE 8

4.2.3 Increasing Elasticity of Faculty Pay to Post-graduation Earnings

Figure 9 plots the coefficient estimates when we measure within field across universities elasticities over five time periods. The elasticity of faculty pay to student earnings has increased significantly over the years, from around 20% in the early 2000s to 50% after 2020.

INSERT FIGURE 9

4.2.4 Increasing Elasticity of Faculty Pay to Post-graduation Earnings

Table 6 displays the coefficient estimates when we instruments local idio-syncratic shocks specifics to university times field, as we control for university times year and university times field fixed effects. Elasticity of academic pay to post-graduation earning is above 50% and significantly higher for Assistant professors.

INSERT TABLE 6

5 Economic Mechanism

This section investigates the mechanism driving the elasticity of faculty pay to student earnings, its growth over the recent decades, and heterogeneity across fields.

5.1 Institutional Changes: Context and Predictions

Until the 1970s, three core principles in Academia supported relatively uniform compensation across academic disciplines : collegiality, academic freedom, and vocation. Collegiality arose from the conception of the university as a *unified* intellectual community, an ideal the very etymology of "university" reflects, organized around the collective pursuit of knowledge that characterized the foundations of the first universities in the Middle Ages. Faculty members –regardless of discipline– were regarded as equal contributors to the institution's academic mission.[21] The concept of academic freedom arose later. Understood as the protection of intellectual autonomy, the concept was reinforced by the de-commodification of scholarly labor. Salaries were not intended to reflect the market value of disciplinary outputs, but instead to support independent inquiry –shielded from political, commercial, or economic pressures. Finally, the notion of academic vocation framed professors not merely as employees, but as members of a profession defined by intrinsic motivations: a commitment to knowledge, mentorship, and public service. This vocational ethos downplayed financial incentives, reinforcing solidarity across disciplinary lines.

Starting in the late 1970s, a series of institutional shifts led universities to place less emphasis on these traditional academic principles, often revising their charter to allow for differentiated compensation across fields.[22] The spread of progressivist ideals, framing education as a vehicle for personal empowerment, technical innovation, and social advancement, promoted a turn toward skilled learning, job-readiness and the expansion of applied programs. Rising student interest in fields such as business, engineering, and computer science place pressure on universities to recruit competitively in these domains. At the same time, the evolution of American universities into research-intensive institutions, following the German model, fragmented academic life into specialized departments. This disciplinary

[21] Dean Henry Rosovsky explains in 1982: "We have the view that we are one Faculty. A Harvard professor of English is as valuable as a professor of Biochemistry." He adds: "Our differentials between salaries in the sciences, humanities, and social sciences are smaller than they are at almost any other university in the country. This has an important impact on the morale of the entire Faculty: we're all engaged in a common intellectual enterprise." `https://www.thecrimson.com/article/1982/6/10/faculty-salaries-a-red-letter-year-pwhen/`

[22] For example, UCLA in the 1980s.

segmentation encourages internal competition over resources and hiring authority, undermining uniform compensation norms. Simultaneously, universities have become increasingly reliant on targeted funding streams, including earmarked grants, contracts, and donations directed at specific departments or schools. Another major shift has been the rise of empiricism in higher education and public policy in general, with a growing emphasis on measurement, accountability, and evidence-based management. This encouraged the use of economic incentives to attract faculty and boost productivity, aligning academic work more closely with quantifiable outputs. Compounding these institutional changes, the decrease in public funding and the resulting steep rise in tuition fees in recent decades has reshaped the social contract of higher education. Students and families now more often view college as a private investment in human capital rather than a public or intellectual good. This perspective has heightened demand for demonstrable returns on education, pushing universities to allocate resources toward disciplines resulting in high future earnings. Recently, the adoption of decentralized budget systems – such as Responsibility-Centered Management (RCM) – further intensifies competition for tuition revenue, endowment funding, and faculty lines. Finally, antitrust reforms and labor market liberalization in the 1980s and 1990s curtailed informal agreements among universities that had previously limited labor market competition.

We can draw predictions at the university, field, and university-field levels for this institutional context. At the university level, we could expect a higher elasticity to post-graduation earnings in private or non-unionized universities. Across fields, the elasticity should be higher when university revenues are higher.

5.2 Scalability: University Revenues per Faculty

We investigate why in some fields professors capture a larger share of the surplus generated by their students compared to other academic fields by investigating students' willingness to pay through tuitions or donations.

5.2.1 Tuition Revenue per Professor

We compute the average annual tuition revenue per research faculty in field f and university u as follows:

$$\text{Tuition Revenue per Research Faculty}_{f,u} =$$
$$\frac{\text{students}_f}{\text{faculty}_f} * (s_{und,f,u} tuition_{und,f,u} + (1 - s_{und,f,u}) tuition_{grad,f,u}) \quad (6)$$

where $\frac{\text{student}_f}{\text{faculty}_f}$ is the average student-to-research faculty ratio in field f based on our sample of universities. $s_{und,f,u}$ represents the share of undergraduate students at university u and field f. $tuition_{und,f,u}$ and $tuition_{grad,f,u}$ are the annual undergraduate and graduate tuition, respectively, at university u and field f.

Figure 10 first plots the relationship between the average annual tuition revenue per research faculty and academic pay. We observe a positive correlation between tuition revenue per research faculty and faculty relative wage. For example, tuition revenue per research faculty in Finance is more than double that of other fields on average. Consistent with Johnson and Turner (2009), we find that higher tuition revenue per research faculty is driven in part by a higher student-to-professor ratio.

INSERT FIGURE 10

5.2.2 Donations and Endowment Income

Donations are another significant source of revenues for universities both through immediate use and endowment accumulation, which in turn produces income. This source of revenue is particularly important for the high research intensity universities. Thus, as per 2015, the top 10 largest public universities endowments total USD $76 bn. We calculate donations per research faculty (scaled) in field f as follows:

$$\text{Donation Intensity}_f = \frac{\frac{\text{Sum of all donations}_f}{\text{Sum of all donations}}}{\frac{\text{\# professors}_f}{\text{Total \# research faculty}}} \quad (7)$$

Panel B in Figure 10 compares the donation per faculty (scaled) across academic fields. Donation per research faculty is significantly higher in Finance than in other fields, including other business fields.

We also find that, on average, fields benefiting from donations correspond to the donor's industry. Hence, donations disproportionately originate from alumni working in the Finance industry. This is consistent with the literature showing that donors give to their alma mater first, in part to confirm their "sense of identity" (Akerlof and Kranton 2000).

5.2.3 Wage Skewness and Willingness to Pay

The large heterogeneity in both tuitions and donations across fields, which is larger than the heterogeneity in student future earnings, suggests a higher willingness to pay in some fields than others. One possible driver of the willingness to pay might be the skewness in the wage distribution. Figure A9 in the Internet Appendix plots the distribution of graduate student wages one year after graduation across academic fields. The wage distribution is more skewed in fields where professor pay is higher.

Finally, we exploit Forbes' dataset on billionaires to get a sense of the skewness of the wage distribution.[23] We collect the list of billionaires in the U.S. in 2021 and plots the number of billionaires across industries. Figure A10 in the Internet Appendix indicates that the Finance industry has the highest number of billionaires, close to 600, then followed by Computer Sciences and Manufacturing.

5.3 Scarcity: Ratio of PhD Candidates to Faculty

One possible factors driving the higher returns to research output we observe in some fields could be a limited supply of PhD graduates, which would lead universities to compete for a limited pool of talents. We exploit data on the number of PhD graduates across fields from IPEDS and on the academic placement rate from the Survey of Earned Doctorates, which is an annual census conducted by the National Center for Science and Engineering Statistics. We take the average academic placement rate across the 2010 to 2018 surveys and the average number of PhD degrees granted across fields over the same period.

[23] `https://www.forbes.com/real-time-billionaires`

Figure 11 plots the ratio of PhD graduates per faculty versus the academic placement rate across fields. While the share of PhD graduates joining an academic career amounts to more than 70% in business fields, including finance, it is significantly lower in other academic fields. In addition, the number of Finance PhD graduates per professor is significantly lower than in other fields.[24]

INSERT FIGURE 11

5.4 Elasticity, Scalability, and Scarcity

Table 7 shows how faculty pay elasticity to student earnings varies with the scarcity of the pool of talent, measured by the ratio of PhD candidates to professors, and the scalability, measured by the number of students per professors.

INSERT TABLE 7

This evidence of competition for talents is supported by the wage returns to citations measured at the faculty level: the wage returns to citations is higher in high paying fields. This surplus however disappears once controlling for university or even university type fixed effects.

6 Non-academic Outside Option

An alternative explanation for the large and growing heterogeneity in academic pay across fields is that it reflects variation in non-academic outside options. According to this view, universities primarily compete with industry –rather than with one another– when hiring and retaining faculty, particularly in applied disciplines. This mechanism is not mutually exclusive with the within-academia competition framework developed in the previous section. In fact, both explanations hinge on the willingness of universities to offer higher wages in response to competitive pressure, and both implicitly rely on a marginal productivity of labor argument.

[24] A related question is why are the numbers of phd graduates across fields not adjusting for the associated job vacancies in the corresponding field in the medium to long run? While institutional rigidities or incentives might be important ingredients, we do not take a stance on the exact friction at play.

Non-academic outside options were frequently cited in administrative discussions that motivated changes to faculty charters during the 1980s and 1990s (see Section 5.1). While we do not dismiss the relevance of these external opportunities in shaping faculty compensation, the evidence we present in this section suggests that their influence is, at most, second-order relative to the role of within-academia competition. We document three stylized facts that support this interpretation.

6.1 Inverse Relationship Between Academic Pay and Industry Placement Rates

We first examine the relationship between academic wages and the share of PhD graduates entering industry across fields. Using data from the Survey of Earned Doctorates (SED) and our academic wage dataset, we find that among high-paying academic fields, there is a negative correlation between salaries and the proportion of PhD graduates pursuing non-academic careers. Given that non-academic outside options are more likely to play a pronounced role in academic pay for fields were a large share of PhD graduates join the industry, we interpret this fact as inconsistent with outside options being the dominant explanation for the existence of high paying fields.

6.2 Industry Wage Distributions Are Not Aligned With High Academic Pay

A related hypothesis would be that academic pay is driven by the tail of the distribution of industry wages, as PhDs and academics may access the most selective and highly compensated jobs within an industry. Using wage distribution data from the American Community Survey (ACS) and our dataset on academic compensation, we compare the skewness and tail behavior of industry and academic wage distributions across fields. In disciplines like computer science and biology, the distribution of industry wages is highly right-skewed, suggesting the potential for relatively abundant high financial returns outside academia. Yet academic finance, which commands some of the highest faculty salaries, exhibits less fat-tailed

industry opportunities.

6.3 Non-Finance PhDs Outperform Finance PhDs in Financial Industry Placement and Pay

However, one critic would be that the ACS data is not granular enough to zoom in on the adequate right-tail of compensation in finance, with positions in hedge funds or private equity funds being scarce but singularly well compensated. We therefore assess access to the financial sector for PhDs across fields using the Post-Secondary Employment Outcomes (PSEO) survey and the ACS. We find that mathematics PhDs are more likely to enter finance than finance PhDs themselves. Moreover, conditional on entering the financial industry, math, physics, and engineering graduates tend to earn higher wages than their finance counterparts.

This evidence contradicts the notion that finance PhDs are uniquely equipped to leverage the highest paying industry opportunities and instead suggests that graduates from highly technical disciplines might have an edge in that regard. Consequently, high faculty salaries in finance academia are unlikely to reflect a narrowly tailored external outside option.

Together, these empirical facts are hard to reconcile with the view that academic wage growing dispersion is driven primarily by external labor market opportunities. The empirical regularities we present run counter to the predictions of most standard framework incorporating an outside option, in which higher wages should compensate for greater external opportunities or opportunity costs of academic employment (e.g. Becker, 1964).

7 Conclusion

This paper provides new evidence on the growing disparities in faculty wages across academic fields, investigating the role of student future earnings. Using a comprehensive dataset on over 200,000 professors and student wages across U.S. and Canadian universities, we establish a causal relationship between student earnings and faculty wages. We show that beyond student earnings levels, a higher

elasticity to student earnings in fields such as finance is fueled by factors like tuition revenues, donations, and bargaining power due to a limited supply of PhD graduates. These findings highlight the role of market forces in shaping academic compensation

Our results suggest that wage differentials across industries can have long-lasting effects by spilling over into academia, thereby influencing the supply of education and the allocation of talent in the economy.

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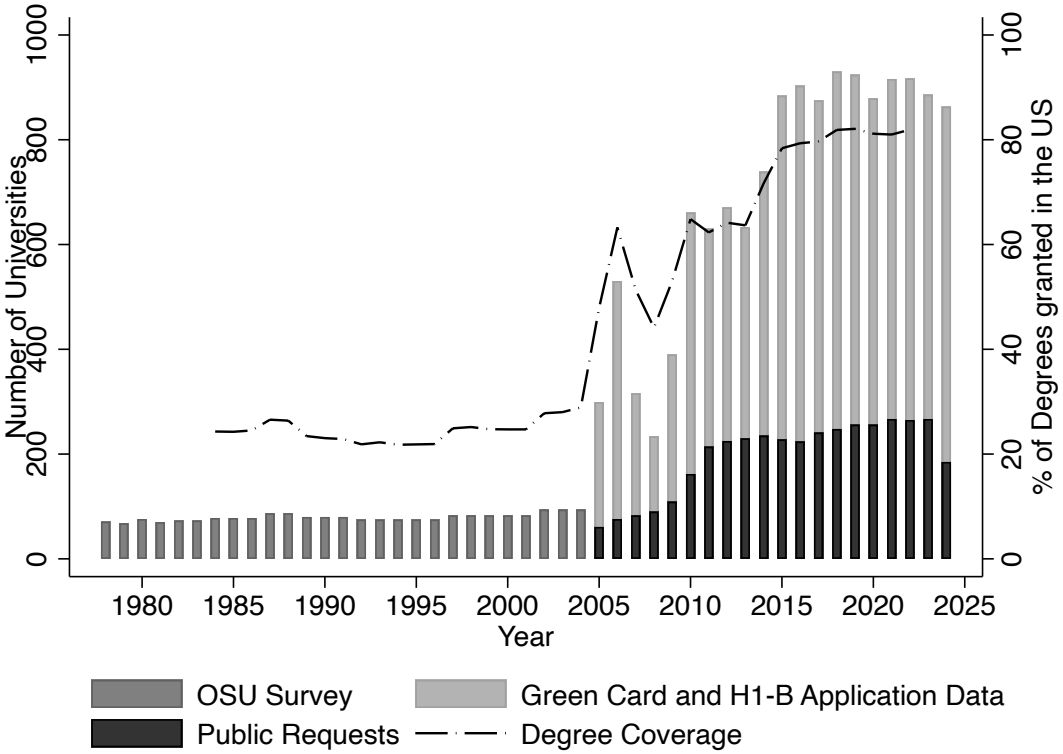
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8 Figures

Panel A. Coverage across Years and Data Sources



Panel B. Coverage across States and Data Sources

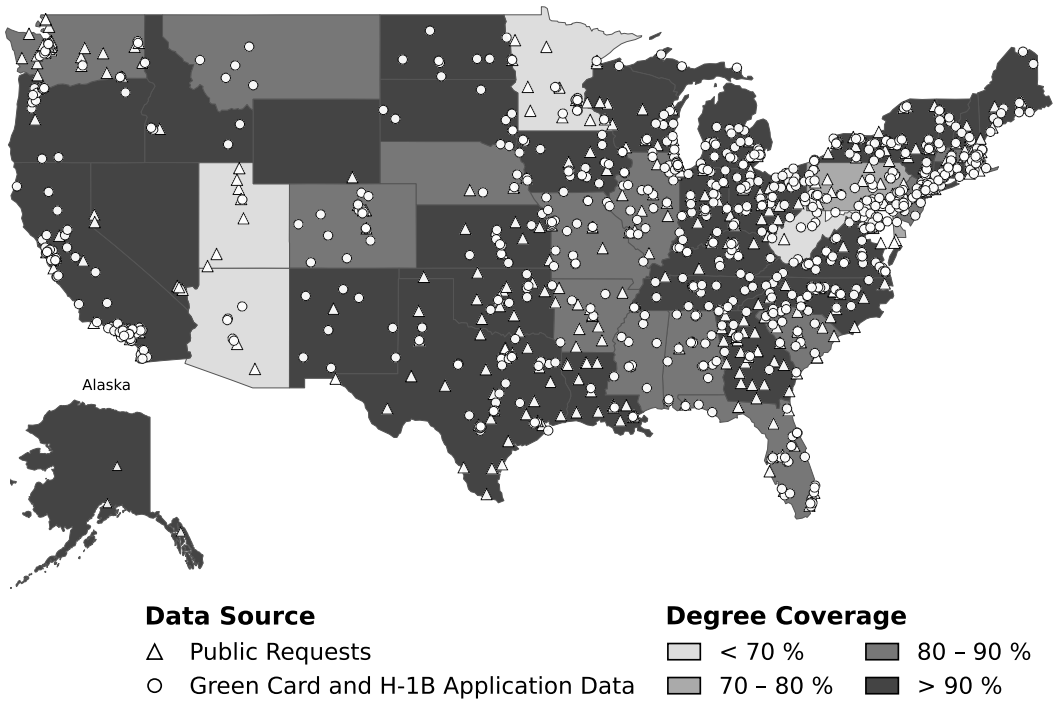


Figure 1. Faculty Salary Data Coverage and Sources

This figure illustrates the university and degree coverage of our faculty salary dataset, by data source over time in Panel A and by state in Panel B. Degree coverage is defined as the ratio of all bachelor's degrees conferred by the universities in our sample to the total number of bachelor's degrees. Data on degrees conferred comes from the Integrated Postsecondary Education Data System (IPEDS).

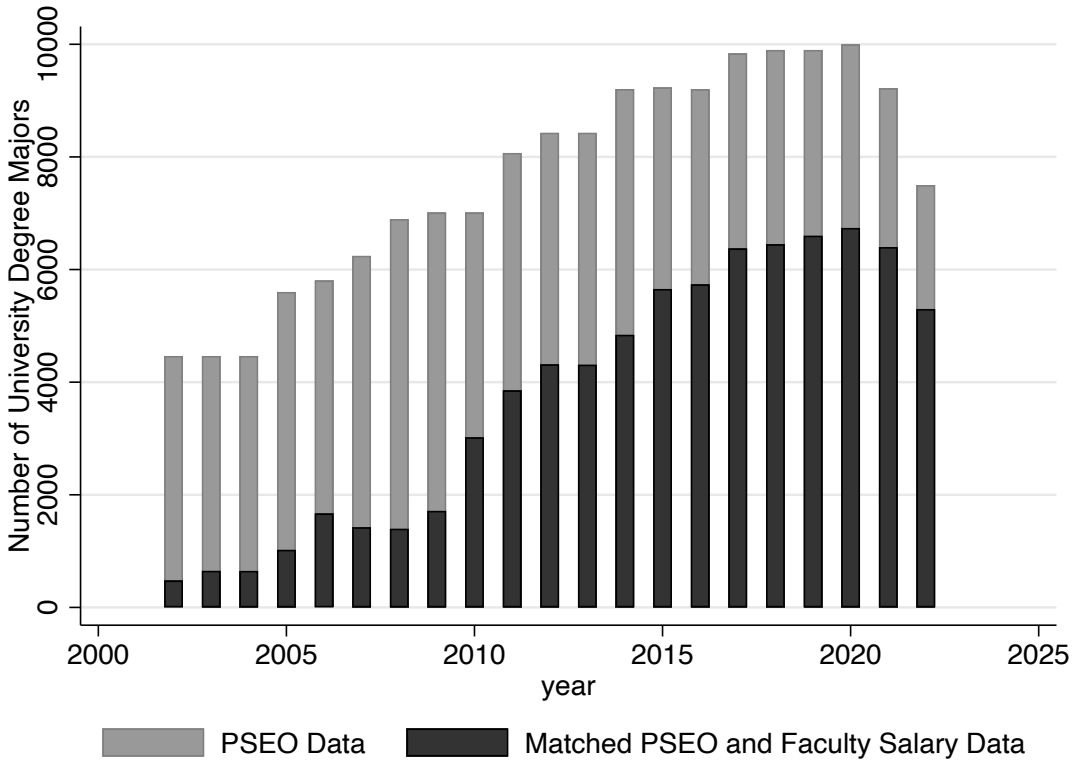


Figure 2. Student Post-Graduation Earnings Data Coverage

This figure summarizes the coverage of the PSEO data across university-field cells for both undergraduate and graduate students, as well as its overlap with our faculty salary dataset. The universities are four-year institutions, and the fields correspond to the 20 academic fields used in our analysis, each typically encompassing multiple degree majors. The PSEO reports post-graduation earnings and employment outcomes for up to 10,000 university-field combinations across roughly 480 four-year institutions from 2002 to 2022. Our faculty salary dataset matches up to 70% of these university-field combinations after 2015.

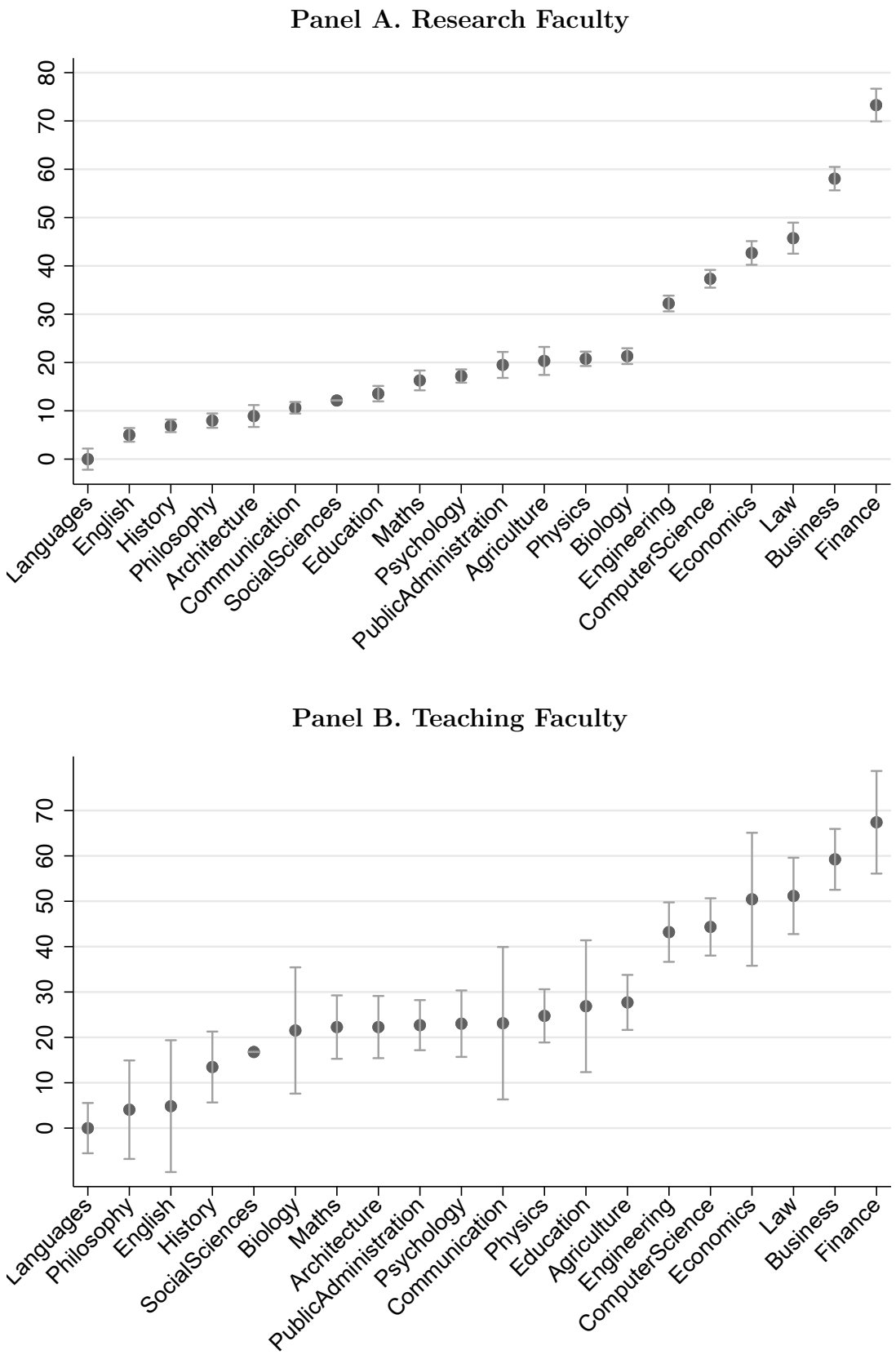
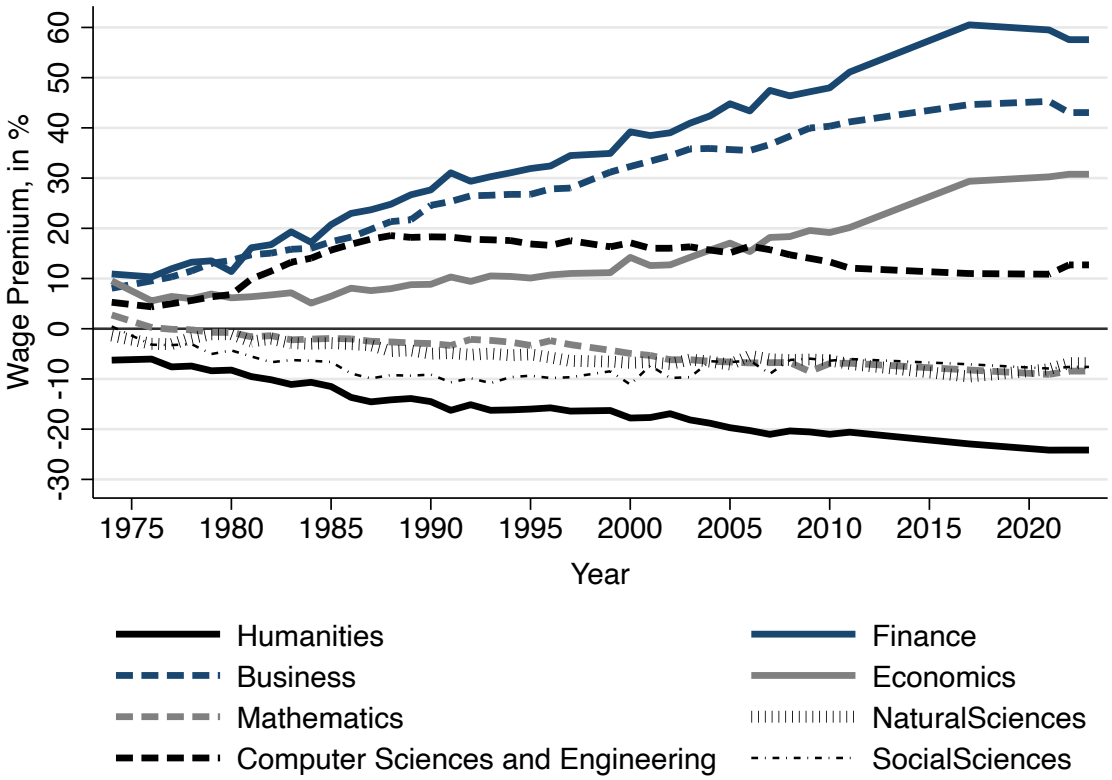


Figure 3. Faculty Pay Differentials across Fields (2015-2024)

This figure displays wage premia by academic field relative to Languages for the 2015-2024 period. Panel A displays results for research faculty; Panel B for teaching faculty. The dots represent coefficients from OLS regressions of the log of annual gross wage on field dummies, with Languages as the reference category. All regressions include fixed effects for university × year, academic rank × year, wage format × year (base salary versus total compensation), and data source × year. Coefficients are reported in percentage terms. Error bars indicate 95% confidence intervals, with standard errors clustered at the university level.

Panel A. OSU Faculty Survey Data (1974-2023)



Panel B. Individual-Level Faculty Salary Dataset (1996-2023)

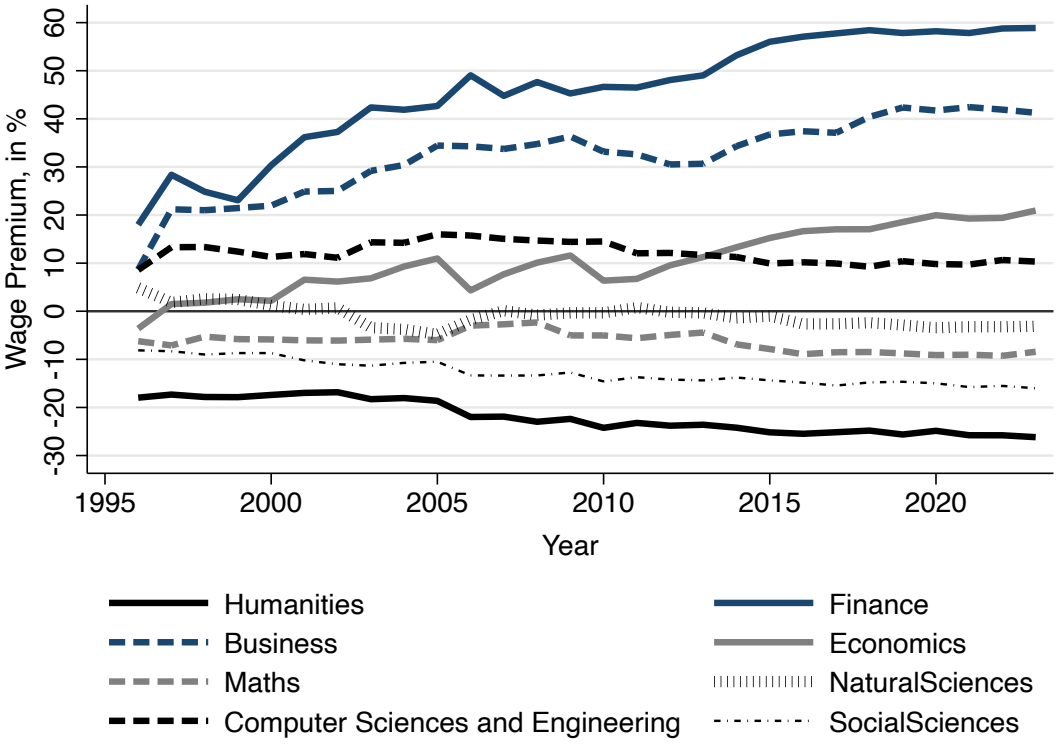


Figure 4. Evolution of Academic Pay across Fields

This figure plots the evolution of wage premia across academic fields from 1974 to 2023 in Panel A using the Oklahoma State University faculty survey data and from 1996 to 2023 in Panel B using our individual-level data faculty salary dataset. The lines plots the coefficient of field dummies in wage regression estimated every year, the reference being the sample mean, in percent. See Section 3.1 for more information on the specifications and samples.

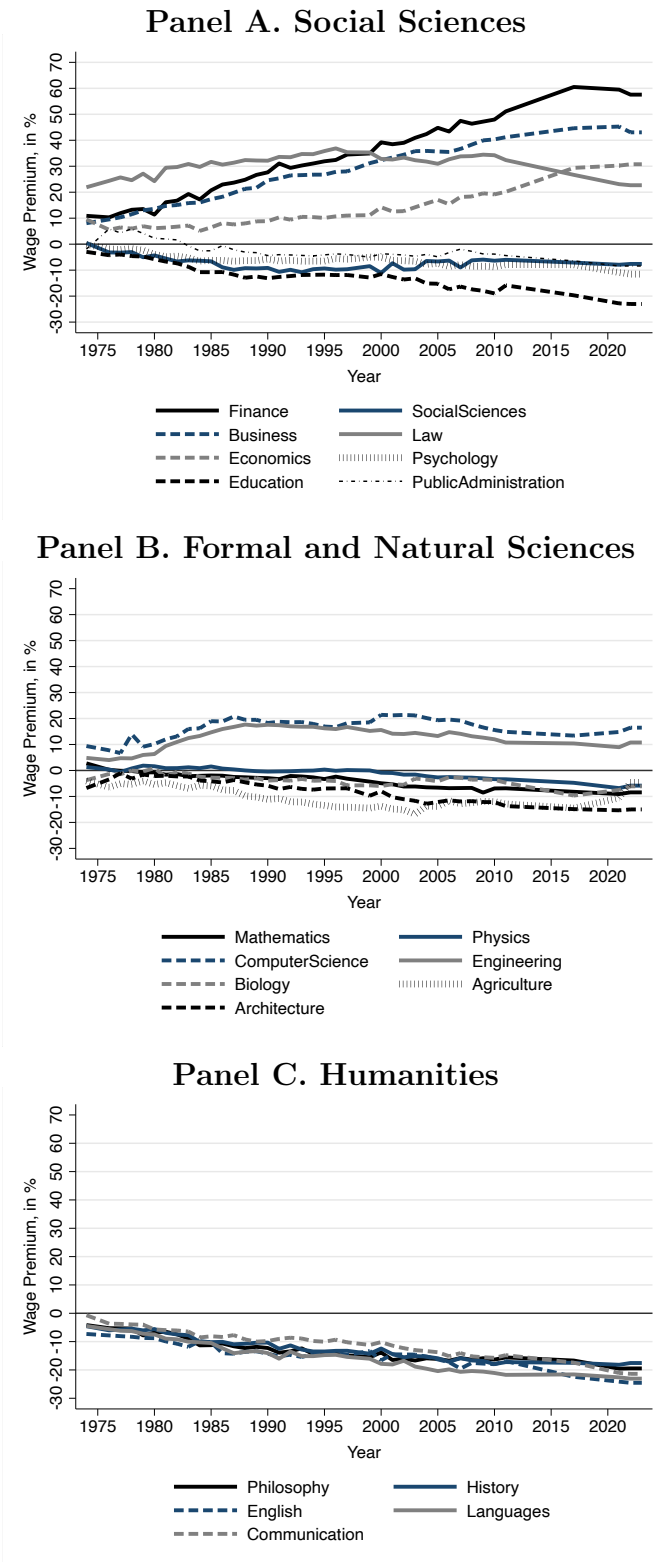


Figure 5. Evolution of Academic Pay across Fields: All Fields

This figure plots the evolution of wage premia across the 20 academic fields from 1974 to 2023 using the Oklahoma State University faculty survey data. The fields are grouped in Social Sciences (Panel A), Formal and Natural Sciences (Panel B), and Humanities (Panel C). The lines plots the coefficient of field dummies in wage regression estimated every year, the reference being the sample mean, in percent. See Section 3.1 for more information on the specifications and samples.

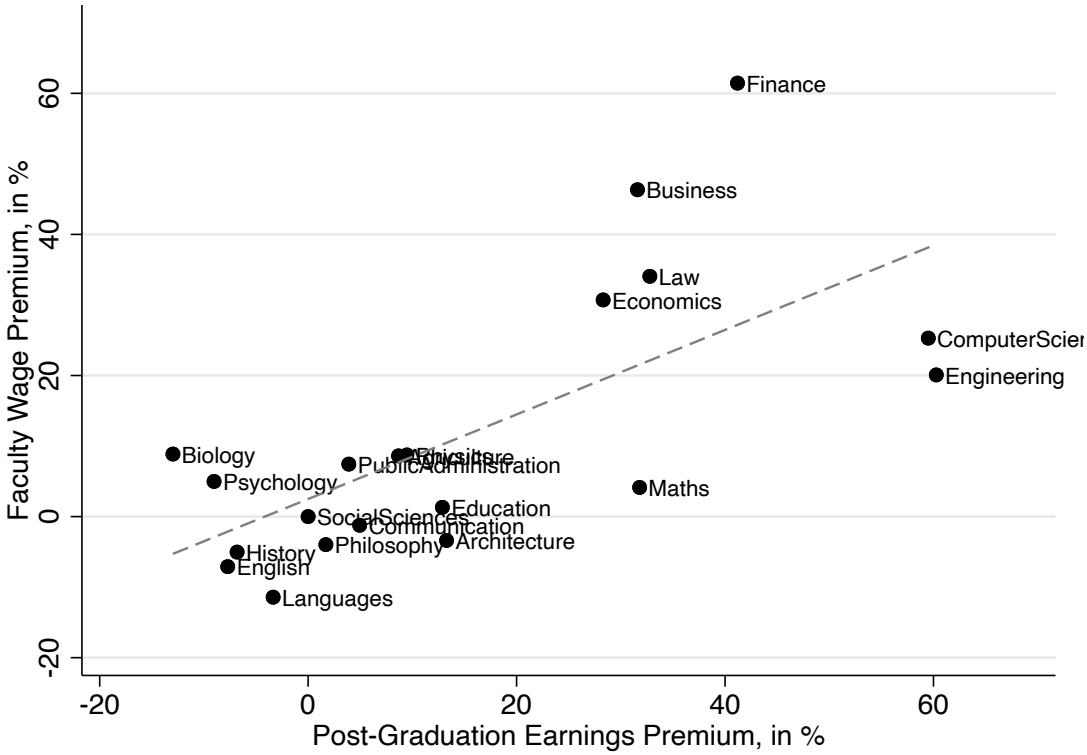
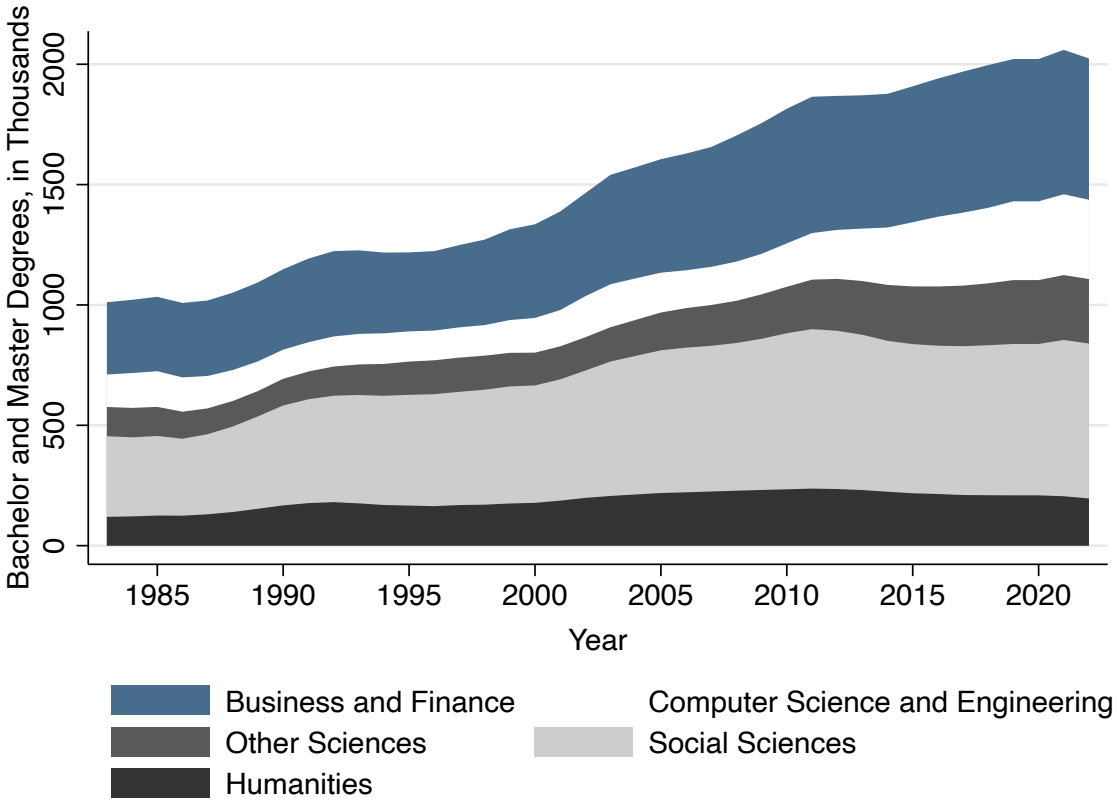


Figure 6. Faculty Pay versus Student Post-Graduation Earnings Premia across Fields

This figure illustrates the relationship between wage premia across academic fields in faculty pay and student post-graduation earnings. The dots represent coefficients from OLS regressions of the log of annual gross wage on field dummies. Faculty salary data is from public record requests and H1B/green card application data covering more than 300,000 professors across 1,500 U.S. and Canadian universities. Student post-graduation earnings data is from the PSEO.

Panel A. Growth in Student Count across Fields (1983-2023)



Panel B. Student Count per Faculty across Fields (2015-2022)

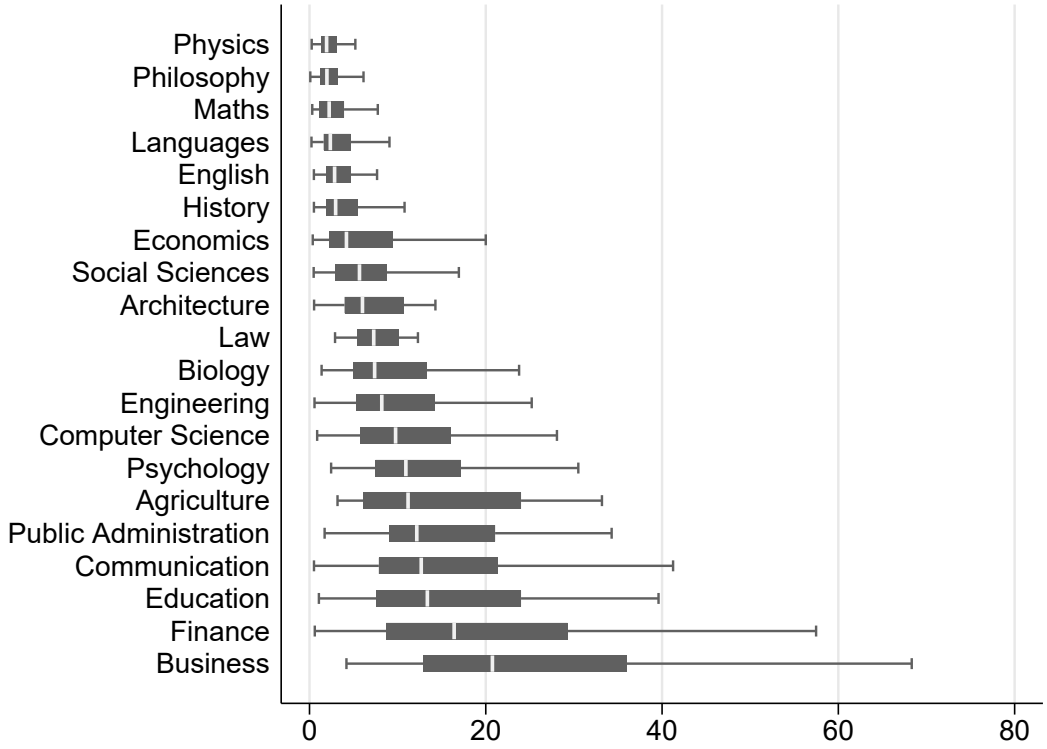


Figure 7. Student Count Trends and Heterogeneity across Fields

This figure displays the growth in student count per grouped fields in Panel A, and student count per faculty across academic fields in Panel B. In Panel B, each box plot displays the lower and upper adjacent values, along with the 25th percentile, median, and 75th percentile. Total number of faculty is obtained from a sample of institutions in our faculty salary data, while student count at these institutions comes from IPEDS.

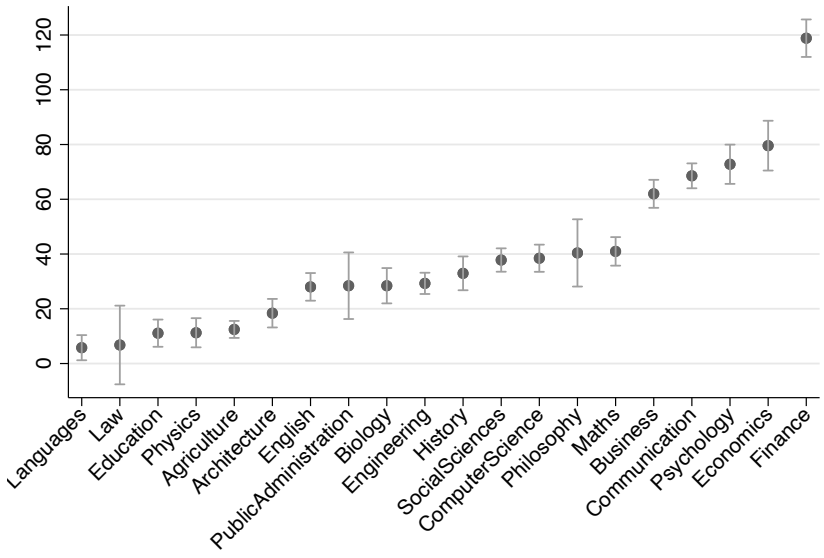


Figure 8. Elasticities of Faculty Pay to Post-Graduation Earnings.

This figure plots within-field elasticities of faculty wages to student wages across universities. Each elasticity is obtained from the within-field regression of the log of the yearly faculty pay on the log of the median undergraduate student wage one year after graduation in the same university and field. The regression includes academic rank times year, wage format times year, and degree level times year fixed effects. The data on student wages one year after graduation is derived from the US Census Bureau's Post-Secondary Employment Outcomes dataset, which covers the years 2001 to 2019. The median undergraduate student wage one year after graduation is matched with the average academic wages by academic field, year, and rank. Error bars indicate 95% confidence intervals, with standard errors clustered at the university level.

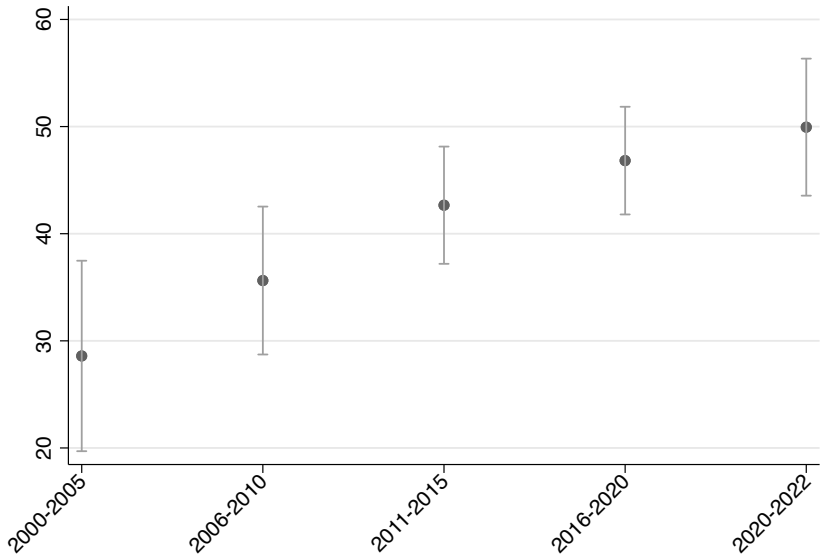


Figure 9. Growing Elasticity of Faculty Pay to Post-Graduation Earnings.

This figure plots elasticities of faculty wages to post-graduation earnings across time periods. Each elasticity is obtained from the regression of the log of the yearly faculty pay on the log of median post-graduation earnings in the same university, field, and year, with year times field fixed effects and academic rank, wage format, and degree level interacted with year fixed effects. Error bars indicate 95% confidence intervals, with standard errors clustered at the university level.

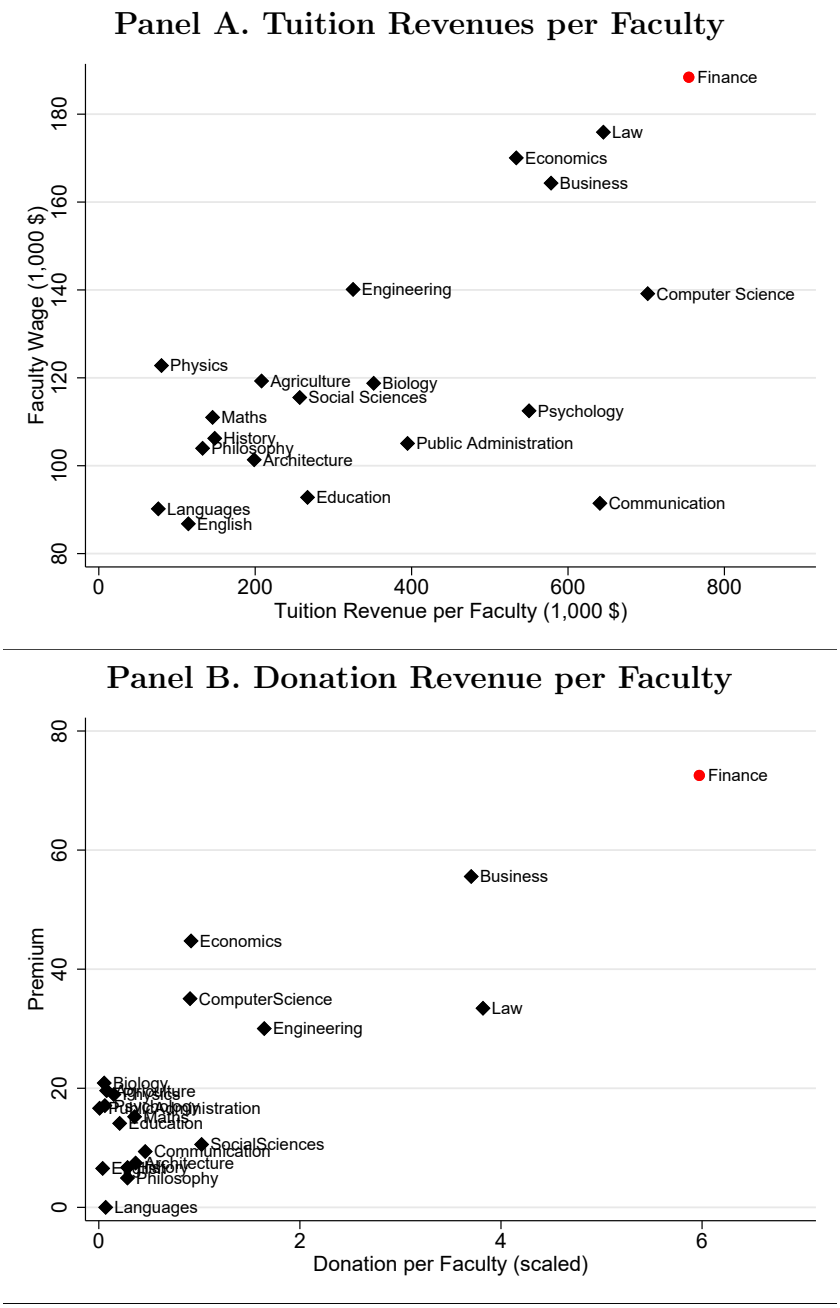
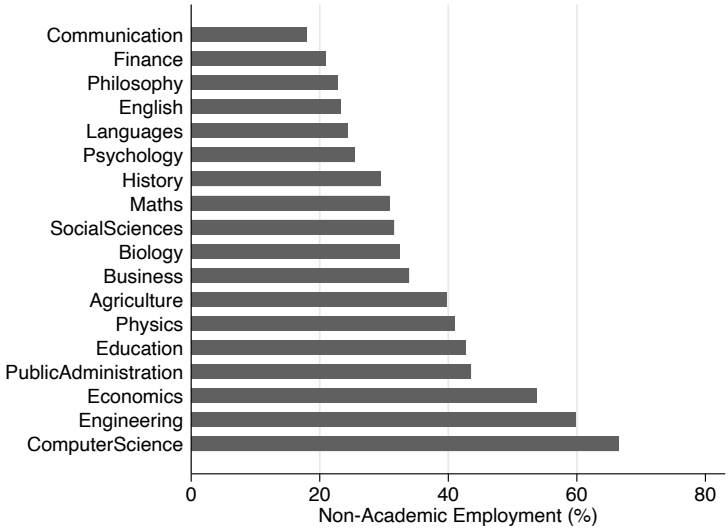


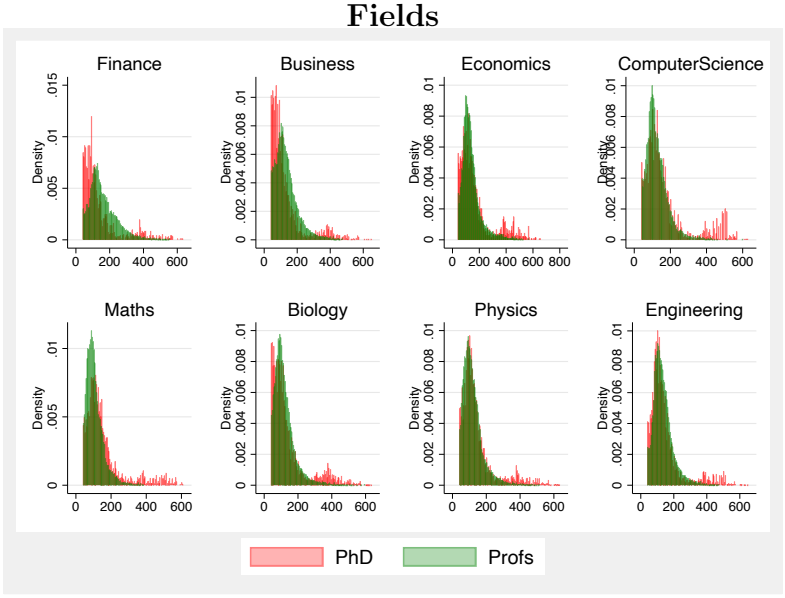
Figure 10. Revenue per Faculty

The figure illustrates the relationship between faculty pay and revenue per faculty across fields. We single out tuition revenues(Panel A) and donation revenue (Panel B). We calculate the tuition revenue per professor by dividing the combined undergraduate and graduate tuition revenues across all sample institutions in each academic field by the total number of faculty employed in that field for 2022. For undergraduate tuition revenue, we multiply three factors for each institution and field: (1) the number of bachelor's degrees conferred, (2) the average duration of bachelor's programs in that field, and (3) a weighted average tuition rate that accounts for the proportions of in-state and out-of-state students. Similarly, graduate tuition revenue is calculated by multiplying: (1) the number of master's degrees conferred, (2) the average length of master's programs in that field, and (3) the published average tuition rates for graduate programs.

Panel A. Non-Academic Placement Rates for Academics across Fields



Panel B. PhD Graduate Income: Industry versus Academia across Fields



Panel C. Finance Industry Placement and Income

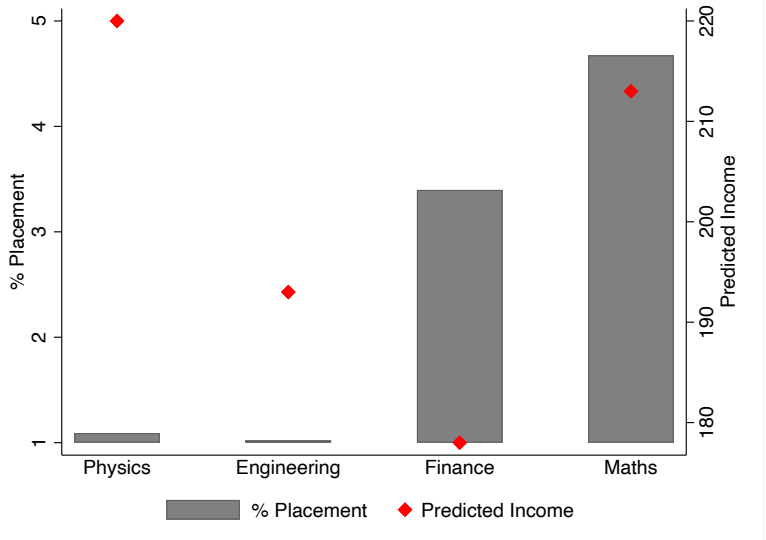


Figure 11. Heterogeneity across Fields in Industry Placement and Outside Options for Academics

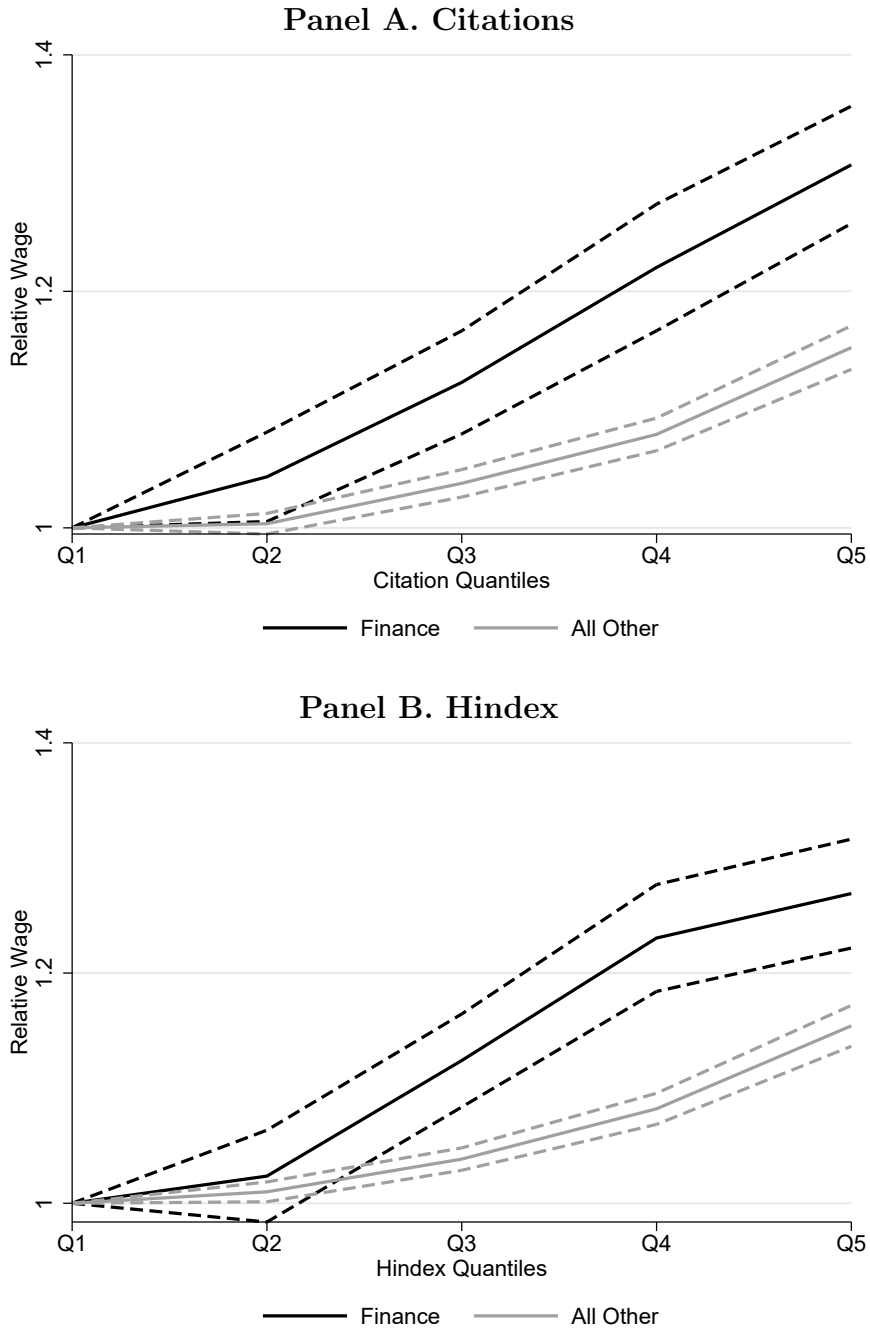


Figure 12. Wage Returns to Research Output

Panel A and B compare returns to research output in finance versus other fields. Research output is measured using citation and Hindex quintiles, in Panels A and B, respectively. Quintiles are defined within fields and positions. The graphs plot the coefficients $1 + \beta_i + \beta_{i,f}$ in black and $1 + \beta_i$ in grey in the regression $\ln(w_{h,t}) = \sum_{i=1}^{5} \beta_i q_i + \sum_{i=1}^{5} \beta_{i,f} \mathbb{1}_f q_i + \mu_u + \mu_{p,f} + \mu_t + \epsilon_{h,t}$. The dependent variable $\ln(w_{h,t})$ is the log of the yearly base salary. The model includes university, field$\times$ position, and year fixed effects. Dashed lines indicate 95% confidence bounds based on standard errors clustered at the university level.

9 Tables

Table 1. Summary Statistics: Faculty Wages

	Total Compensation						Base Salary			Counts	
	2015-2024				2005-2014	1995-2004	2015-2024	2005-2014	1995-2004	Total	
	Mean	**Median**	**P95**	**SD**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**# Obs**	**# Profs**
Total Sample	126.5	110.6	249.7	64.8	115.1	99.4	114.3	93.5	69.2	1,363,745	317,793
All Research Faculty	132.0	115.6	255.9	64.9	118.5	99.7	119.8	96.4	70.0	1,245,681	276,540
By Academic Field											
Finance	192.3	170.0	364.6	89.4	165.3	116.7	182.4	135.3	91.5	47,796	9,958
Law	189.3	171.9	369.8	88.1	174.3	124.1	198.4	161.4	111.2	27,309	5,692
Business	170.8	150.4	335.5	84.5	149.9	114.3	150.9	116.5	86.3	85,693	25,335
Economics	160.1	139.7	316.3	80.0	136.6	103.3	151.2	119.7	86.3	44,312	11,282
Engineering	151.0	135.7	273.8	64.0	134.7	108.0	127.2	107.6	84.1	140,577	32,635
Computer Science	146.9	131.1	266.7	62.9	132.1	106.0	124.6	103.9	78.6	60,690	17,287
Physics	133.9	118.8	252.6	61.3	121.4	100.8	120.4	100.5	72.6	122,939	24,461
Biology	129.7	116.2	238.8	58.0	117.6	102.9	114.5	94.6	67.0	105,419	20,365
Agriculture	122.1	113.3	208.9	45.3	104.7	84.0	110.6	96.6	74.4	28,938	6,635
Maths	120.4	107.8	218.9	51.9	110.3	92.5	105.9	88.5	66.3	77,946	17,851
Psychology	119.5	106.6	217.1	52.0	111.0	97.3	107.7	90.0	62.5	52,985	10,098
Public Administration	118.9	103.0	225.1	56.3	107.0	94.3	110.2	90.0	60.9	26,332	5,749
Social Sciences	116.7	103.5	213.6	50.9	106.0	96.6	105.3	86.3	61.9	110,936	23,564
Philosophy	114.6	103.0	208.5	49.5	103.4	98.0	102.3	85.7	62.3	21,546	4,502
Architecture	114.4	101.0	208.5	47.6	100.5	84.5	100.4	84.7	62.2	17,249	4,030
History	107.0	95.1	192.4	46.2	97.2	90.5	103.2	85.2	62.4	45,533	8,551
Education	106.5	96.5	182.2	40.0	99.0	92.7	87.4	72.8	59.7	62,872	13,718
Languages	103.2	91.9	187.9	44.1	95.2	86.4	95.0	79.6	57.3	52,038	10,872
English	101.4	91.0	180.1	42.1	92.6	86.2	95.8	80.7	58.5	73,050	14,683
Communication	101.2	91.3	176.0	39.8	91.8	68.5	93.2	77.6	59.6	41,521	9,272
By Rank											
Full Professor	158.1	141.9	297.1	72.9	139.7	109.7	154.2	117.7	83.6	558,911	90,090
Associate Professor	112.2	102.7	191.2	43.3	101.4	84.5	101.9	81.1	61.3	346,242	56,517
Assistant Professor	99.8	89.7	181.9	41.8	85.8	68.8	94.1	71.4	53.2	308,714	124,261
By University Classification											
Very High Research Intensity	151.0	131.7	295.5	74.8	131.4	101.6	140.8	111.4	81.9	628,983	140,861
High Research Intensity	124.0	110.7	223.6	52.9	110.3	93.0	103.0	81.6	67.1	217,949	48,027
Doctoral Universities	103.1	93.4	173.5	38.7	91.0	66.3	90.9	71.0	57.5	48,824	11,766
Other	107.8	99.7	185.8	40.6	100.7	96.6	85.9	74.7	56.3	349,925	75,886
By Data Source											
Public Requests Data	132.0	115.6	255.9	64.9	118.5	99.7	124.2	97.7	70.0	1,173,368	204,227
Green Card/H1B Applications							98.1	74.7		72,313	72,313
All Teaching Faculty	77.3	67.5	149.5	38.1	66.2	76.1	69.0	50.4	36.4	118,064	31,578

This table reports summary statistics on faculty wages across faculty type (research- or teaching-track), wage measure (total compensation or base salary), and time period. Summary statistics for research-track faculty are further disaggregated by academic field, academic rank, university classification, and data source. The base salary represents the 9-month base salary, excluding summer stipends and bonuses, while the total compensation includes all components of faculty pay. The dataset is an unbalanced panel consisting of over 1.2 million faculty-year observations from more than 300,000 professors at over 1,500 U.S. and Canadian 4-year institutions, covering the period from 1993 to 2024. For U.S. and Canadian public universities, we gather faculty wage data through public record requests under freedom of information laws. We identified academic fields from department affiliations, and, if not available, a textual analysis of automated Google search, as well as field directories. We supplement this sample with data from the U.S. Department of Labor's green card and H1B application records. All wage figures are reported in current U.S. dollars.

Table 2. Summary Statistics: Student Post-Graduation Earnings

Post-Graduation Earnings	1 Year After Graduation					5 Years After Graduation					Instrument		
	2016-2021 *N=33,537*				2010-2016 *N=23,593*	2016-2021 *N=26,095*				2010-2016 *N=19,559*	2016-2021	2010-2015	2000-2009
	P50		P25	P75	P50	P50		P25	P75	P50	Mean	Mean	Mean
	Mean	SD	Mean	Mean	Mean	Mean	SD	Mean	Mean	Mean			
Total Sample	42.9	15.1	32.2	54.5	36.1	59.1	17.2	45.4	76.0	51.2	75.8	66.6	57.5
By Academic Field													
Computer Science	65.7	19.6	49.1	84.8	56.4	91.8	25.4	70.4	121.8	74.8	91.3	79.4	68.1
Engineering	63.7	9.4	50.0	76.7	59.3	85.4	12.9	70.0	104.8	77.6	93.1	82.4	70.4
Law	60.3	17.5	37.6	97.9	60.7	88.1	16.7	58.7	132.8	97.0	99.7	87.6	75.8
Finance	48.7	7.6	37.3	60.3	40.9	70.3	12.1	53.8	91.4	59.8	84.5	73.9	64.2
Maths	48.5	11.4	33.2	65.3	40.3	68.2	16.1	50.3	92.0	56.5	79.5	69.5	60.0
Economics	44.7	7.2	32.2	57.9	37.5	68.5	10.4	50.4	91.3	56.8	77.8	67.8	58.5
Business	43.7	8.8	32.7	55.4	37.5	62.3	12.3	47.7	80.6	53.8	82.6	72.3	62.7
Architecture	41.5	8.3	32.2	50.6	34.5	57.4	6.6	46.7	69.5	48.5	88.1	76.5	66.2
Education	41.3	10.5	32.9	49.5	35.5	50.1	9.0	41.6	59.3	46.1	56.4	50.4	43.4
Public Administration	39.0	9.5	30.4	48.7	34.7	51.3	9.6	40.5	64.2	45.6	70.8	62.9	53.2
Physics	37.4	9.1	26.0	51.5	35.6	59.1	11.1	42.7	80.1	54.8	78.1	69.0	59.3
Agriculture	37.1	9.0	27.5	47.9	33.8	53.4	9.8	40.1	71.0	48.0	76.1	67.2	57.8
Communication	33.8	5.5	24.8	43.6	29.2	50.6	7.4	38.0	66.2	43.5	76.1	66.2	57.8
Social Sciences	32.8	5.9	23.4	43.8	28.4	49.9	8.5	36.7	66.2	43.4	74.9	65.6	56.8
Languages	32.1	6.2	22.5	43.8	28.6	47.7	6.2	35.0	63.4	42.6	67.5	59.3	51.3
Philosophy	30.9	5.1	21.2	43.8	26.7	47.8	8.0	32.6	68.1	41.6	69.8	60.9	53.0
English	29.8	5.0	21.1	40.4	26.7	44.8	5.9	32.6	58.0	40.3	68.9	60.5	52.6
History	29.8	5.2	21.1	40.9	26.6	46.4	6.0	33.9	60.5	41.3	67.5	59.3	51.7
Psychology	29.4	5.0	21.4	38.7	26.3	45.5	6.1	33.7	59.2	40.2	66.9	59.1	50.9
Biology	28.7	5.3	20.6	38.7	26.2	52.0	6.6	37.1	68.9	46.8	67.4	59.6	51.3
By Degree Level													
Graduate	57.9	17.8	44.9	72.9	49.9	70.3	22.3	56.1	89.1	61.5	83.3	73.6	63.3
Undergraduate	41.0	13.6	30.6	52.2	34.4	57.8	15.9	44.1	74.4	50.0	74.8	65.7	56.7
By University Classification													
Very High Research Intensity	46.2	17.3	34.8	58.7	38.7	64.1	19.2	49.0	83.2	55.0	78.6	68.9	59.4
High Research Intensity	42.5	13.6	32.0	53.8	36.1	58.0	16.0	44.9	73.8	50.3	74.6	65.7	56.6
Doctoral Universities	40.2	11.4	30.8	50.2	35.1	54.0	12.4	42.5	67.5	47.8	73.0	64.5	56.1
Other	38.2	10.9	28.4	48.9	32.5	52.9	12.0	40.5	67.3	46.7	73.7	64.8	55.8

This table presents summary statistics for our yearly panel of post-graduation earnings and the constructed instrument variable. Post-graduation earnings are sourced from the U.S. Census Bureau's Post-Secondary Employment Outcomes (PSEO) dataset. From this dataset, we obtain the 25th, 50th, and 75th percentiles of student earnings at the university-degree major-cohort level that we match with our faculty salary dataset. The resulting panel includes 76,000 observations across 366 universities, with around 5,000 degree majors per year over the 2002-2022 period. We construct the instrument variable by combining the student placement data from the PSEO with salary data from the American Community Survey with. Specifically, we calculate mean salaries from the American Community Survey at the 2-digit NAICS industry, Census division, and year level. We then weight these industry-region-year wages by the share of graduates from each university-field combination employed in the corresponding industry-region-year cell, as reported in the PSEO. All earnings figures are expressed in thousands of current U.S. dollars.

Table 3. Faculty Pay Premia across Fields (2015-2024)

	All Research	Top Scholars	Position			University Type		University Classification		Department Source		
			Assistant	Associate	Full	Private	Public	R1	Other	Request	Directories	Google
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
𝟙.Finance	0.73***	0.57***	0.85***	0.70***	0.63***	0.77***	0.74***	0.92***	0.56***	0.76***	0.99***	0.57***
	(0.02)	(0.05)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.07)	(0.05)
𝟙.Business	0.58***	0.35***	0.66***	0.54***	0.51***	0.67***	0.58***	0.68***	0.46***	0.57***	0.84***	0.50***
	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)	(0.04)
𝟙.Law	0.46***	0.28***	0.43***	0.41***	0.43***	0.48***	0.48***	0.50***	0.31***	0.50***	0.66***	0.37***
	(0.02)	(0.08)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)	(0.08)	(0.04)
𝟙.Economics	0.42***	0.31***	0.47***	0.39***	0.41***	0.46***	0.43***	0.51***	0.30***	0.42***	0.69***	0.34***
	(0.02)	(0.05)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)	(0.03)
𝟙.Computer Science	0.37***	0.10***	0.40***	0.36***	0.33***	0.32***	0.38***	0.40***	0.31***	0.38***	0.58***	0.31***
	(0.01)	(0.04)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.07)	(0.02)
𝟙.Engineering	0.31***	0.08**	0.32***	0.30***	0.31***	0.24***	0.33***	0.34***	0.27***	0.34***	0.56***	0.28***
	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.07)	(0.01)
𝟙.Physics	0.20***	-0.01	0.19***	0.17***	0.20***	0.13***	0.21***	0.24***	0.12***	0.21***	0.57***	0.17***
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.07)	(0.02)
𝟙.Biology	0.20***	-0.06	0.20***	0.17***	0.19***	0.21***	0.20***	0.24***	0.13***	0.21***	0.24***	0.17***
	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)	(0.08)	(0.01)
𝟙.Agriculture	0.19***	-0.02	0.20***	0.19***	0.17***	0.20***	0.19***	0.21***	0.18***	0.20***	0.37***	0.16***
	(0.02)	(0.07)	(0.01)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)	(0.07)	(0.02)
𝟙.Public Administration	0.19***	0.09*	0.16***	0.17***	0.20***	0.13***	0.19***	0.25***	0.09***	0.20***	0.33***	0.16***
	(0.02)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.03)	(0.10)	(0.02)
𝟙.Psychology	0.16***	0.03	0.14***	0.14***	0.17***	0.15***	0.17***	0.21***	0.09***	0.18***	0.44***	0.13***
	(0.01)	(0.04)	(0.01)	(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.01)	(0.02)	(0.09)	(0.01)
𝟙.Maths	0.16***	-0.01	0.16***	0.14***	0.15***	0.14***	0.16***	0.19***	0.10***	0.17***	0.48***	0.12***
	(0.01)	(0.04)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.08)	(0.01)
𝟙.Education	0.13***	0.11	0.13***	0.11***	0.13***	0.11**	0.13***	0.12***	0.08***	0.14***	0.29***	0.11***
	(0.01)	(0.13)	(0.01)	(0.01)	(0.02)	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)	(0.08)	(0.02)
𝟙.Social Sciences	0.11***	0.03	0.11***	0.10***	0.12***	0.11***	0.12***	0.14***	0.06***	0.12***	0.32***	0.09***
	(0.01)	(0.04)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.07)	(0.01)
𝟙.Communication	0.10***	-0.05	0.08***	0.09***	0.12***	0.08***	0.10***	0.11***	0.05***	0.12***	0.30***	0.07***
	(0.01)	(0.06)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.07)	(0.01)
𝟙.Architecture	0.08***	-0.38**	0.07***	0.08***	0.09***	0.09***	0.08***	0.10***	0.07***	0.09***	0.28***	0.06***
	(0.01)	(0.18)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.08)	(0.02)
𝟙.Philosophy	0.07***	-0.05	0.05***	0.06***	0.09***	0.03	0.07***	0.09***	0.03***	0.10***	0.25***	0.03***
	(0.01)	(0.21)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.09)	(0.01)
𝟙.History	0.06***	0.17***	0.04***	0.05***	0.07***	0.04	0.06***	0.06***	0.03***	0.08***	0.32***	0.03***
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.08)	(0.01)
𝟙.English	0.04***	-0.23*	0.03***	0.03***	0.05***	-0.00	0.04***	0.03***	0.02**	0.05***	0.22***	0.02*
	(0.01)	(0.13)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.07)	(0.01)
Fixed Effects												
University × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Position × Year	Yes	Yes	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wage Format × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Data Source × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-	-	-
Observations	694,158	11,695	187,890	192,029	289,681	17,337	625,958	359,653	334,505	377,168	29,647	227,804
R^2	0.67	0.48	0.70	0.68	0.55	0.77	0.65	0.59	0.70	0.68	0.67	0.62

This table presents wage premia by academic field relative to Languages for the 2015-2024 period. The sample is restricted to research faculty only. We estimate OLS regressions of the log of annual gross wage on field dummies, with Languages as the reference category. Column 1 presents wage premia for the full sample of research faculty. Column 2 restricts the sample to scholars ranked in the top 2000 in their field. Columns 3-5 show premia by academic rank: assistant, associate, and full professors. Columns 6-7 compare premia across private and public universities. Columns 8-9 display premia by university classification: R1 universities (doctoral universities with very high research activity) and all others. Columns 10-12 examine premia by department information source: public requests, field directories, and Google-sourced information. The baseline specification in Column 1 includes fixed effects for university × year, academic rank × year, wage format × year (base salary versus total compensation), and data source × year (public record requests versus H1B or green card application data). Fixed effects used in other specifications are indicated in the table. Standard errors are clustered at the university level and reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Elasticity of Faculty Pay to Post-Graduation Earnings: OLS

	Log(Faculty Pay)$_{f,u,y}$											
	Within University and Year Elasticity Across Fields						**Within Field and Year Elasticity Across Universities**					
# Years Post-Graduation	One Year			Five Years			One Year			Five Years		
Post-Graduation Earnings Percentile	25th	50th	75th	25th	50th	75th	25th	50th	75th	25th	50th	75th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Post-Graduation Earnings)$_{u,f,y}$	0.40***	0.45***	0.48***	0.50***	0.58***	0.59***	0.34***	0.43***	0.45***	0.51***	0.59***	0.54***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Fixed Effects:												
University × Year	Yes	Yes	Yes	Yes	Yes	Yes	-	-	-	-	-	-
University × Rank	Yes	Yes	Yes	Yes	Yes	Yes	-	-	-	-	-	-
Field × Year	-	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Field × Rank	-	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Rank × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree Level × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	169,000	169,000	169,000	112,795	112,795	112,795	169,367	169,367	169,367	113,093	113,093	113,093
R^2	0.68	0.68	0.68	0.67	0.68	0.69	0.67	0.67	0.68	0.68	0.69	0.69

This table reports regression coefficients from estimating the log of the average annual faculty salary at the university, degree level, academic field, academic rank level on the log of student post-graduation earnings in the corresponding university, field, and degree. Student earnings are sourced from the U.S. Census Bureau's Post-Secondary Employment Outcomes (PSEO) dataset. We match the 25th percentile, median, and 75th percentile of post-graduation earnings to the average annual faculty salary by academic rank in the same university, degree level, and year. All specifications include academic rank × year, wage format × year, and degree level × year fixed effects. Columns 1-6 estimate within-university, across-field elasticities by including university × year and university × rank fixed effects. Columns 7-12 estimate within-field, across-university elasticities by including field × year and field × rank fixed effects. Standard errors are clustered at the university level and at the field × year level, and are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Elasticity of Faculty Pay to Post-Graduation Earnings: IV

	Log(Faculty Pay)$_{f,u,y}$											
	Within University and Year Elasticity Across Fields						**Within Field and Year Elasticity Across Universities**					
# Years Post-Graduation	One Year			Five Years			One Year			Five Years		
Post-Graduation Earnings Percentile	25th	50th	75th	25th	50th	75th	25th	50th	75th	25th	50th	75th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\widehat{\text{Log(Post-Graduation Earnings)}}_{u,f,y}$	0.70***	0.74***	0.81***	0.87***	0.91***	0.87***	1.10***	0.90***	0.76***	0.71***	0.62***	0.55***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.23)	(0.18)	(0.15)	(0.14)	(0.13)	(0.11)
F-statistics	340	400	543	345	432	645	34	45	65	54	22	54
Fixed Effects:												
University × Year	Yes	Yes	Yes	Yes	Yes	Yes	-	-	-	-	-	-
University × Rank	Yes	Yes	Yes	Yes	Yes	Yes	-	-	-	-	-	-
Field × Year	-	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Field × Rank	-	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Rank × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree Level × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136,267	136,267	136,267	88,819	88,819	88,819	136,681	136,681	136,681	89,128	89,128	89,128
R^2	0.13	0.15	0.15	0.15	0.23	0.26	-0.23	0.01	0.07	0.12	0.16	0.17

This table displays the results of the instrumental variable analysis, in which students post-graduation earnings are instrumented by the synthetic wage index calculated in equation (4). The synthetic wage index is constructed using placement data from the Post-Secondary Employment Outcomes dataset at the degree and year level across industry and location and wage data from the American Community Survey. We match the wage index with average academic wages by academic rank, field, university, and year. Standard errors are clustered at the university level and are reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Within University-Field Idiosyncratic Shocks to Post-Graduation Earnings and Faculty Pay: IV

	$\textbf{Log(Faculty Pay)}_{\textbf{f,u,y}}$							
# Years Post-Graduation	One Year				Five Years			
# Academic Rank	All			Assistant Professors	All			Assistant Professors
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{\text{Log(Post-Graduation Earnings)}}_{\text{u,f,y}}$	0.80***	0.64***	0.80***	0.97***	0.85***	0.98***	0.54***	0.74***
	(0.03)	(0.23)	(0.23)	(0.27)	(0.03)	(0.35)	(0.18)	(0.26)
F-statistics	500	8	11	12	432	9	10	13
Fixed Effects:								
University × Field	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	-	Yes	Yes	Yes	-	Yes	Yes	Yes
University × Year	-	-	Yes	Yes	-	-	Yes	Yes
Field × Degree Level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field × Rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136,505	136,505	136,108	49,324	88,974	88,974	88,682	32,113

This table displays the results of the instrumental variable analysis on shocks to post-graduation earnings, in which students post-graduation earnings are instrumented by the synthetic wage index calculated in equation (4). The synthetic wage index is constructed using placement data from the Post-Secondary Employment Outcomes dataset at the degree and year level across industry and location and wage data from the American Community Survey. We match the wage index with average academic wages by academic rank, field, university, and year. Standard errors are clustered at the university level and are reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Mechanism: Elasticity, Scalability, and Scarcity

	Log(Faculty Pay)					
	Undegraduate			Grad + Undegrad		
	All	High Scal.	Scarcity	All	High Scal.	Scarcity
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Student Earnings)	0.21***	0.34***	0.57***	0.32***	0.42***	0.69***
	(0.08)	(0.10)	(0.15)	(0.08)	(0.11)	(0.19)
University X Field	Yes	Yes	Yes	Yes	Yes	Yes
Observations	454,813	133,612	55,051	454,813	133,612	55,051
R^2	0.58	0.57	0.49	0.58	0.57	0.49

This table investigates how the elasticity varies depending on scalability, defined as a higher number of students per faculty, and scarcity, defined as a low number of PhD candidates per faculty. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Elasticity of Faculty Pay to Research Output

	Log(Faculty Pay)									
	Total Citation Quintiles					H-Index Quintiles				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintiles	0.08***	0.05***	0.04***	0.02**	0.02***	0.08***	0.05***	0.03***	0.01	0.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Quintiles × 1.Finance			0.10***	0.08***	0.03***			0.09***	0.07***	0.02**
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Business			0.09***	0.06***	0.04***			0.09***	0.06***	0.04***
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Economics			0.07***	0.06***	0.04***			0.08***	0.07***	0.05***
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Biology			0.06***	0.04***	0.04***			0.07***	0.05***	0.05***
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Maths			0.05***	0.04***	0.04***			0.06***	0.05***	0.05***
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Psychology			0.05***	0.03***	0.05***			0.07***	0.05***	0.07***
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Physics			0.05***	0.04***	0.04***			0.06***	0.05***	0.04***
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.ComputerScience			0.05***	0.02	0.04***			0.05***	0.03**	0.04***
			(0.02)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Philosophy			0.04**	0.03	0.03			0.05***	0.03**	0.04**
			(0.02)	(0.02)	(0.02)			(0.02)	(0.02)	(0.02)
Quintiles × 1.PublicAdministration			0.04***	0.02*	0.02			0.05***	0.03**	0.03**
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.SocialSciences			0.04***	0.02**	0.03**			0.04***	0.03***	0.03***
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Engineering			0.03**	0.02	0.03***			0.03***	0.03**	0.03***
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.History			0.02	0.01	0.01			0.03*	0.02*	0.01
			(0.01)	(0.01)	(0.01)			(0.02)	(0.01)	(0.01)
Quintiles × 1.Communication			0.02	0.01	0.02			0.03*	0.02	0.02
			(0.01)	(0.01)	(0.02)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Education			0.01	0.00	0.01			0.02**	0.01	0.01
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.English			0.01	0.00	0.00			0.02	0.01	0.00
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Law			-0.00	-0.00	0.00			0.01	0.01	0.01
			(0.02)	(0.02)	(0.02)			(0.02)	(0.02)	(0.02)
Quintiles × 1.Agriculture			-0.01	0.00	-0.01			0.00	0.01	0.00
			(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
Quintiles × 1.Architecture			-0.01	-0.00	-0.01			-0.00	-0.00	-0.02
			(0.01)	(0.01)	(0.01)			(0.01)	(0.02)	(0.01)
Fixed Effects										
University × Year	-	Yes	-	Yes	Yes	-	Yes	-	Yes	Yes
Field	Yes	Yes	Yes	Yes	-	Yes	Yes	Yes	Yes	-
Field × University	-	-	-	-	Yes	-	-	-	-	Yes
Rank × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience Quintiles	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wage Format × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83,609	83,562	83,609	83,562	83,480	83,609	83,562	83,609	83,562	83,480
R^2	0.53	0.61	0.54	0.61	0.67	0.52	0.61	0.53	0.61	0.67

This table reports coefficients from OLS regressions where the dependent variable is log annual gross wage. The independent variables are quintiles of research output measured by total citations (Columns 1-5) and H-index (Columns 6-10). Columns 3-5 and 8-10 additionally include interactions between research output quintiles and field dummies, with Languages as the reference category. All specifications include fixed effects for wage format × year (base salary versus total compensation), academic rank × year, and experience quintiles, where experience is measured as years since first publication. Columns 1-4 and 6-9 additionally include field fixed effects, while columns 5 and 10 include field × university fixed effects. Columns 2, 4-5, 7, and 9-10 include university × year fixed effects. Data are from the merge of our academic wage database with Scopus and include 83,609 faculty year observations representing 18,479 professors across 192 public universities. Standard errors are clustered at the university level and reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.