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

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Abstract

We examine long-term trends in faculty compensation and its underlying drivers in North America, using a comprehensive administrative dataset covering most research institutions. We document three primary facts. First, wage dispersion across academic fields has widened significantly over the past 50 years, with economics, business, and especially finance exhibiting a large and growing premium. Second, faculty wages are strongly and positively correlated with their students' post-graduation earnings across fields. Third, the relative supply of PhD students varies also substantially across fields, with high paying fields training relatively fewer PhD students. Using granular data on student earnings at the university-field-year level, we estimate the elasticity of faculty pay with respect to students' post-graduation earnings to be around 0.7. This elasticity varies significantly across fields and has increased over time. Our results align with a model of occupational choice, where higher industry wages simultaneously increase demand for faculty, through greater student enrollment and university revenues, and raise the opportunity cost of doctoral training in corresponding fields. Field-specific frictions further shape how this labor market tightening translates into faculty wages. Overall, our findings illustrate how academic wages are increasingly shaped by broader labor market dynamics, with field-specific responsiveness amplifying the transmission of private-sector wage differentials into growing faculty pay dispersion.

JEL classification: I23, I26, J31, N32

Website for data vizualisation: `https://www.academicpaylab.org/`

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1 Introduction

While the aggregate returns to postsecondary education have risen substantially since the late 1970s (Goldin and Katz 2008), these gains have been remarkably heterogeneous across fields of study. Substantial earning differentials persist even when accounting for institution type, selectivity, and peer quality (Kirkebøen et al. 2016), often surpassing the gap between high school and college graduates (Altonji et al. 2012). These inter-field disparities have widened over time (Altonji et al. 2014).[1] As a result, the choice of college major has become a crucial determinant of the level, trajectory, and risk of lifetime 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, most notably, on the determination of faculty compensation.[3] Beyond their implications for tuition and university costs, faculty wages serve as a critical price signal that influences the allocation of talent across disciplines, the quality of instruction, and the frontier of innovation.[4] Although prior research provides suggestive evidence of a widening dispersion in faculty wages across academic fields (e.g., Courant and Turner (2019)), a comprehensive assessment is lacking. This paper addresses several key questions: How has the cross-sectional distribution of academic wages evolved over recent decades? To what extent does cross-field wage dispersion mirror student labor market outcomes? If such a relationship exists, is it uniform across fields and what economic mechanism underlies it?

This paper documents a secular increase in faculty wage dispersion across fields since the 1970s and uncovers a robust relationship between academic compensation and returns to higher education. We estimate the elasticity of faculty pay with respect to student post-graduation earnings to be around 0.7, implying that rising inter-industry wage differentials account for a substantial share of this trend. However, cross-field heterogeneity in this elas-

[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 labor 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 (2024); 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 (2026), 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).

ticity also plays a significant role in the observed academic wage dispersion. To explain these patterns, we develop a framework in which higher industry wages affect faculty pay through two complementary channels: a demand-side channel, where increased student demand for high-earning fields generates greater university revenues and raises faculty demand, and a supply channel, where the opportunity cost of doctoral training rises with industry wage premiums. We test the implications of the framework by examining how the resulting tightening of the academic labor market exerts upward pressure on wages, particularly in fields characterized by revenue models highly responsive to student demand and supply-side frictions in the PhD pipeline. Our analysis demonstrates how broad labor market dynamics, mediated by field-specific characteristics, increasingly shape both the level and dispersion of faculty compensation.

To conduct our empirical analysis, we first assemble a longitudinal administrative dataset of individual-level faculty pay across the majority of universities in the U.S. and Canada.[5] Our primary dataset tracks over 330,000 faculty across 1,459 universities and 20 fields from 1993 to 2023, comprising more than 1.45 million individual-level observations. These administrative records include detailed information on academic field, rank, compensation –both base salary and total pay – and institutional affiliation. To enlarge the temporal scope of our analysis, we augment these data with university-field-level survey data dating back to 1974. We construct this database using 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 supplement these records with green card and H1B application data, leveraging the significant share of non-U.S. citizens employed in academia. A key challenge for our empirical analysis is to precisely and consistently identify faculty academic fields. We address it by using a three step approach: textual analysis of department affiliations when available (63% of observations), results from Google searches using names and affiliations collected through an API (31%), and academic field directories (5%).

We merge this faculty pay dataset with a yearly panel of student post-graduation earnings, constructed using the U.S. Census Bureau's Post-Secondary Employment Outcomes (PSEO) data. The PSEO links individual-level graduation records from post-secondary

[5]We define "universities" as post-secondary institutions that award four-year bachelor's degrees.

institutions to the Longitudinal Employer-Household Dynamics program data, providing median earnings one, five, and ten years after graduation, along with their industry and geographical placement, for academic programs across participating universities. Our faculty salary dataset covers 76% of the 488 four-year institutions included in the PSEO. We link this panel of academic programs with the average faculty pay in the same university and field. We arrive at a yearly panel of 3,700 academic programs per year across 368 universities over the 2002-2022 period, with matched information on both faculty pay and students post-graduation earnings. Finally, we supplement our dataset with (i) information on the number of degrees conferred across fields, universities, and years using data from IPEDS, (ii) measures of research impact derived from the bibliographic database Scopus.

We establish three primary empirical facts using this comprehensive dataset. First, we document a widening dispersion in faculty pay across fields since the 1970s, primarily driven by business, law, economics, and especially finance.[6] 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.[7] 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, and for assistant professors.

Second, faculty pay is positively correlated with student post-graduation earnings in the cross section of academic fields. Specifically, the average faculty wage premium by field, controlling for rank, year, and affiliation, is strongly correlated with the corresponding post-

[6] We group accounting and finance together in the field referred to as *finance*.

[7] 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.

graduation earnings premium of students in those same fields, even after adjusting for student socio-demographic characteristics. Compensation in higher education is thus partially aligned with labor market outcomes for graduates, a linkage largely absent in secondary education. However, the ratio of faculty wage premiums to student earnings premiums varies widely across disciplines, suggesting significant heterogeneity in the elasticity of faculty pay with respect to student labor market returns.

Third, there is significant and persistent cross-field variation in the quantity of PhD candidates relative to the total student body, with ratios spanning from 0.1% to 5%. Notably, the ranking of fields by this measure has remained stable over the past three decades. Moreover, in the ten highest-paying fields, faculty compensation exhibits a negative correlation with the ratio of trained PhD students to the total student population. This pattern points to field-specific imbalances between student demand and faculty supply, as proxied by the number of PhD candidates, which in turn may affect wage outcomes. The persistence of these rankings suggests the presence of underlying structural frictions tied to field-specific characteristics.

Having established these three stylized facts, we turn to estimating 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 regression model that relates faculty pay to students' post-graduation earnings, using our yearly panel of academic programs from 2002 to 2022. The model includes three alternative sets of fixed effects to isolate different sources of variation: rank-by-year fixed effects (to estimate the elasticity across all observations), complemented by university-by-year fixed effects (to estimate elasticities across fields within universities), or field-by-year fixed effects (to estimate elasticities across universities within fields). Across all specifications, we find that academic wages are strongly related to undergraduate student wages, with elasticities in the range of 0.4 to 0.7. This relationship remains consistent whether the elasticity is measured within universities across fields, within fields across universities, or using student earnings at the 25th, 50th (median), or 75th percentiles. To further validate our findings, we replicate the analysis using College Scorecard data on median student earnings one year after graduation and obtain similar estimates.

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, resulting from IPEDS data limitations, 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 wage index at the university-by-field level, based on the industries and geographical areas where the university has historically placed students from that field, combined with the data from the American Community Survey (ACS) on wages in those industries and areas. The intuition behind the instrument is that, all else being equal, faculty in universities or fields that historically place students in regions and industries experiencing disproportionate wage growth see an increase in student post graduation earnings plausibly exogenous to the contemporaneous quality of education they provide.

The elasticity estimated through instrumental variable analysis is of similar magnitude to that obtained from the OLS regressions, thereby alleviating concerns about potential endogeneity from the sources previously discussed.[8] In addition, this instrument allows us to estimate the elasticity within academic program across time by addressing PSEO data limitations in the time series, such as changes in sample representativeness across years. Hence, our preferred specification includes university $\times$ field fixed effects, which absorb cross-sectional variation across universities and fields, as well as year fixed effects, which account for aggregate time trends. Identification in this framework arises from university-field-specific shocks in the instrument. Using this specification, we estimate a within-academic-program-over-time elasticity of 0.5 to 0.7. Thus, the widening dispersion in student future earnings across industries over recent decades has contributed significantly to the growing heterogeneity in faculty pay across academic disciplines.

However, the increasing dispersion of academic wages result also from a pronounced heterogeneity across fields in the elasticity of faculty pay to their student future earnings. Measuring elasticities within each field reveals for instance that the elasticity of faculty pay to student earnings in finance and economics is two to three times higher than the average. In contrast, the elasticity is much lower than average in languages, education, law, and physics. In addition, our instrument does not rule out all sources of endogeneity.

[8] A *leave-out-mean* approach for student post-graduation earnings, where we instrument student earnings with the average earnings of students in the same field and state excluding their own institution, confirms our findings.

Specifically, one cannot exclude that industry-specific shock affect also the opportunity cost of starting a PhD, hence tightening the faculty labour market and affecting wages through a less direct channel.

Therefore, to guide the interpretation of our results and explore this heterogeneity in elasticity across fields, we next develop a simple theoretical framework incorporating both demand-side and supply-side channels of transmission from returns to education to faculty pay. We build on the model of labor market for skilled professionals by Ryoo and Rosen (2004), in which occupational wages respond to shifts in market demand, and imperfect supply adjustments amplify this response. In academic labor markets, supply frictions are particularly pronounced, due to the length of PhD training, and a distinctive feedback mechanism: the same forces driving demand for professors also restrict their supply. Specifically, an increase in industry wages raises the private returns to education, fostering student demand for courses and degrees in corresponding field. Universities respond by expanding faculty positions, raising demand for faculty. Yet, these same wage increases raise the opportunity cost of academic careers, reducing the pool of potential PhD students and constraining faculty supply. This dual effect can amplify demand-supply mismatches, generating large and persistent wage responses. Field-specific institutional features, such as how student demand translates into university revenues and field-specific PhD supply frictions, further shape these dynamics, explaining the cross-field variation in faculty pay elasticities and widening dispersion observed in recent decades.

The framework allow us to propose a taxonomy of field characteristics that may affect the elasticity to student earnings. Estimating our main OLS and IV specification across split samples, we show that the elasticity is higher within field with a high sensitivity of revenue to student demand and frictions in the pipeline of PhDs. We proxy for the institutional revenue sensitivity in a field using its labor intensity, the incremental return to master studies in this field, as a high premium should increase the demand for graduate studies where universities can charge higher tuitions, and its donation intensity. We proxy for frictions in the PhD supply using the incremental return of a PhD degree in the industry, which reflects the opportunity cost of doctoral training, and the share of inputs in the teaching and research production functions coming from PhD students, which affects institutional support for expanding doctoral programs.

We also document key equilibrium patterns that are consistent with our simple theoretical framework. First, university revenue per professor is higher in high-paying fields, suggesting a higher marginal revenue product for faculty in these fields. Second, consistent with universities competing for a limited pool of PhDs, particularly in fields with a high elasticity of faculty wages to student earnings, we show that returns to talent vary significantly across fields. Using both citation and H-index quintiles as proxies for academic talent, we find that returns are higher in fields with a high elasticity to student earnings.

Finally, we argue that this heterogeneity is unlikely to be primarily driven by professors outside options after joining academia. First, fields with high academic wages and high elasticity to student future earnings exhibit a low share of non-academic placement for PhDs. Second, the fields exhibiting pronounced right tails in compensation for PhD working in the industry, such as engineering and computer science, do not exhibit particularly high academic wages. Finally, decreasing premium with experience in top fields, suggest universities' monopsony power increases with time. We also discuss important implications of our findings for the cost structure and accessibility of higher education.

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 2023), 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; Lowry et al. 2025). By documenting and rationalizing the widening field differentials, this paper brings a supply-and-demand perspective to this discussion. Our findings also uncover the growing connection between academia and broader labor maker dynamics.[9]

Second, our work relates to the literature on wage differentials across industries, skills, and majors and their broader implications.[10] Several studies show how earnings levels (Arcidiacono 2004; Wiswall and Zafar 2014, 2015), trajectories (Hampole 2024), and risks

[9]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).

[10]See the literature on inter-industry wage differentials. Since the 1980s, the finance industry, for example, has offered increasingly higher and more skewed wages compared to other sectors (Philippon and Reshef 2012; Célérier and Vallée 2019).

(Nielsen and Vissing-Jørgensen 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 degressivity" 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 act as a price signal that can affect talent allocation, learning, and innovation in the economy.

Third, we add to the growing literature on the production function of higher education by documenting heterogeneous labor costs across fields. Johnson (2009) and Middaugh et al. (2003) provide evidence that instructional costs vary substantially 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 documents empirically which fields are associated with higher labor costs and which field characteristics drive this heterogeneity.

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 evidence of the increasing interconnectedness of universities with broad labor market dynamics. This ties into a longstanding debate about whether universities should be insulated from market forces to produce knowledge‘ for its own sake or whether they should focus on producing marketable skills (Veblen 1918; Bloom 1987).

The paper is organized as follows. Section 2 describes the faculty and student employment outcome 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 develop our theoretical framework to explore the potential channels at play. Section 6 discusses alternative explanations and implications. Section 7 concludes.

2 Data Sources and Methodology

This section describes the construction of the panel dataset of faculty pay across fields, universities, academic ranks, and years, and explains how we merge these 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.[11]

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 1,458 universities across all U.S. states and Canada.[12] 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.[13]

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 individuals, not only state residents. Depending on

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

[12] 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`

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

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 as well as the department affiliation. While the dataset covers the period 1993 to 2024, this is an unbalanced panel, with the coverage varying across universities from 5 to 30 years.

Our final dataset compiled from public record requests covers approximately 387 public universities across all U.S. states. These institutions, which represent 50% of all U.S. public four-year institutions, account for more than 90% of all bachelor's degrees granted by these institutions in 2019 .[14] The dataset also includes the 16 Canadian public universities located in Ontario, as well as the University of British Columbia.

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. Finally, we exclude observations with base salary or total compensation below a minimum threshold.[15]

The resulting public records dataset includes over 2.5 million observations and 480,000 unique combinations of first name, last name, and university, which we classify across academic fields.

[14]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`.

[15]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.[16]

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 at the application level. 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.[17] 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. 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 field, university categories, and

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

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

faculty ranks.

2.2 Classifying Faculty into Academic Fields

2.2.1 Field Definition

To define academic field, we follow 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 the 18 academic fields from the CIP classification 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 fields. Our 18 academic fields include Agriculture, Architecture, Biology, Business, Communication, Computer Science, Economics, Education, Engineering, English, Finance, History, Languages, Law, Maths, Philosophy, Physics, Psychology, Public Administration, and Social Sciences.

In addition, we single out two departments whose average faculty wages are more than 20% above their parent field averages: (i) Accounting and finance, which we group in one department when they are separated, referred to as *Finance* (parent field is Business), and (ii) Economics (parent field is Social Sciences). 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.[18]

[18]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."

2.2.2 Field Classification

A key challenge in our analysis is to accurately determine each faculty's academic fields. To do so, we proceed in three steps that we describe in more detail in Section I of the Internet Appendix.

First, 65% of observations in our dataset, corresponding to 72% of unique faculty, includes original department information. This is the case for all Green Card and H1-B application records, as well as for a subset of public records. We use this information to map faculty to academic fields, following the classification described in Table A2.

Second, we complement this mapping using existing field directories. Where necessary, we augment these directories with participant lists from major academic conferences to identify departments and associated academic fields.

Third, for faculty not yet classified, we implement automated Google search queries combined with a text-based classification algorithm. 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 result for classification.

Our final dataset includes all faculty (i) with an identified academic field and (ii) belonging to one of the 20 academic fields retained in our analysis.

2.2.3 Summary Statistics

Table 1 presents summary statistics for our final faculty salary dataset. 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 1.4 million faculty-year observations, representing approximately 331,500 unique professors employed at 1,459 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 and placement by academic program, university, field, 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.

2.3.1 Data Description

The Longitudinal Employer-Household Dynamics program (LEHD) at the U.S. Census Bureau builds the PSEO dataset by matching individuals listed in the graduation records of participating universities to Census earnings data. Over the 2002-2022 period, 480 four-year institutions across 31 states have partnered with the Census Bureau.

For each academic program, graduation records include information on student identity, degree level, field of study, and graduation year. The LEHD then links these records to post-graduation outcomes, including earnings as well as industry and geographic employment location. These outcomes are measured one, five, and ten years after graduation. 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 are retained.

For confidentiality reasons, the PSEO dataset reports the median annual earnings instead of individual data, along with the 25th and 75th percentiles, per academic program, university, and year. In addition, earnings are aggregated into three-year graduation cohorts for undergraduates and five-year cohorts for graduate students. For placement data, the dataset reports the number of graduates in each industry and region, which we use to construct our instrument. Regions follow the nine Census divisions, and the university region is split between the university's state and the rest.

Figure 2 summarizes the coverage of the PSEO data across years and its overlap with our faculty salary data. The figure illustrates the staggered entry of universities in the PSEO panel over the 2002-2022 period. In total, the PSEO provides post-graduation earnings and employment outcomes for roughly 10,900 programs in the fields we study at the undergraduate and graduate'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 sample, covering circa 78% of the academic programs included in the panel.

INSERT FIGURE 2 HERE

To assess the robustness of our results, we replicate our analysis using College Scorecard data. While the Scorecard covers a larger set of universities, it reports outcomes at the field level only starting in 2015, does not include the placement information required to construct our instrument, and provides earnings measures only one year after graduation. Moreover, it reports only median earnings and restricts the sample to students who received financial aid. We provide additional details on the Scorecard data and the corresponding methodology in the Internet Appendix.

2.3.2 Linking Methodology

We link our faculty pay dataset with the PSEO panel data at the *academic program level*. We do not match the two datasets at the faculty level because (i) our dataset on faculty pay is not exhaustive in most universities and fields, especially when the main source is the H1B or Greencard application records, (ii) professors often teach across multiple academic programs. We therefore proceed in three steps.

First, we construct the PSEO panel as follows. We restrict the PSEO data to all undergraduate and graduate academic programs included in our 20 academic fields and offered by four-year institutions.[19] To obtain a yearly panel over the 2002-2022 period, we infer survey years and expand each cohort observation across the relevant survey windows, i.e., three years for undergraduate cohorts and five years for graduate cohorts, repeating identical earnings values within each window.[20] All earnings measures are converted to current dollars to ensure consistency with our faculty salary data. Finally, we expand the PSEO data panel to align with the faculty pay panel across the three academic ranks, resulting in a dataset structured at the academic program $\times$ rank $\times$ year level. The panel includes each academic program's university and field information.

Second, we aggregate our faculty salary dataset, after keeping only research tenure-track faculty, at the *field* $\times$ *university* $\times$ *rank* $\times$ *year* level using mean salaries, with each cell representing, on average, five individual observations.

Third, we link the two datasets at the academic program $\times$ rank $\times$ year level using

[19] We map each PSEO academic program to one of our 20 academic fields using its CIP code.

[20] We approximate annual enrollment using the number of graduates in each cell, dividing by cohort length and multiplying by program length (four years for undergraduate programs and two years for graduate programs). For example, if a three-year undergraduate cohort includes 300 graduates, we impute 100 graduates per year and, assuming a four-year program, approximate 400 enrolled students per year.

the information on the academic's program field and university. The final matched panel is therefore structured at the academic program × rank × year level and links faculty pay in a given program, university, year, and rank to the earnings of students who graduated from that program one, five, or ten years earlier. This final sample includes around 173,000 observations across 368 universities, covering around 3,700 academic programs per year, expanded across the three academic ranks, over the 2002-2022 period.

2.3.3 Summary Statistics

Table 2 provides summary statistics on student post-graduation earnings in our final merged dataset, when we keep only one observation per academic program, university, and year, i.e. we collapse all ranks.

INSERT TABLE 2 HERE

2.4 Additional Data

Yearly Panel of Student and PhD Count across Fields and Universities

We supplement our dataset with information on the number of degrees conferred across fields, universities, and years using data from IPEDS. The IPEDS dataset provides the annual numbers of bachelor's, master's, and PhD degrees awarded by each post-secondary institution across its academic programs starting from the 1983-1984 academic year.

We build a yearly panel dataset of the number of students across fields and universities by multiplying the number of degrees granted in a field and university as a major by the normal completion time in years for this degree.[21] Table A4 in the Internet Appendix provides summary statistics on the yearly number of students across fields, universities and periods.

In addition, this data provides us with the count of conferred PhD degrees across fields (and universities). When scaled by the total number of students or faculty in their field, we interpret these quantities as a proxy for the supply of candidates for faculty positions at the field level.

Donations across Fields

[21] The median normal completion time is four-year for a bachelor degree and 2 years for a master degree.

We obtain data on donations from the *Chronicle of Philanthropy*'s database, which lists all donations to non-profit organizations in the U.S. exceeding 1 million dollars. This database provides detailed information on each donation, including the donation amount and a textual description of its intended purpose. Our focus is on donations made to U.S. postsecondary institutions during 2005-2018. We calculate total amount of donations received by field, which we scale by the corresponding number of faculty to obtain a measure of donation intensity.[22] likely to spread Table A4 in the Internet Appendix provides summary statistics on all donations above $1 million received by universities over the 2005-2018 period.

Faculty Research Output

Finally, we exploit measures of research impact from the bibliographic database Scopus, linked by faculty name and university to our public university wage database. Scopus provides information on academic publications and citations, including articles published in academic journals and books from over 30 major publishers. This ensures that our analysis includes research output across all fields, including those where faculty research is predominantly focused on book writing. This merged database includes more than 83,000 faculty-year observations, representing 30,902 professors across 267 public universities.

Table A8 in the Internet Appendix presents summary statistics on the h-index, number of citations, and publication counts across fields. There is large heterogeneity in these metrics by field. For instance, in Finance, the average number of citations, h-index, and publications are 275, 5, and 11, respectively. In contrast, these figures are significantly higher in Physics, reaching 2,936 for citations, 21 for the h-index, and 106 for publications, and lower in Humanities, where the average number of citations is 33. To ensure comparability, we therefore measure output within field, e.g. by looking at quartiles of citations or top publications.

3 Three Stylized Facts

This section documents three primary stylized facts on academic labor markets: (i) large and growing wage differentials across fields (ii) a positive and non-linear relationship between

[22]While large donations are concentrated among high ranked schools, their potential effect is broader as they can affect the whole labor market in a field through inter-university competition.

faculty pay and students' post-graduation earnings in the cross-section of fields; and (iii) significant heterogeneity in the ratio of PhD graduates to total students across fields.

3.1 Large and Growing Differentials in Faculty Pay

Faculty Pay Heterogeneity across Fields

Table 1 provides summary statistics of faculty wages by field, position, rank, and university classification across various time periods. Unconditionally, faculty pay is higher on average in Finance, Law, Business and Economics, as well as in universities with high and very high research activity. These patterns are particularly clear during the most recent period, i.e. from 2015 to 2024.

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

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

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.[23] Finally, $\mu_{tc,t}$ and $\mu_{source,t}$ are fixed effects for pay format, i.e. base salary versus total compensation, and data source, i.e. public records vs. H1B/green card applications, interacted with year fixed effects. Standard errors are clustered at the university level.

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

Both research tenure-track and teaching faculty exhibit significant wage heterogeneity across fields. Among research tenure track faculty, Finance stands out as the highest-paying field, with a 73% wage premium relative to Languages, the lowest-paying field in the sample. Other fields with relatively high wages include Business, with a 57% premium, as well as Law,

[23] accounting respectively for 32%, 27% and 37% of our observations after 2015, 3% of observations lack information on academic rank after 2015.

Economics and Computer Science, with premiums of 45%, 42% and 37% respectively. Wage premiums for teaching faculty are similar in rank, though slightly smaller in magnitude, to those observed for tenure-track faculty.

INSERT FIGURE 3

These pay differentials across employees within a same institution, holding constant education, experience, and job task content, appear particularly large.

Dispersion Patterns across Ranks, University Classification, and Field Classification

Table 3 reports the regression coefficients obtained when estimating equation (1) while splitting the sample by faculty rank, by university type and research intensity.

By faculty rank, wages differentials are most pronounced at the assistant level (Column 2), followed by the associate (Column 3) and full professor levels (Column 4).

Across universities, while inter-field wage differentials are consistent across private and public institutions (Columns 5 and 6), they are significantly larger among R1 institutions, those with 'very high research activity' under the Carnegie Classification (Column 7), than among other universities (Column 8). In these institutions, the wage premium for Finance relative to Languages stands at 92%, to compare to 56% for the rest of the sample. This wage premium at R1 universities is comparable in magnitude to the one between Language faculty and kindergarten teachers.[24] It is also more than 20 percentage point larger in R1 versus other universities in Business, Law, Economics, at 68%, 51%, and 51%, respectively.

In Column 10, we show that the wage differentials still hold among top scholars. We exploit data extracted from the website `Research.com` to identify researchers that ranked among the top 2,000 of their fields in terms of citations and publications.[25] We merge this sample with our dataset on faculty pay. Among these top scholars, the Finance, Business, Law, and Economics fields still pay significantly more than other fields.

Last, to check the robustness of our data, we examine wage differentials across our three field classification methods: using administrative department information (Column 10), field and conference directories programs (Column 11), and Google searches (Column

[24]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.

[25]We extracted the data in September 2025.

12). Measured differentials are robust across classification methods. The premiums in top-paying fields are higher for faculty listed in professional directories, consistent with them being more likely to be at universities with high research intensity.

INSERT TABLE 3

Growing Wage Differentials across Fields

To analyze long-term trends in wage differentials across academic fields, we first leverage the data from the Oklahoma State University faculty survey. This dataset provides annual information on salaries and faculty counts, disaggregated by university group, field, and faculty rank, for nearly every year between 1974 and 2023. The Oklahoma State University survey classifies universities by geographic regions for most of the period, and by Carnegie Foundation classification in 1999, and from 2011 onwards.

For each field and year, we estimate the following model:

$$\ln(w)_{f,ug,rank} = \beta_{field_f}\mu_{field_f} + \mu_{ug} + \mu_{rank} + \epsilon_{f,ug,rank}, \tag{2}$$

where $w_{f,ug,rank}$ denotes the average yearly wage in field f, group of universities ug, and at the rank of assistant, associate, or full professor. We include university group and academic rank fixed effects, $\mu_u g$ and μ_{rank}, respectively, while μ_{field_f} is a field indicator. Hence, the coefficient β_{field_f} measures the wage premium in field f relative to the average across all fields in that year. All regressions are weighted by the number of professors in each university group $\times$ field $\times$ faculty rank cell.

Panel A of Figure 4 illustrates the significant widening dispersion of pay across academic fields. The figure displays the evolution of the pay premiums across fields, some being grouped for readability: *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 cross-field pay range expands fivefold over the sample period, increasing from approximately 15 percentage points in 1975 to more than 80 percentage points by 2023. This expansion is steady from the late 1970s until 2015, when the trend begins to moderate.

INSERT FIGURE 4

We repeat a similar exercise using our individual-level panel dataset over the 1996-2023 period and estimate equation (2) at the individual level. Panel B of Figure 4 presents the results, which evidence a similar widening dispersion of pay across fields.

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

INSERT FIGURE 5

3.2 Positive Relationship Between Faculty Pay and Student Post-Graduation Earnings

We report summary statistics for post-graduation earnings by field in Table 2. Unconditionally, field-level faculty pay is strongly aligned with student earnings, as evidenced by a substantial rank correlation of 0.65. While some discrepancies exist, for example, Computer Science leads in student earnings but is not the highest-paying field for faculty, the cross-field patterns are consistent.

To further investigate the relationship between faculty pay and student earnings, Panel A in Figure 6 plots faculty wage premiums as estimated using equation (1) over the 2015-2024 period, against post-graduation earnings premiums across fields. We estimate these post-graduation earning premiums using our PSEO panel data of post-graduation earnings one year after graduation over the 2016-2021 period. Regressions are weighted by the number of graduate students in each academic program.

Two key patterns emerge: (i) faculty and student earnings premiums are strongly correlated, with a correlation coefficient of 0.70; and (ii) the ratio of faculty to student earnings premiums varies substantially across fields. Hence, in some fields, such as Business, Finance, and Economics, faculty enjoy higher relative premiums than their students, while in others, such as Mathematics, Computer Science, and Engineering, the reverse holds. This latter fact suggests the existence of a latent variable that affects the relationship.

Panel B in Figure 6 shows similars patterns when estimating the industry wage premiums across fields using lifetime earnings. One concern would be that the earning differentials are driven only by early career compensation. To address this concern, we use data from

the American Community Survey over the period 2009-2019 to build a dataset of life-time earnings across fields.[26,27]

INSERT FIGURE 6

3.3 Large Heterogeneity in the Relative Supply of PhD Graduates

To proxy for the relative supply of PhD graduates, we compute the ratio of research doctoral degrees conferred in a field to the student count in the same field by combining our yearly panels on student count and PhD degrees across universities and years.

Panel A in Figure 7 plots the average of this ratio over the 2015-2022 period for each field. The relative supply of PhDs exhibits a large inter-field heterogeneity, with the ratio of graduates to total students varying by a factor of fifty across fields. The relative supply is the lowest in Finance and Business, with the ratio being around 0.1% and the highest in Physics, Biology and Engineering, where it amounts to more than 4.65%.

Panel B of Figure 7 plots the evolution of this ratio across years. It illustrates how persistent the heterogeneity is across fields.

INSERT FIGURE 7

When hiring faculty, some fields therefore face a relatively scarce supply of potential candidates, as the pool of PhD candidates is smaller. In contrast, other fields have a relatively large pool to draw from compared to the size of their student body.

[26]Conducted by the U.S. Census Bureau, this survey reaches around 3.5 million households in the U.S. every year, gathering information on education, employment, family situations, and demographic characteristics. In addition to information on the highest level of education, yearly income, and demographics, the survey provides key information on the undergraduate field of study.To build our sample, we utilize the multi-year file covering 2009-2019, which encompasses approximately 35 million observations. We refine this dataset by including only workers who possess at least one undergraduate degree, are aged between 23 and 65 and are all residents from the 50 states or the District of Columbia. This process results in a final sample of about 6 million U.S. individuals.

[27]We compute work-life earnings across education fields for graduate students using the following simple formula:

$$\text{Total Work-life Earnings}_f = \sum_{\tau=23}^{67} \beta_\tau \omega_{\tau,f}$$

where $\omega_{\tau,f}$ is the yearly income of a worker of age τ who graduated from field f. We assume $\beta = 1/(1+3\%)$, accounting for a 3% yearly discount rate. We obtain the wage values $\omega_{\tau,f}$ from the average residuals of a wage regression that includes a large set of controls such as gender, race, ethnicity and survey-year fixed effects within each field f and age τ cell.

4 Measuring the Elasticity of Faculty Pay to Post-Graduation Earnings

We estimate the elasticity of faculty pay to students' post-graduation earnings using our 2002-2022 yearly panel of academic programs that links faculty pay in these programs to their students' employment outcomes. We find a large and robust elasticity across multiple dimensions: within year across all observations, within university-year across fields, within field-year across universities, and within field-university over time. The results are consistent across both OLS and instrumental-variable specifications, with elasticity estimates ranging from 0.4 to 0.9. However, the elasticity exhibits substantial heterogeneity across fields, with estimates in some disciplines more than twice the average magnitude.

4.1 OLS Specification and Results

To estimate the elasticity of faculty pay with respect to student outcomes, we use an annual panel of academic programs containing median and interquartile earnings for graduates at one- and five-year horizons. Our sample includes 8,561 programs across 368 universities from 2002 to 2022, averaging 3,700 programs per year. By expanding the data by faculty rank (assistant, associate, and full professor), we construct a panel at the university × field × year × rank level, yielding a final sample of over 172,000 observations (see Section 2).

We estimate the elasticity of faculty pay to post-graduation earnings using the following OLS specification:

$$\ln(w_{f,u,t,r}) = \beta \ln(\omega_{f,u,t}) + \mu_{rank_i,t} + \mu_{tc,t} + \mu_{dl,t} + \mu_i + \epsilon_{f,u,t,r}, \tag{3}$$

where $w_{f,u,t,r}$ denotes the average salary of tenure-track faculty of rank r (assistant, associate, or full professor) in field f, university u, year t, and $\omega_{f,u,t}$ stands for the median, 25th, or 75th percentile earnings in year t of students who graduated one or five ears earlier from academic program of field f at university u. The terms $\mu_{rank_i,t}$, $\mu_{tc,t}$, and $\mu_{dl,t}$ denote fixed effects for academic rank, compensation format (base vs. total pay), and degree level, each interacted with year to account for time-varying heterogeneity across these dimensions. μ_i denotes a vector of fixed effects that vary by specification. Standard errors are two-way

clustered at the university level and field × year level. The regressions are weighted by the number of degrees conferred by each academic program, to account for the fact that in our panel each program-rank cell corresponds to a single observation regardless of program size.[28]

Panels A, B, and C of Table 4 present estimates of β from equation 3 across the earnings distribution, using the median, 25th, and 75th percentiles, respectively. Columns 1 to 4 focus on student earnings one year after graduation, while columns 5 to 8 extend the horizon to five years. Across each of these settings, we progressively saturate the specifications with more stringent sets of fixed effects, allowing us to assess the robustness of the relationship across different dimensions of the data: (i) in Columns 2 and 6 we introduce university × year fixed effects to estimate the elasticity within universities across fields, (ii) in Columns 3 and 7, field × year fixed effects to estimate the elasticity within field across universities, and, finally, (iii), field × university fixed effects to measure the elasticity across years within academic programs relative to the average.

For all three panels, Column 1 shows a strong within-year relationship between academic wages and student post-graduation earnings. The estimated elasticity ranges from 0.45 to 0.57 when using earnings measured one year after graduation. The elasticity is of comparable magnitude when we estimate it within university-year across fields in Column 2, and within field-year across universities in Column 3.

Across panels and specifications, the elasticity is approximately 20% larger when using student earnings measured five years after graduation. This pattern is consistent with academic wages being set, in part, to attract potential PhD students in an academic career, as these individuals are more likely to compare academic compensation with the industry earnings they would obtain would they work in the related industry over a typical five to seven-year PhD horizon.

By contrast, Columns 4 and 8 show a much lower elasticity when identification relies on within university-field variation over time. This likely reflects limitations of the PSEO data

[28] As explained in Section 2.2, we do not build this panel at the faculty level for two main reasons. First, professors often teach across multiple programs, which complicates assignment. Second, our faculty pay dataset is exhaustive only for a subset of universities, especially when sourced from H1B and green card applications. The program × academic rank yearly panel allows us to include academic rank fixed effects to address potential composition effects in this dimension. Results are comparable when using a non-expanded panel dataset.

in the time series dimension. First, the PSEO panel is unbalanced, with only two waves of data on average per academic program, every three or five years. To construct an annual panel, we expand earnings values across survey years, which reduces precision in time-series variation. Second, sample representativeness varies across waves, which introduces additional noise in program-level earnings dynamics. These sources of measurement error motivate our use of an instrument based on Census data to better capture time variation in student post-graduation earnings.

Finally, we confirm the robustness of our findings using the College Scorecard dataset, which provides median student earnings one year after graduation for a large set of institutions. Table A6 in the Internet Appendix shows that estimates are of the same magnitude, ranging from 0.47 to 0.56 using the Scorecard dataset. We also estimate elasticities separately using undergraduate and graduate earnings and obtain similar results.

INSERT TABLE 4

4.2 Heterogeneity in Elasticities

We next examine whether the elasticity of faculty pay varies across fields. Such heterogeneity would exacerbate faculty pay heterogeneity if academic compensation is more sensitive to student earnings in some fields already experiencing rapid wage growth.

For this purpose, we estimate Equation (3) separately within each field with rank $\times$ year, wage format $\times$ year, and degree level $\times$ year fixed effects. Therefore, we measure the elasticity of faculty pay to student post-graduation earnings in the cross section of universities within each field.

Figure 8 plots the estimated β when using the median student wage as the dependent variable. Standard errors are clustered at the university-year level. We find that while faculty pay elasticity to student post-graduation earnings is high on average, it varies significantly across fields. This elasticity amounts to 1.2 in Finance and 0.8 in Economics, while it is less than 0.1 in fields such as Languages or Education. Within high-paying fields, the heterogeneity is still pronounced, as at 1.2 this elasticity is more than three times higher in Finance than it is in Computer Science or Engineering (around 0.4).

INSERT FIGURE 8

This large heterogeneity in the elasticity of faculty pay to students' earnings across fields suggests that faculty labor markets are both segmented across fields and characterized by different frictions affecting wages. These field characteristics, which result in heterogeneity in elasticity, likely play an important role in amplifying market forces for academic compensation, as some of the fields related to the highest paying industries, such as Finance, also exhibit particularly large elasticities.

Last, we investigate whether the elasticity of faculty wage to students post graduation earnings varies over time. Figure 9 plots the coefficient estimates β when we measure this within-field across-universities elasticity within time periods. The elasticity of faculty pay to student earnings has almost doubled from the 2000s to the 2020s, from around 28% up to 50%. This evolution suggests that the economic forces linking faculty wages to returns to education have strengthened over the recent decades.

INSERT FIGURE 9

4.3 Instrumental Variable Analysis

The previous subsection presents estimates of the elasticities of faculty pay to their students' earning outcomes using an OLS specification. However, this approach has several limitations that challenge a causal interpretation and the precision of our estimates. First, when the elasticity is measured within fields and across universities, latent factors such as university prestige, resource endowments, or local labour market conditions, may simultaneously influence faculty pay and student earnings. When the elasticity is estimated within universities across fields, reverse causality could be a concern: higher faculty compensation could attract or motivate better instructors, thereby improving teaching quality and, ultimately, enhancing student skills and post-graduation earnings. Finally, when using within academic program time variations, our estimates may be subject to measurement errors due to PSEO data limitations, which are particularly problematic in time-series analyses and could bias our results.

Leave-out-Mean Analysis

A first and parsimonious step to mitigate endogeneity concerns is to employ a *leave-out-mean* approach for student post-graduation earnings. Specifically, we instrument a univer-

sity's graduate earnings with the average earnings of students in the same field and state, excluding the focal university's own observations. This procedure ensures that our estimates are not driven by idiosyncratic, university-specific shocks, such as specific departmental investments, that could simultaneously influence both faculty compensation and the labor market outcomes of its own graduates. We present the results of this approach in Table 5. We observe similar magnitudes for the estimated elasticities.[29]

INSERT TABLE 5

Shift-Share Instrument Definition and Construction

To further address the endogeneity concerns and particularly the measurement error issue, we construct a synthetic post-graduation earnings index at the university × field × year level that serves as an instrument for observed post-graduation earnings in our structural equation (3). The intuition for our methodology follows the Bartik approach (Bartik 1991): all else equal, institutions that historically place students in industries and regions experiencing faster wage growth will exhibit higher growth in their graduates' earnings. The instrument exploits the persistence of university placement patterns across regions and industries, driven by institutional expertise, reputation, and network effects.

Formally, 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 employed in Census division g and 2–digit NAICS industry n. We compute this average across all PSEO survey waves the university has participated in over the 2002-2022 period (3 waves on average).[30] $\varpi_{g,n,t}$ is the average wage of workers in Census division g and industry n in year t, which we measure using individual data from the American Community Survey.[31]

Specification and Results

[29] We exclude the specification with university × field fixed effects, where the measurement error resulting from IPEDS data limitations appears to be amplified, as temporal changes in data coverage at the university level are added to the within program one.

[30] Universities have entered the PSEO sample in various wave since its creation in 2002.

[31] We compute the average across all individuals from the age of 25 to 65 years old.

Our first stage specification is the following:

$$\ln(\omega_{d,f,u,t}) = \ln(Z_{f,u,t}) + \mu_{rank_i,t} + \mu_{tc,t} + \mu_{dl,t} + \mu_i + \epsilon_{f,u,t,r}, \tag{5}$$

and the second stage :

$$\ln(w_{f,u,t,r}) = \beta \widehat{\ln(\omega_{d,f,u,t})} + \mu_{rank_i,t} + \mu_{tc,t} + \mu_{dl,t} + \mu_i + \epsilon_{f,u,t,r}, \tag{6}$$

where $w_{f,u,t,r}$ denotes the average salary of tenure–track faculty in field f, university u, year t, and rank r (assistant, associate, or full professor). The variable $\omega_{d,f,u,t}$ measures student earnings one or five years after graduation by academic program characterized by its field f, university u, and year t, at the 25^{th}, 50^{th}, or 75^{th} percentiles. μ_i denotes a vector of fixed effects that vary by specification.

We begin by setting $\mu_i = \mu_{f/u,t}$, where $\mu_{f/u,t}$ are university $\times$ year or field $\times$ year fixed effects in Columns 2, 3, 6 and 7. These specifications identify variation primarily across programs while absorbing general trends at the rank, degree type, field, or university level.

To strengthen the causal interpretation of β, we set $\mu_i = \mu_{f,u}$, university $\times$ field fixed effects. Therefore the specification absorbs both cross-sectional university-field variation and aggregate time trends. Identification then arises from university-field-specific shocks in the instrument. The identifying assumption is that wage growth in regions and industries where a program historically places graduates affects faculty wages only through its impact on student post–graduation earnings.

Results of the instrumental analysis are displayed in Tables 6 and 7. We first confirm in Table 6 that our instrument is strong, with F-Statistic clearly above the usual thresholds for determining such instruments. The coefficient for the first stage is close to one in all specifications, which is reassuring regarding the previously mentioned limitations of our methodology.

Turning to the second stage, the magnitude of the estimated elasticity of faculty wages to students post-graduation earnings is strikingly robust to this instrumental variable approach, including for the tightest specification identifying from university-field idiosyncratic shocks. Our IV estimates are largely concentrated between 0.7 and 0.9. Even in our most saturated specification, we find an elasticity of 0.73 with respect to one-year student earnings and

0.45 at the five-year horizon. This is significantly higher than the estimates in the OLS, consistent with our instrument addressing the measurement errors in the PSEO that affect the measures of elasticity within academic programs over time.

INSERT TABLES 6 AND 7

Identifying Assumptions and Caveat

This instrument strengthens both the causal interpretation and the robustness of our estimates by mitigating key limitations of the PSEO data and addressing concerns regarding reverse causality and latent variables. First, by averaging placement patterns over the sample period, we improve the precision of our shares and reduce sampling noise inherent in small PSEO cells. Second, utilizing Census-based average wages at the industry-region level alleviates concerns about variations in representativeness within academic programs over time. Third, because the identifying variation arises from industry-region wage shocks, the instrument plausibly addresses bias from time-varying, university-specific latent factors and reverse causality.

The key identifying assumption for the validity of our instrument is that the aggregate wage shocks $\varpi_{g,n,t}$ are exogenous to the idiosyncratic factors affecting faculty compensation at specific institutions. Formally, this requires that after controlling for our set of fixed effects, the regional-industry wage trends are uncorrelated with local unobserved shocks to faculty pay, i.e. $\text{Cov}(\ln \varpi_{g,n,t}, \epsilon_{f,u,t,r}) = 0$.

While contemporaneous placement shares $s_{f,u,g,n}$ might be endogenous to institutional characteristics, the Bartik framework remains valid as long as the shocks themselves are as good as randomly assigned across fields and universities.[32] A violation of the exclusion restriction would occur if these shocks were to affect faculty wages at the university-field level through a channel other than student demand for education.

A primary candidate for such a violation is the opportunity cost of starting an academic career: local (regional × industry) labor market shocks may simultaneously influence faculty pay by steering talent in related fields away from academic careers, prior to doing a PhD

[32]See Goldsmith-Pinkham et al. (2020). The persistence of placement patterns may support the claim that shares are predetermined and thus orthogonal to unexplained variation in faculty wages, i.e., $\text{Cov}(s_{f,u,g,n}, \epsilon_{f,u,t}) = 0$. However, we adopt a conservative approach that relies on the shocks for identification and motivates a specification with university-field fixed effects.

or at the time of the academic job market. While the market for academics is national, a contraction in the supply of candidates due to well-compensated outside options may differentially affect faculty wages across departments as a function of their specific specialization and rank. For illustration, a wage rise in the New York financial sector could simultaneously raise the earnings of graduates from high-ranked finance programs and force those same departments to increase faculty pay to compete with the private sector for top PhD talent.

Consequently, the instrument cannot realistically distinguish between a demand-side effect driven by students returns to education and a supply-side shift in the availability of PhD talent. This nuance motivates our subsequent investigation of the economic mechanisms underlying the central relationship we uncover. The theoretical framework in the following section formalizes these two channels to guid our interpretation of the empirical results and explore explanations for the heterogeneity in elasticity across fields.

5 Economic Mechanism

This section examines the mechanism underlying the relationship between faculty pay and their students' post-graduation earnings and its heterogeneity across fields. To do so, we develop a simple demand-and-supply model of occupational choices applied to academia. This framework helps us identify a set of field-specific characteristics that may contribute to frictions in academic labor markets, and, in turn, lead to heterogenous faculty pay elasticity to students' post-graduation earnings across fields.

5.1 Institutional Context

Until the 1970s, three core principles of academia supported relatively uniform compensation across fields in the U.S.: collegiality, academic freedom, and vocation. Collegiality arose from the conception of the university as a unified intellectual community, a conception the 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.[33] Understood as the protection of intellectual autonomy, the concept of academic freedom 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, social, 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 and fostered solidarity across disciplinary lines.

Starting in the late 1970s, a series of social and institutional shifts led U.S. universities to place less emphasis on these traditional academic principles, often revising their charter to allow for differentiated compensation across fields.[34] 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 placed pressure on universities to recruit competitively in these domains. At the same time, the evolution of American universities into research-intensive institutions, following the Humboldtian model, segmented academic life into specialized departments. This disciplinary segmentation encouraged internal competition over resources and hiring authority, weakening uniform compensation norms. Simultaneously, universities became increasingly reliant on targeted funding streams, including earmarked grants, contracts, and donations directed at specific departments or schools. The rise of empiricism in higher education and public policy in general, with a growing emphasis on measurement, accountability, and evidence-based management encouraged the use of economic incentives to attract faculty and boost productivity, aligning academic work more closely with quantifiable outputs.

Adding to 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

[33]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/`

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

capital rather than a public or intellectual good. This perspective has heightened demand for measurable 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.

5.2 Conceptual Framework

These institutional details motivate a framework for faculty wage determination *within fields*, grounded in market forces, with the goal of understanding the cross-field heterogeneity in faculty pay elasticity to student earnings.

We build on the model of labor market for skilled professionals by Ryoo and Rosen (2004), in which occupational wages respond to shifts in market demand, and imperfect supply adjustments amplify this response. In their framework, supply frictions stem primarily from high entry costs, due to the additional years of education or specialized credentials required to enter a skilled profession, and from changing career prospects in alternative occupations.

In academic labor markets, supply frictions are particularly pronounced, due to the length of PhD training, and further compounded by a distinctive feature of academia: the same economic forces that drive the demand for professors also tend to restrict their supply. Specifically, an increase in industry wages raises the private returns to education, fostering student demand for courses and degrees in that field. Universities typically respond to this enrollment growth by expanding faculty positions, thus raising demand for faculty. At the same time, however, higher industry wages also increase the opportunity cost of pursuing an academic career for prospective PhD students, effectively shrinking the pool of future professors.

This dual effect of industry wages on academic labour markets can amplify demand-supply mismatches and generate large and persistent wage responses. Institutional features that differ across academic fields, such as the extent to which increased student demand translates into higher university revenues, further shape these dynamics. Together, these factors can explain the observed cross-field variation in the responsiveness of faculty wages

to student earnings and the widening dispersion of pay across fields over the last decades.

Demand and Supply Equations

To formalize this intuition, we derive a simple static demand-and-supply model of occupational choices applied to the academic setting.[35]

The demand N_f for research professors in a field f increases with returns to education in this field X_f, measured by students' lifetime earnings, and decreases with academic wages w_f in this field:

$$wage_f = -\alpha_f N_f + \beta_f X_f$$

where α_f is the inverse of the slope of the demand functions, and β_f is positive, reflecting how industry wages translate into university demand for faculty.

- α_f increases with a field *faculty-labor intensity*. Assuming the academic production function incorporates both capital and labor, fields with higher capital intensity, such as the physical sciences, likely exhibit a lower α_f. In fields with high *faculty-labor intensity*, an increase in the demand for faculty will have larger effects on wages, partly because universities can more easily increase class size.[36]

- β_f increases with *university revenue elasticity* to demand for enrollment. We focus on two sources of university revenues: tuitions and donations. Tuition revenue elasticity vary with the share of graduate degrees in the field, as universities typically have more flexibility in setting tuitions for master programs. Second, fields with a higher level of donations, due to either a skew in labor market outcomes or a stronger propensity for alumni to give back to their alma mater rather than to other charities, have a higher β_f. Tuition cap and freezes also mechanically affect β_f.[37]

Turning to the supply, we assume that the stock of professors N_f in field f increases with academic $wage_f$ and decrease with returns to education X_f in this field. These higher

[35]We do not consider a dynamic model as our main objective is to identify structural differences across fields that account for the heterogeneity in elasticity. In addition, this heterogeneity has persisted in ranking, while it increased in magnitude, over the last five decades.

[36]As the number of students per professors is partly endogenous, we do not consider it as a field fundamental characteristic.

[37]Donors may give to their alma mater first to confirm their "sense of identity" (Akerlof and Kranton 2000).

returns reflect elevated industry pay, which raises the opportunity cost of pursuing a PhD and entering the academic workforce. Therefore, we have:

$$N_f = \eta_f wage_f - \gamma_f X_f$$

- η_f is positive and increases with *PhD program size upward flexibility*. This upward elasticity is higher in fields where PhD students are central to teaching and research activities. On the research side, some fields rely heavily on PhD students to operate laboratories and sustain large-scale research project. On the teaching side, some fields' instructional models rely on small-group tutorials, increasing universities incentives to expand doctoral programs to adjust teaching capacity. In such fields, Phd students' complementarity to faculty is high, reducing frictions to increasing PhD supply.

- γ_f represents the *responsiveness of the PhD supply to industry wages* in field f. This sensitivity varies across disciplines for two primary reasons. First, γ_f depends on the importance of non-pecuniary benefits –such as autonomy, prestige, or intellectual freedom. Fields that attract individuals with a high valuation of these attributes will exhibit lower supply sensitivity to private-sector wage fluctuations.[38] Second, γ_f reflects the incremental return to a PhD in the private sector. In fields where a doctoral degree is highly valued by industry, the net opportunity cost of doctoral study is mitigated. Conversely, where the private return to a PhD over a master's degree is low, the opportunity cost of an academic career is higher, reducing the supply elasticity of PhD graduates.

Elasticity

We combine the demand and supply equations to derive faculty wages as a function of industry wages X_f:

$$wage_f = \frac{\alpha_f \gamma_f + \beta_f}{1 + \alpha_f \eta_f} X_f$$

This expression implies a positive relationship between faculty wage and private returns to education, as we previously document. It also predicts that the elasticity of faculty pay to

[38]For instance, Wiswall and Zafar (2017) find that students in economics and business exhibit distinct preferences for pecuniary workplace attributes.

industry wages should vary along field characteristics.

5.3 Empirical Evidence

Field Characteristics We now empirically test whether the field characteristics included in our simple framework can explain the observed differences in elasticity across fields.[39]

An empirical challenge we face in doing so is that the number of distinct academic fields is limited, and the characteristics we model are often correlated. For example, the opportunity cost of pursuing a PhD may be lower in capital-intensive fields, as university laboratories often provide unique training opportunities that are highly valued in industry. In addition, not all the field characteristics we describe, such as the preference for non-pecuniary benefits, are observable. Given these empirical constraints, we do not attempt to estimate a single "horse race" regression or quantify the role of each parameter.

Instead, we test the comparative statics individually, using sample splits. This parsimonious approach allows us to establish the sign and order of magnitude of each channel while avoiding the risk of over-fitting a few large disciplines. We split sample at the median of each our proxies for key field characteristics.

First, our framework predicts that the elasticity should be higher in fields with a higher *labor-intensity* α_f (e.g. requiring low capital investment in labs or equipment).[40] To measure field's capital intensity, we use the share of R&D expenditures on capitalized equipment from the NSF's Higher Education Research and Development Survey (HERD).

The elasticity is also higher when the *university revenue elasticity* to demand for education, β_f, is higher. We proxy for β_f using two measures: the share of master's degrees and field donation intensity. We use our dataset on degree counts to compute the share of master's degrees per field. Regarding donation intensity, we exploit the dataset on donations that we constructed using the Chronicle of Philanthropy's database, as described in Section 2.[41]

[39] Our focus on field characteristics as opposed to university characteristics is motivated by inter-university competition on the labor market.

[40] We assume λ_f is higher than η_f.

[41] We calculate donations per research faculty (scaled) in field f as follows:

$$\text{Donation Intensity}_f = \frac{\text{Donations}_f/\text{Total Donations}}{\text{Faculty}_f/\text{Total Faculty}} \tag{7}$$

On the supply side, a higher *opportunity cost of doing a Phd*, represented by γ_f, also implies a higher elasticity. While non-pecuniary benefits are not easily observable, we proxy for the *incremental return to a PhD* in the industry using data from the American Community survey. We estimate this return by running wage regressions within each field, restricting the sample to individuals with at least a master's degree and controlling for standard socio-demographic characteristics. The incremental return is captured by the coefficient on a dummy variable indicating individuals with a PhD degree.

Finally, we proxy for *PhD program size upward flexibility* η_f using the number of co-authors per academic paper. We assume that fields with more co-authors contributing to a paper are more likely to integrate PhD students into the research process.

Table 8 presents the results of the heterogeneity analysis, exploring how the elasticity of faculty salaries to student earnings varies according to these field characteristics. Figure XX in the Internet Appendix plots the average of these variables across fields.

Across all specifications and panels, the coefficients remain positive and highly significant, which confirms the robustness of our central relationship. Turning to the heterogeneity, we find that for both OLS and IV specifications, the elasticity is higher in fields characterized by high labor intensity, high master premium, high donation intensity, high opportunity costs to conduct a PhD, and high PhD research input. While this analysis is primarily descriptive, it helps us understand how difference in field characteristics can contribute to the difference in elasticities and the widening dispersion in faculty pay.

INSERT TABLE 8

Tuition Revenues per Faculty and Returns to Talent across Academic Fields

The model's validity further rests on whether these field-level frictions seem to shift equilibrium quantities in the data.

On the demand side, the framework implies that higher returns to education raise university revenues, thereby increasing the marginal revenue product of professors in those fields. Figure 10 shows evidence that in the cross-section of fields, faculty wages are higher in fields where average tuition revenue per professors are higher, which is broadly consistent with the model prediction.

INSERT FIGURE 10

Our model predicts that demand-supply gaps contribute to a higher elasticity to student earnings in some fields, resulting in higher faculty pay. These supply-demand imbalances lead universities to compete for a scarce pool of talent, which should translate into higher returns to talent in fields with high equilibrium pay.[42] We proxy for talent by looking at research impact.[43]

We employ two complementary measures of research impact: total career citation counts and the h-index. For each measure, we compute quintiles within each field and academic rank. The objective is to control for heterogeneity in the research production function across fields and positions. Next, we run the following specification:

$$\ln(w_{i,t}) = \sum_{i=1}^{5} \beta_i q_i + \mu_u + \mu_t + \mu_p + \epsilon_{h,t} \tag{8}$$

where q_i corresponds to the citation, h-index or i-10 quintile i within a given field. $w_{i,t}$ is the yearly gross wage of faculty i in year t. μ_f, μ_u, μ_t and μ_p are field, university, year and position fixed effects, respectively. Standard errors are double clustered at the university and year levels.

Figure 11 illustrates the higher returns to research impact in high paying fields. The Figure plots the coefficients $1 + \beta_i$ for each field across quintile i for citation counts (Panel A) and h-index (Panel B).

INSERT FIGURE 11

We confirm this result by running the following specification:

$$\ln(w_{i,t}) = \beta q_i + \beta_{Field} q_i \times \mathbb{1}_{Field} + \mu_f + \mu_u + \mu_t + \mu_p + \epsilon_{i,t} \tag{9}$$

where q_i represents the within field research output quintiles of faculty i and $\mathbb{1}_{Field}$ denotes an indicator variable for each field.

Results in Table 9 suggest higher returns to research impact in higher paying fields, across the two measures of research productivity.

[42] While our framework does not explicitly model the returns to talent, this implication follows naturally from the literature on competitive labor markets for skilled professionals.

[43] While imperfect, this proxy for talent is valid for our empirical specification provided that measurement error and potential biases are orthogonal to field-specific characteristics.

INSERT TABLE 9

These results are consistent with universities competing for a limited pool of research active professors.

6 Discussion

After formalizing what we view as the primary mechanism linking faculty pay to returns to education and describing its cross-field heterogeneity, we evaluate several alternative explanations and consider the broader implications of our results.

6.1 Alternative Explanations

"On-the-Job" Outside Options

A related but distinct rationale for the large and growing pay differentials in academia is heterogeneity in the external outside option for academics. Under this view, universities set higher pay in certain disciplines to retain professors who might otherwise leave academia for higher-paying industry jobs. While this channel would reinforce the central role of industry wages in setting faculty pay, it would operate through the threat of *exit from academia* rather than by fueling demand for education in a given field and restricting entry into academic careers as in our demand-and-supply framework.

Although we acknowledge the possible relevance of this channel, the available evidence suggests its influence is likely second order. First, the share of PhD graduates moving to industry is lower in the high elasticity fields such as business, finance, and economics than in computer science and engineering (Figure A3 in the Internet Appendix). Second, the highest industry wages tend not to accrue to PhDs in fields that pay their professors the most, as illustrated in Panel B of Figure A3. Mathematics or engineering PhDs may obtain higher wages than economics or finance PhDs, while the latter typically earn higher salaries in academia. Finally, the threat of faculty exit should be more pronounced in locations with higher concentrations of high-paying industry jobs, since geographical mobility usually decreases with age. However, using Canada as a control group, we find that faculty salary premiums are remarkably similar to those in the U.S.

Heterogeneity in Talent

Relatedly, the dispersion in faculty pay could theoretically reflect underlying differences in the distribution of cognitive ability or talent across fields. Under this hypothesis, higher wages in certain fields would result from higher average levels of talent, which would in turn command superior outside options.

However, data from standardized doctoral entry examinations, a common, albeit imperfect, proxy for aptitude, do not support this interpretation. While fields such as Computer Science and Finance command significant salary premiums, they do not consistently exhibit higher quantitative or verbal aptitude scores compared to lower-paying disciplines. Indeed, mathematics and physics candidates frequently achieve the highest average scores on these measures without receiving commensurate academic wage premiums, as Figure A4 in the Internet Appendix illustrates.

Furthermore, the "innate talent" hypothesis fails to explain the central empirical relationship we document: the robust sensitivity of faculty wages to the post-graduation earnings of their students.[44]

6.2 Implications

The growing dispersion in faculty pay across disciplines has significant implications for the cost structure and accessibility of higher education, potentially straining the balance between its workforce-development and broader civic missions.

As returns to education increasingly influence academic pay, the rising cost of production in high-return disciplines may necessitate a mechanical increase in baseline tuition or the adoption of field-specific differential pricing. This institutional response is likely mediated by the expansion of student credit markets; to the extent that student loans relax current liquidity constraints, they increase the capacity of universities to capture a larger share of the returns to education, thereby facilitating the upward adjustment of faculty wages. Consequently, the alignment of academic pay with external market forces may alter the socio-economic composition of student enrollment. If the costs of maintaining market-competitive faculty compensation are passed through to students via higher tuition and

[44]Heterogeneity in post-graduation earnings of students largely reflect different returns to talent across industries, not necessarily different levels of talent, as per Célérier and Vallée (2019).

debt loads, the resulting equilibrium may induce a sorting effect where less affluent or risk-averse students disproportionately self-select out of high-return disciplines, or from higher education altogether. This could contribute to the steady rise in "collegiate regressivity" documented in Bleemer and Quincy (2025). This phenomenon could therefore diminish the level and diversity of human capital in the economy, potentially generating aggregate welfare losses through the misallocation of talent and the erosion of social mobility.

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 330,000 professors and student wages across U.S. and Canadian universities, we establish a high elasticity of faculty pay to student earnings, which varies across fields. 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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8 Figures

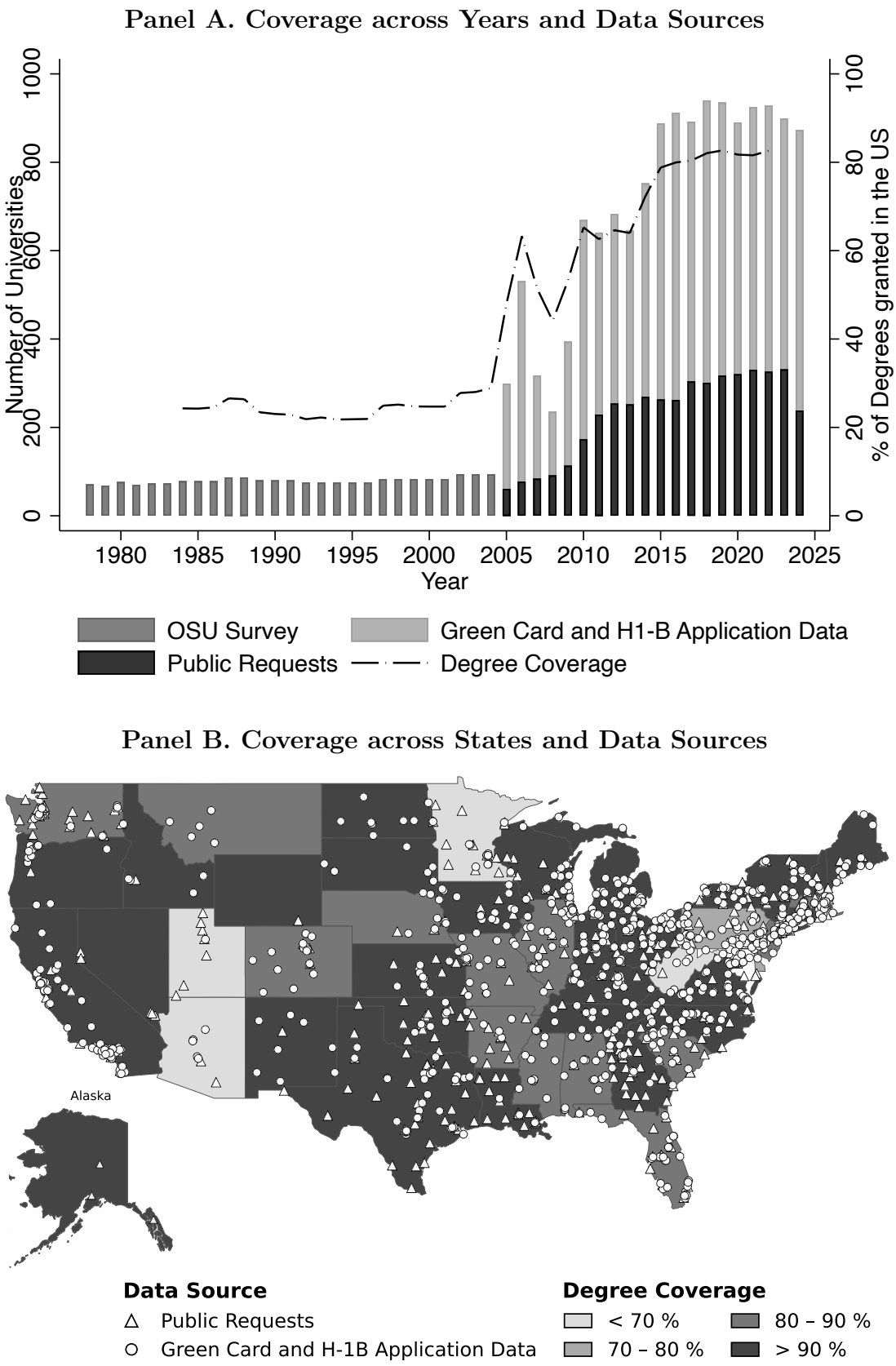


Figure 1. Faculty Salary Data Coverage and Sources

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).

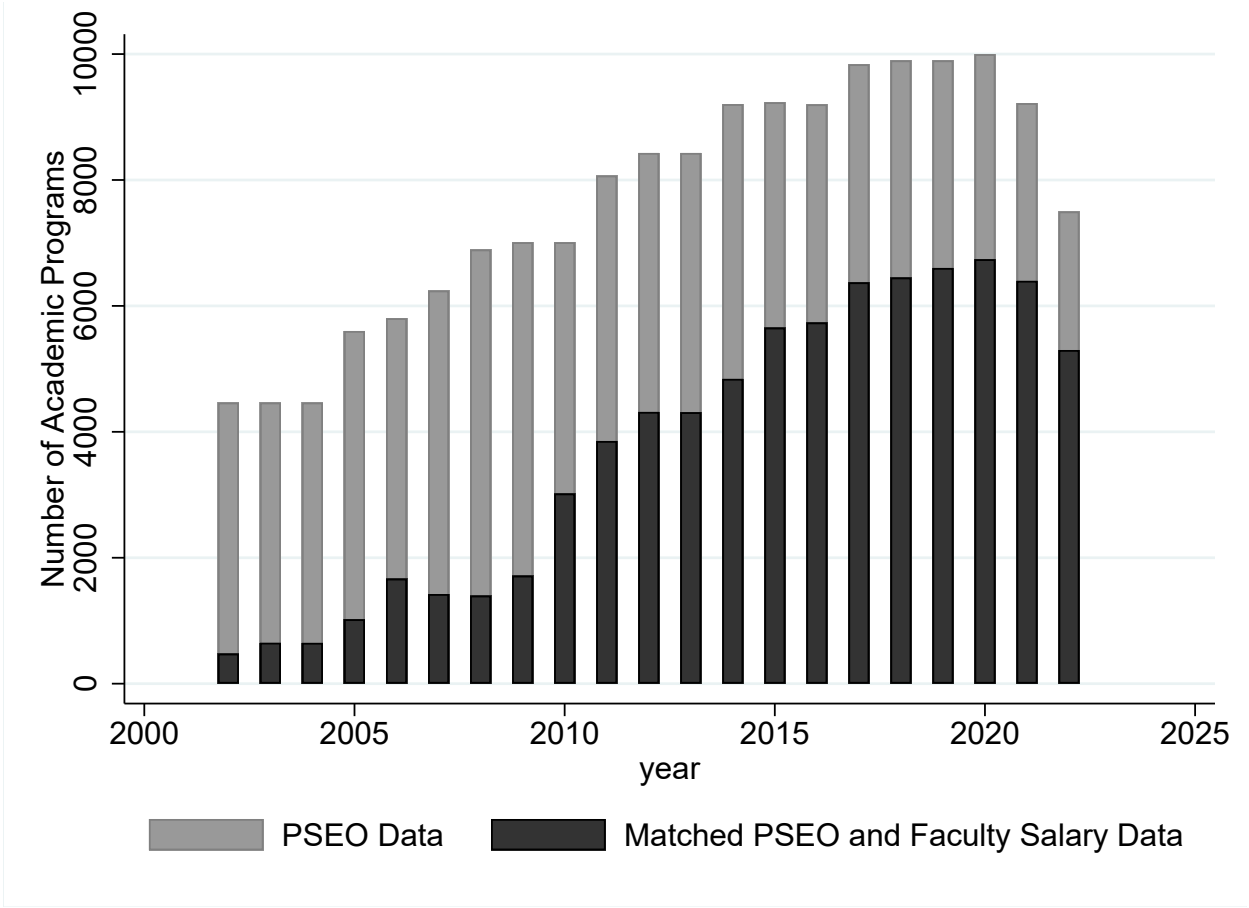


Figure 2. Student Post-Graduation Earnings Data Coverage

This figure summarizes the coverage of the PSEO data across academic programs 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 academic programs. The PSEO reports post-graduation earnings and employment outcomes for up to 10,900 academic programs combinations across roughly 480 four-year institutions from 2002 to 2022. Our faculty salary dataset matches up to 78% of these academic programs in total. The coverage period varyes from 3 to 20 years due to the staggered entry of universities in the PSEO survey.

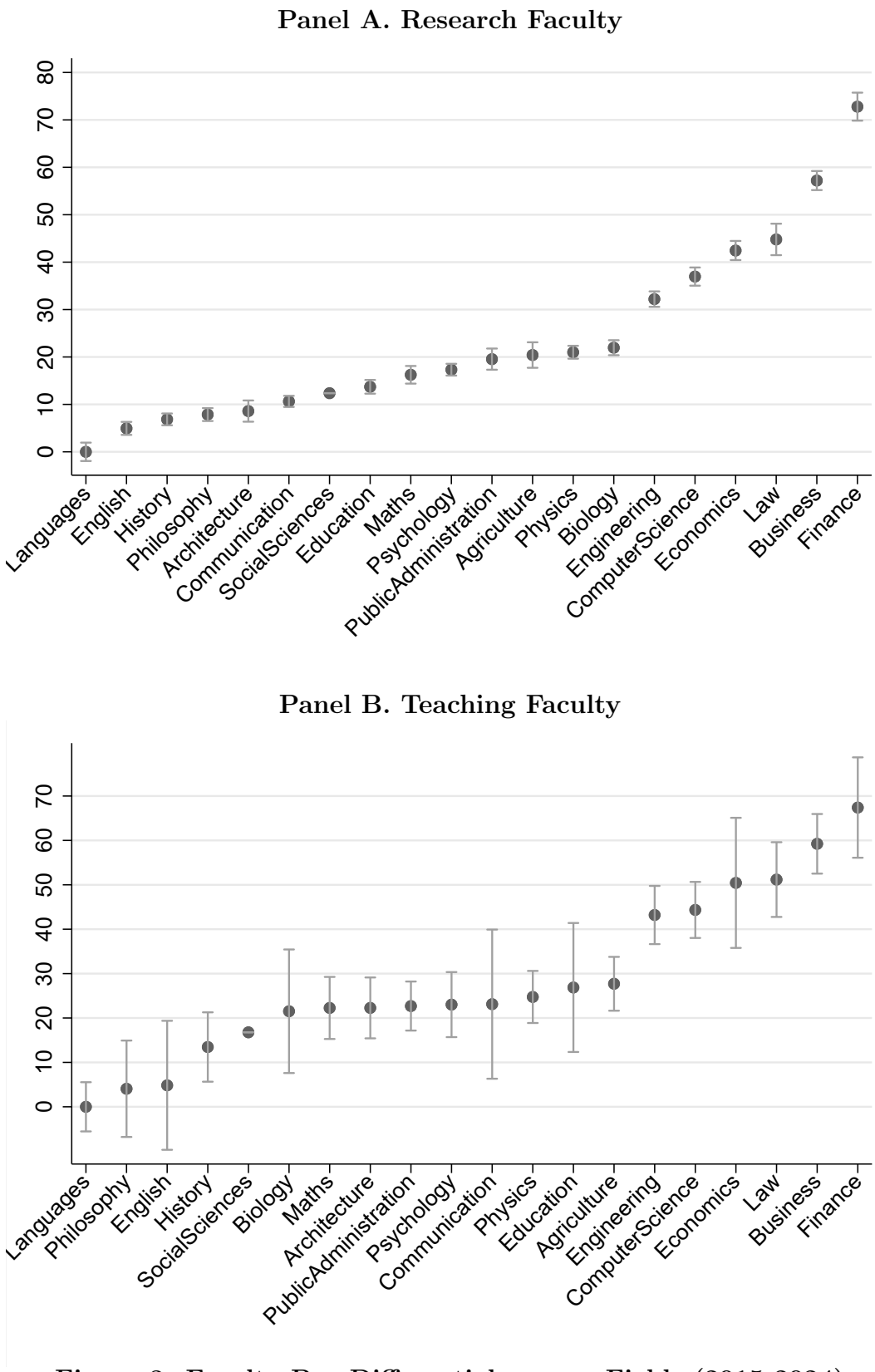
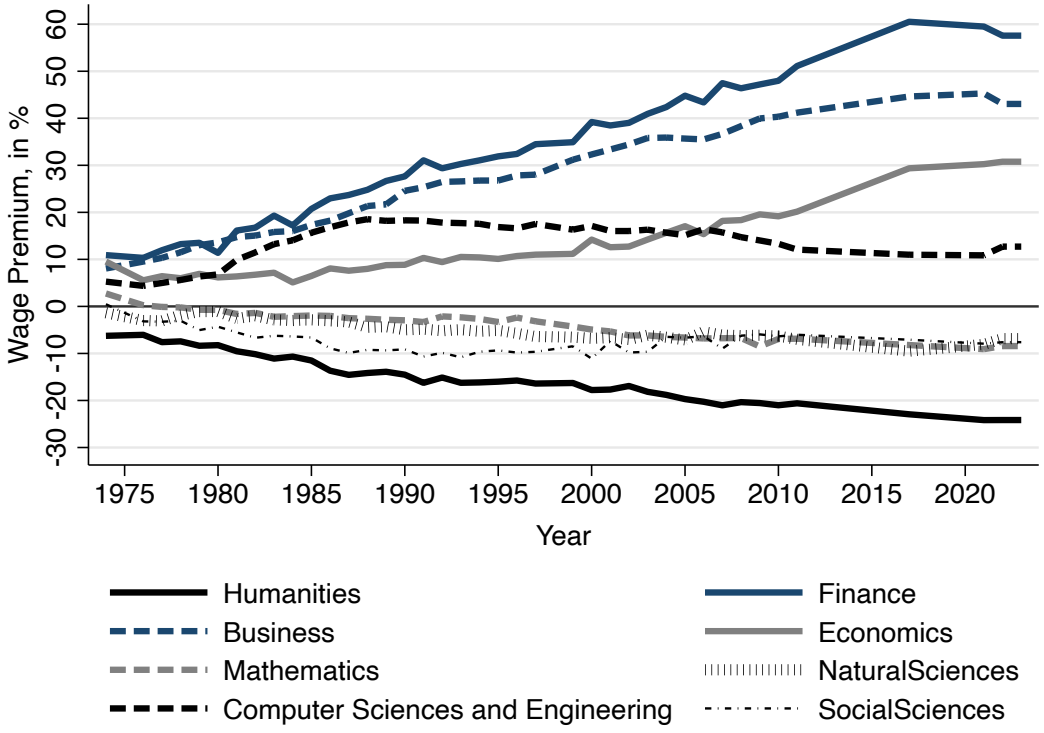


Figure 3. Faculty Pay Differentials across Fields (2015-2024)

This figure displays wage premiums by academic field relative to Languages for the 2015-2024 period. Panel A displays results for research tenure-track faculty only; 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)

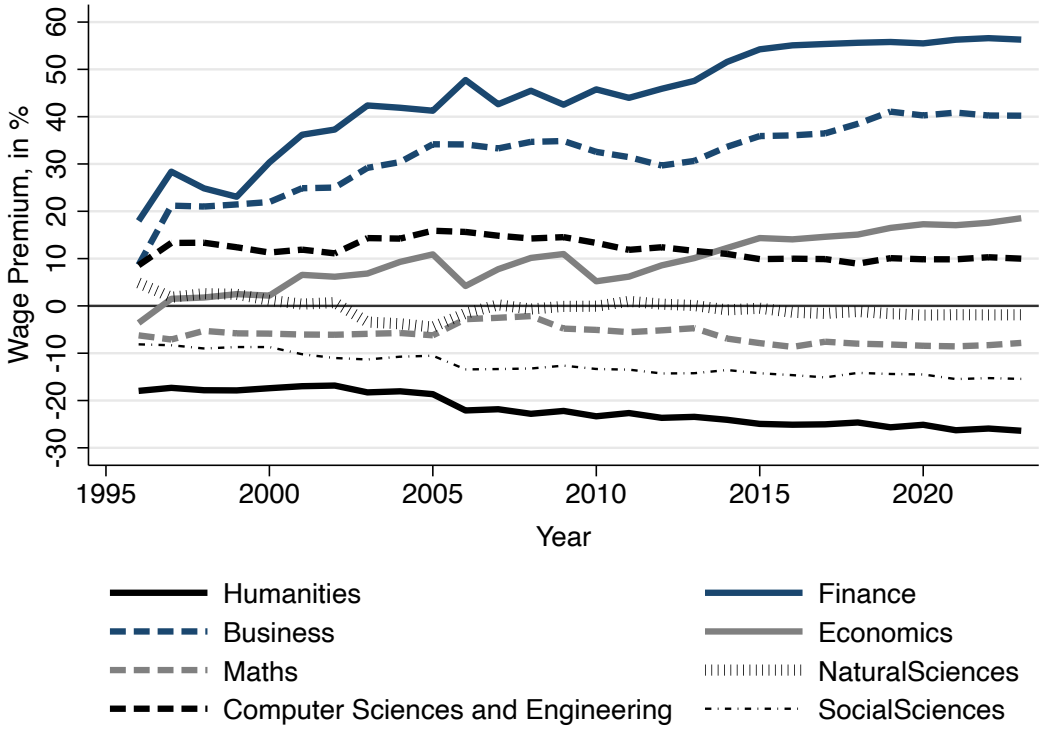


Figure 4. Evolution of Academic Pay across Fields

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.

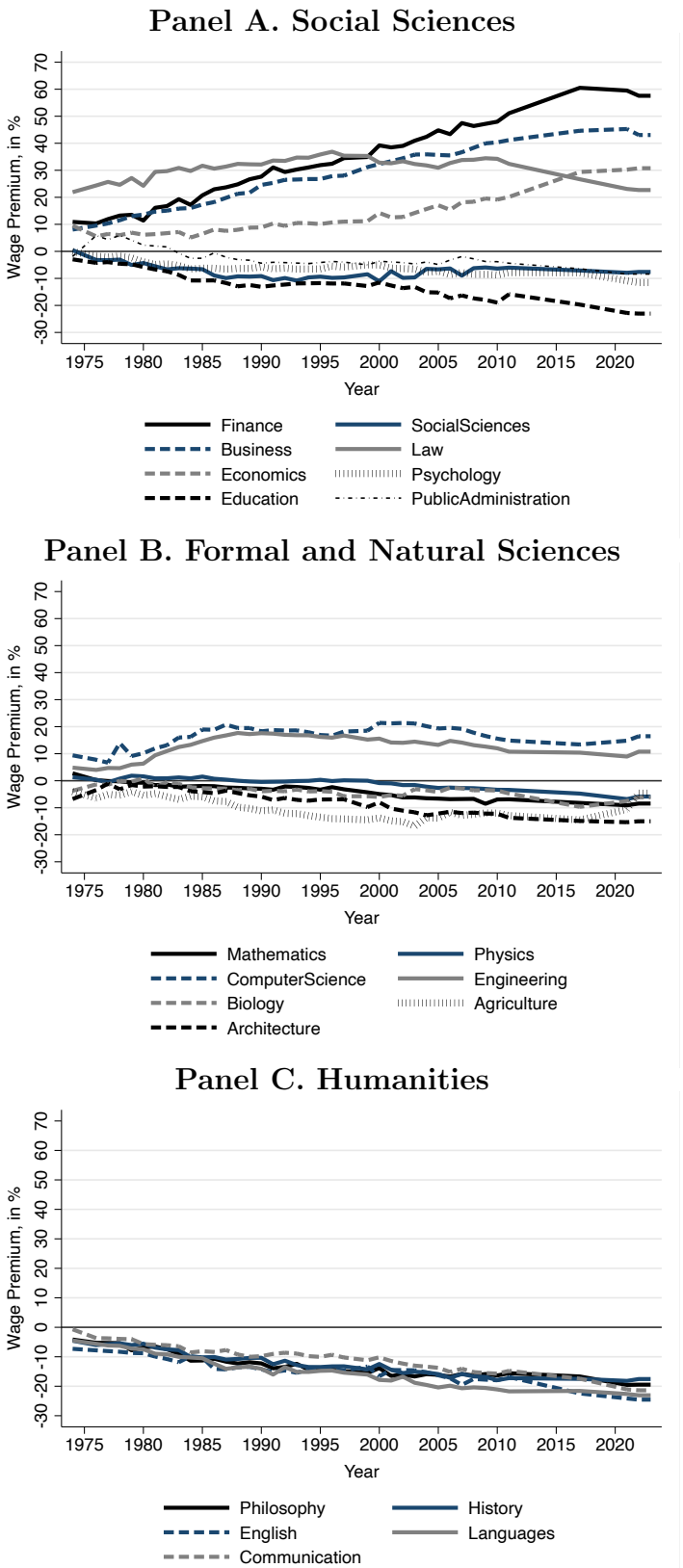
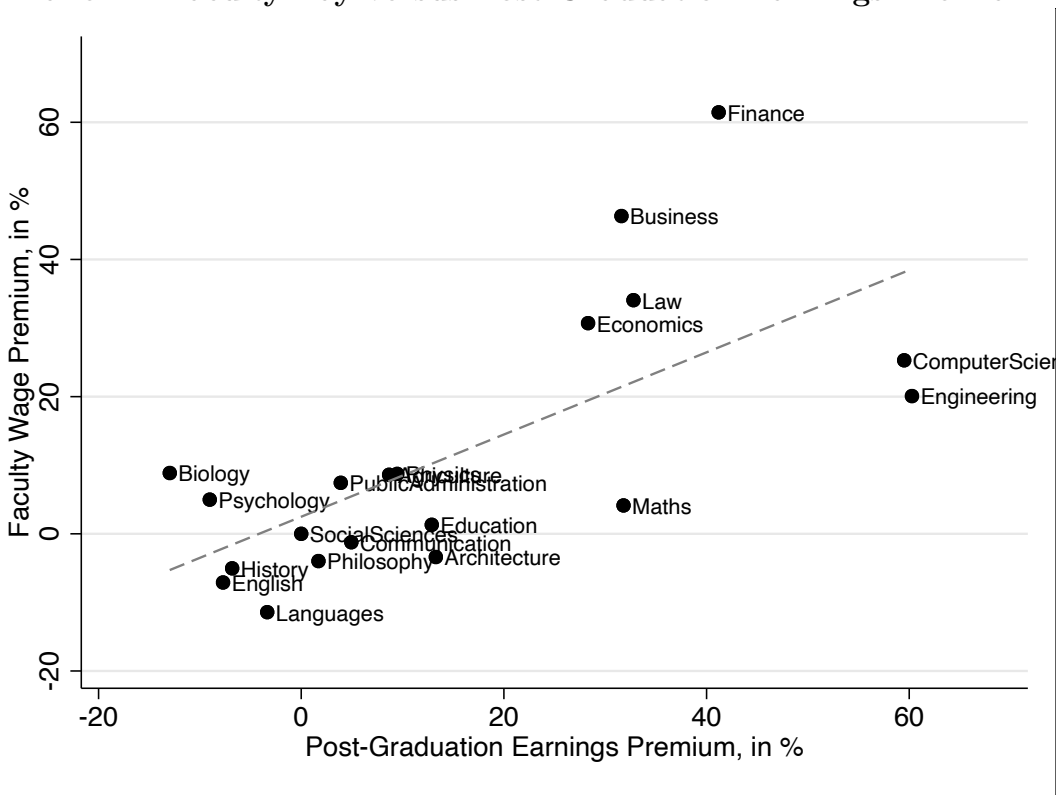


Figure 5. Evolution of Academic Pay across Fields: All Fields

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.

Panel A. Faculty Pay versus Post-Graduation Earnings Premia



Panel B. Faculty Pay versus Lifetime Earnings Premia

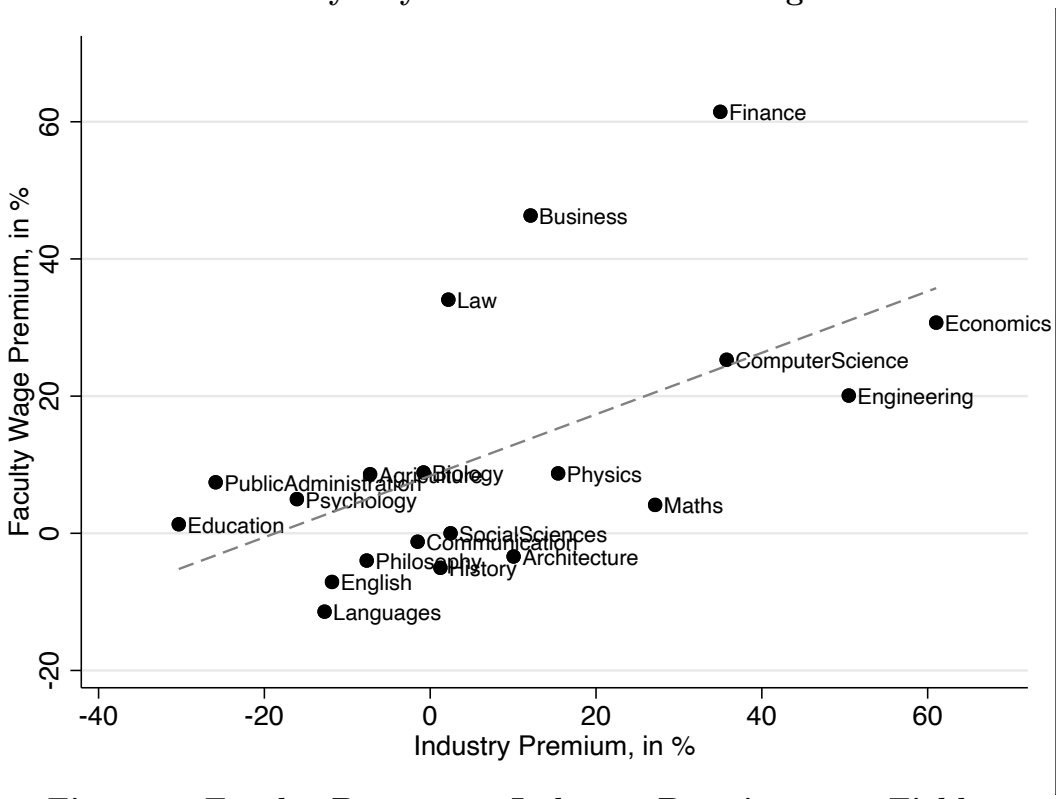
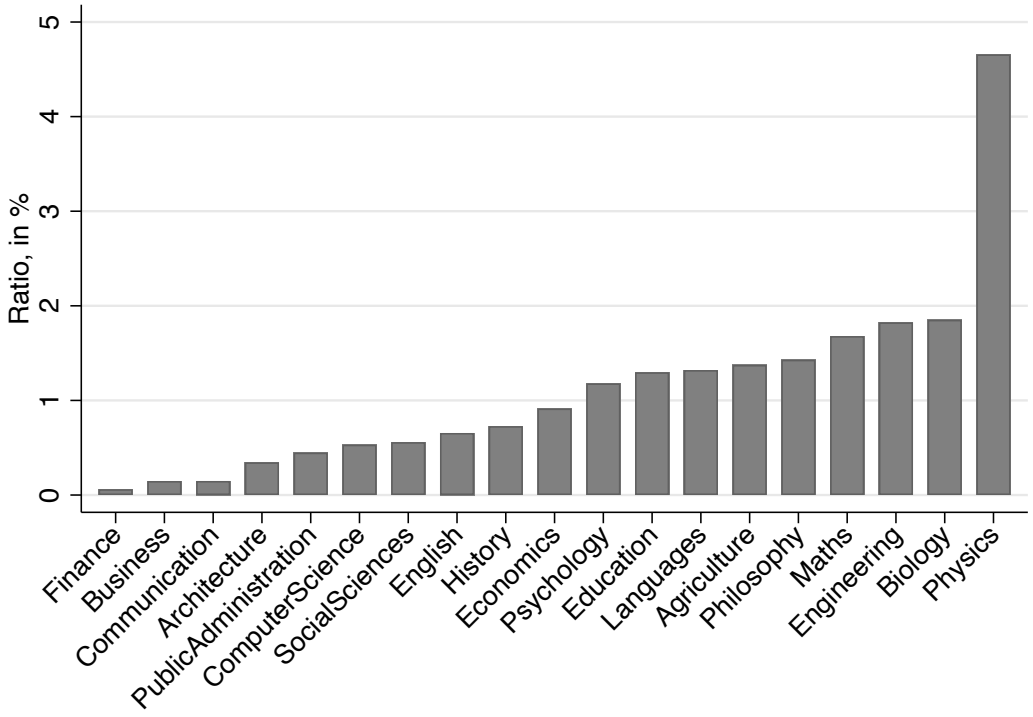


Figure 6. Faculty Pay versus Industry Premia across Fields

This figure illustrates the relationship between wage premia across academic fields in faculty pay and industry premia, measured using post-graduation earnings in Panel A and lifetime earnings in Panel B. The dots represent coefficients from OLS regressions of the log of annual gross wage on field dummies. Student post-graduation earnings data in Panel A is from the PSEO. Student life time earnnings across fields are measured using the 2009-2019 American Community Survey data.

Panel A. Ratio of PhD Graduates to Total Students across All Fields (2015-2022)



Panel B. Evolution of the Ratio of PhD Degrees to Total Students across Grouped Fields

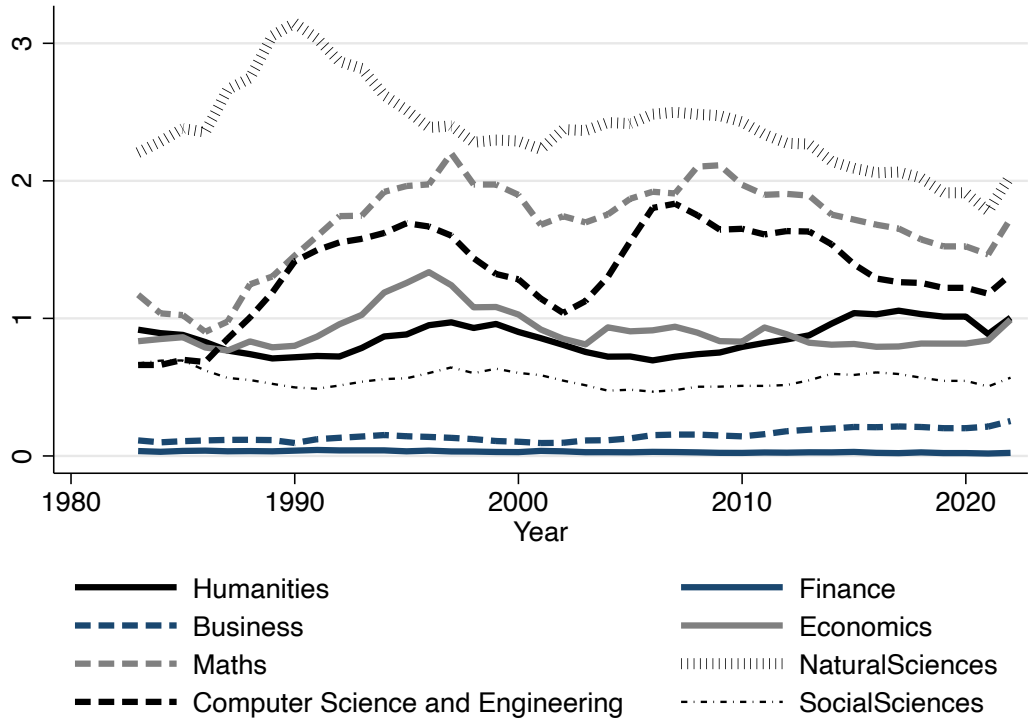


Figure 7. Evolution of the Ratio of PhD Degrees to Total Students across Fields (1990-2024)

This figure plots the ratios of the count of PhD graduates in each field to the total count of students in the same field. Panel A displays the average ratio over the 2015-2022 period across all fields, while Panel B plots the evolution since 1983 for grouped fields. Degree counts by field comes from IPEDS as explained in Section 2.4.

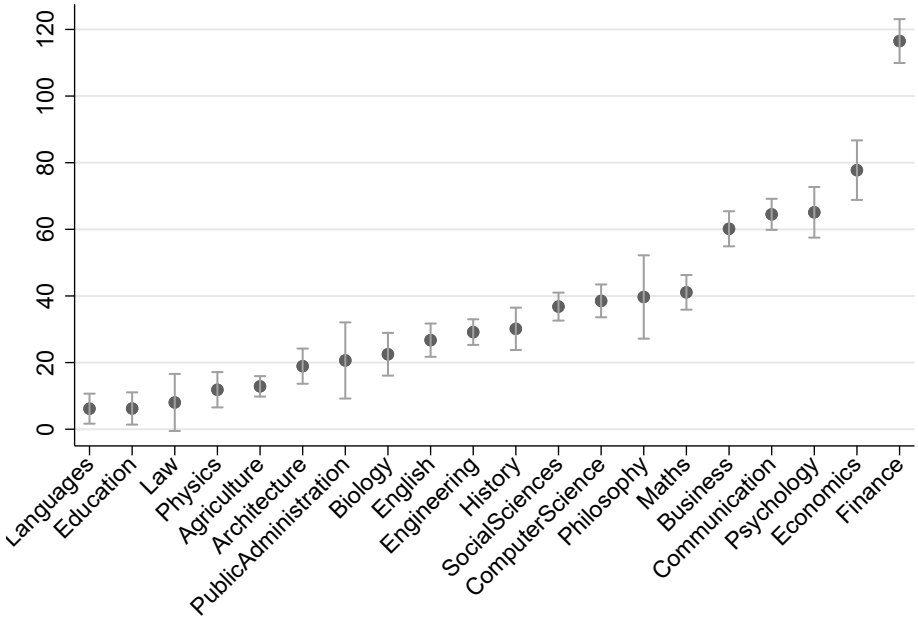


Figure 8. Elasticities of Faculty Pay to Post-Graduation Earnings.

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 × year, wage format × year, and degree level × 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.

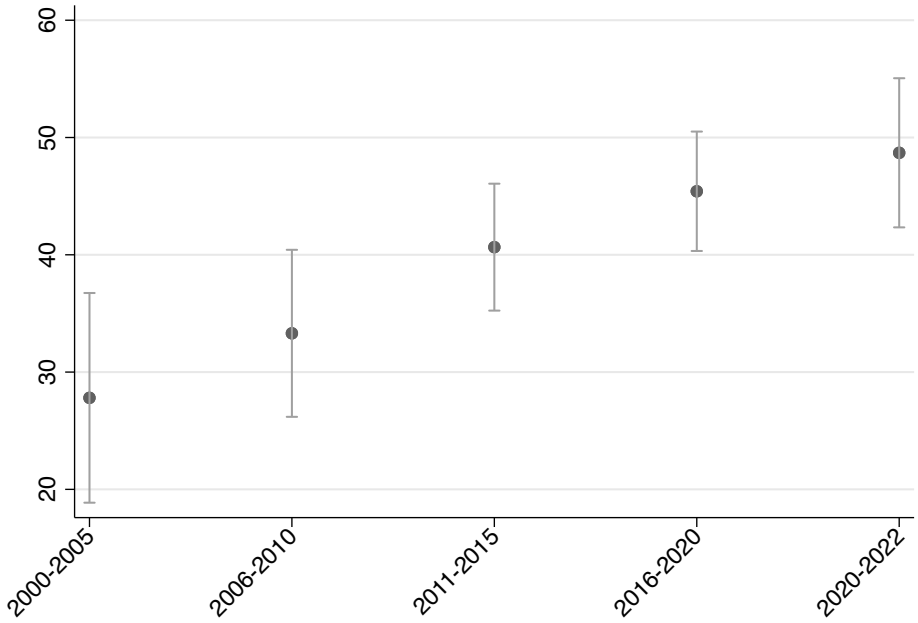


Figure 9. Growing Elasticity of Faculty Pay to Post-Graduation Earnings.

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.

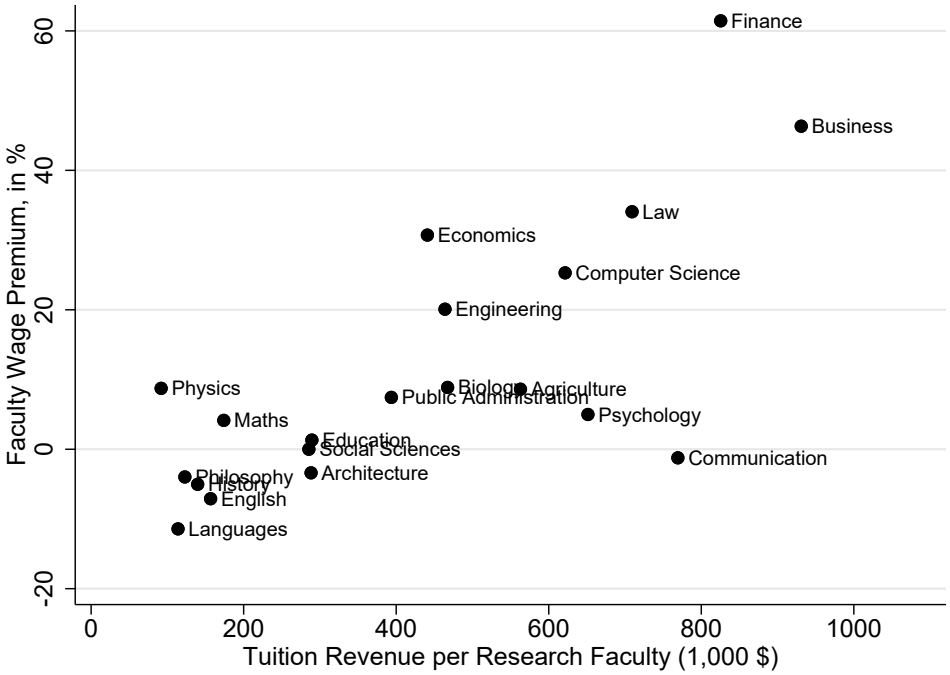


Figure 10. Equilibrium Outcome: Tuition Revenues per Research Faculty

The figure illustrates the relationship between faculty pay and revenue per faculty across fields. 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.

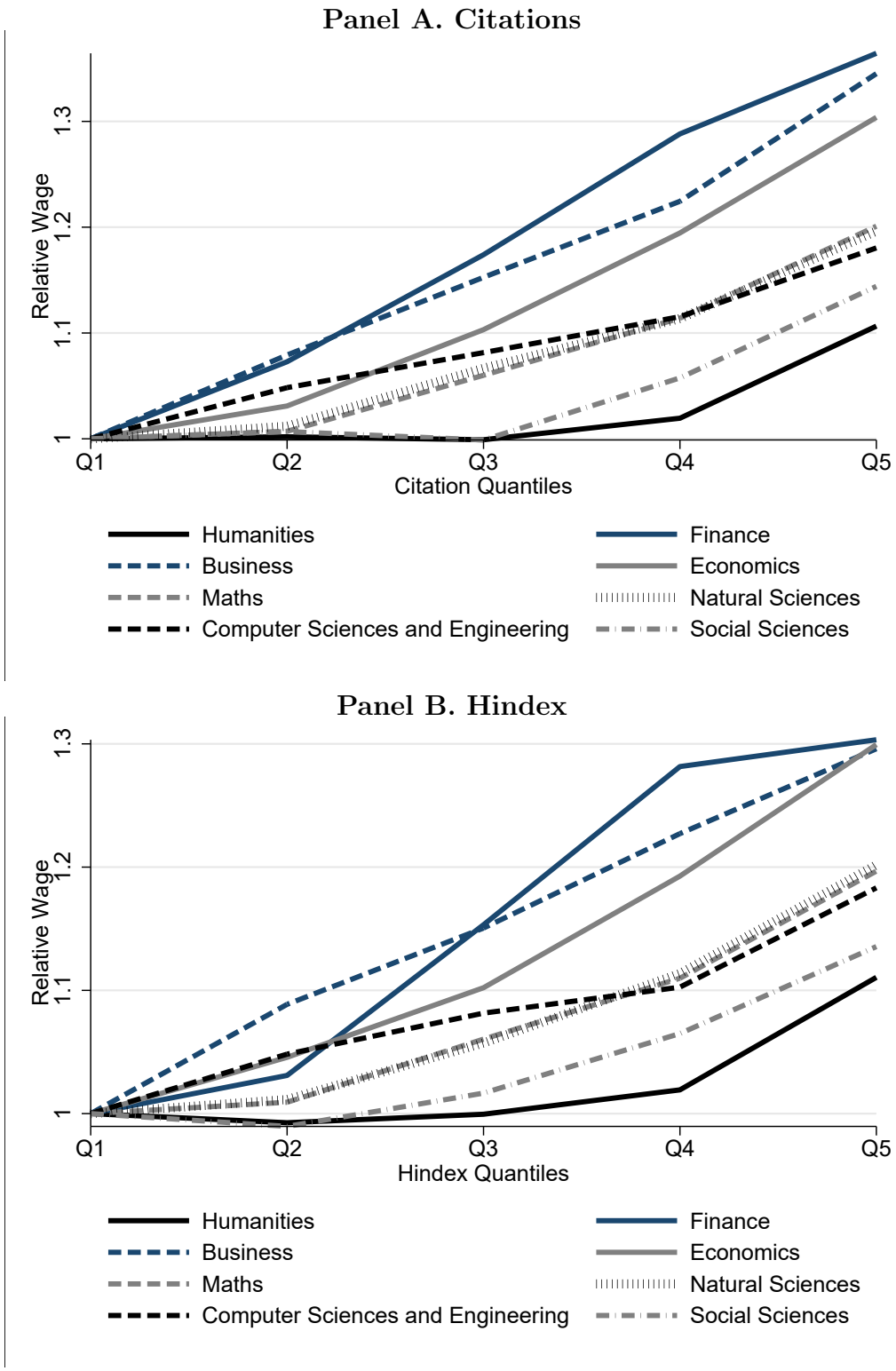


Figure 11. Wage Returns to Research Output

Panel A and B compare returns to research output across fields. Research output is measured using citation and H-index quintiles, in Panels A and B, respectively. Quintiles are defined within fields and positions. The graphs plot the coefficients from the regression $\ln(w_{h,t}) = \sum_{i=1}^{5} \beta_i q_i + \sum_{i=1}^{5} \sum_f \beta_{i,f} \mathbb{1}_f q_i + \mu_u + \mu_{g,p} + \mu_{t,c} + \epsilon_{h,t}$. The black solid line plots $1 + \beta_i$ for humanities, while the other lines plot $1 + \beta_i + \beta_{i,f}$ for each respective field. The dependent variable $\ln(w_{h,t})$ is the log of the yearly base salary. The model includes university, field $\times$ position, and wage format $\times$ year (base salary versus total compensation) fixed effects.

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	126.9	110.6	251.3	65.1	114.6	99.4	115.3	93.6	69.2	1,449,534	331,500
All Research Faculty	131.8	115.1	257.0	65.3	117.6	99.7	120.0	96.2	70.0	1,331,812	292,682
By Academic Field											
Finance	192.1	168.7	368.3	90.7	163.2	116.7	182.7	134.7	91.5	50,880	10,709
Law	184.4	167.5	359.9	86.7	170.4	124.1	196.9	159.7	111.2	28,707	5,947
Business	169.0	149.2	332.1	83.7	149.0	114.3	149.7	116.3	86.3	89,478	26,320
Economics	160.1	139.0	318.8	80.4	135.7	103.3	151.6	119.5	86.3	47,098	11,657
Engineering	150.2	134.9	273.9	64.4	133.8	108.0	127.5	107.5	84.1	150,080	34,231
Computer Science	148.7	132.7	273.5	64.9	130.7	106.0	126.3	103.7	78.6	66,905	18,386
Physics	133.6	118.5	254.5	62.0	120.6	100.8	120.7	100.3	72.6	133,174	26,071
Biology	130.6	116.0	245.0	61.0	116.9	102.9	116.5	94.6	67.0	113,647	21,937
Agriculture	121.4	112.4	209.5	45.5	104.9	84.0	110.5	96.8	74.4	31,786	7,369
Maths	120.1	107.5	219.9	52.1	109.8	92.5	105.9	88.4	66.3	81,958	18,437
Public Administration	119.3	103.0	229.2	57.7	106.2	94.3	110.1	89.6	60.9	28,819	6,408
Psychology	119.3	105.8	220.7	53.5	110.2	97.3	108.5	90.1	62.5	56,757	10,911
Social Sciences	116.7	103.1	216.1	51.6	105.3	96.6	105.7	86.2	61.9	118,396	24,787
Architecture	114.2	100.3	208.4	48.0	100.4	84.5	101.6	84.9	62.2	18,750	4,426
Philosophy	113.9	102.0	208.7	51.0	102.4	98.0	102.9	85.2	62.3	22,769	4,690
Education	107.2	96.3	186.7	42.6	98.3	92.7	88.5	72.9	59.7	66,022	14,478
History	106.0	94.6	190.6	44.8	96.5	90.5	102.9	84.7	62.4	48,568	9,073
Languages	103.2	91.8	188.9	44.1	94.5	86.4	96.2	79.8	57.3	55,480	11,289
English	101.6	91.0	182.7	42.4	92.1	86.2	96.4	80.8	58.5	77,867	15,512
Communication	101.5	90.9	178.6	41.2	91.7	68.5	93.7	77.7	59.6	44,671	10,044
By Rank											
Full Professor	157.4	141.2	298.3	73.5	138.9	109.7	153.7	117.3	83.6	601,783	95,583
Associate Professor	112.1	102.5	191.8	43.5	100.8	84.5	102.0	81.1	61.3	367,995	60,529
Assistant Professor	100.1	89.8	183.4	42.4	85.0	68.8	94.2	71.4	53.2	329,282	130,656
By University Classification											
Very High Research Intensity	150.8	131.6	295.5	74.8	131.2	101.6	141.2	111.3	81.9	667,066	143,927
High Research Intensity	121.1	108.2	218.6	51.8	107.7	93.0	102.4	81.9	67.1	239,057	52,552
Doctoral Universities	100.9	91.4	170.8	38.4	89.5	66.3	90.9	71.0	57.5	53,874	13,743
Other	109.6	100.3	191.5	44.4	100.4	96.6	87.3	74.8	56.3	371,815	82,460
By Data Source											
Public Requests Data	131.8	115.1	257.0	65.3	117.6	99.7	124.2	97.4	70.0	1,259,499	220,369
Green Card/H1B Applications							98.1	74.7		72,313	72,313
All Teaching Faculty	76.9	67.7	142.5	34.1	66.8	76.1	68.4	49.2	36.4	117,722	29,143

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 1.49 million faculty-year observations from more than 331,000 professors at 1,459 North American 4-year institutions, covering the period from 1993 to 2024. 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 available field and conference 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-academic program-cohort level that we match with our faculty salary dataset. The resulting panel includes 77,900 observations across 368 universities, with around 3,700 academic programs 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. 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 academic program 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 Premiums across Fields (2015-2024)

	Log(Faculty Pay)$_{f,u,y}$											
Samples	**All Research**	**Academic Rank**			**University Type**		**University Classification**		**Top Scholars**	**Field Classification Method**		
		Assistant	**Associate**	**Full**	**Private**	**Public**	**R1**	**Other**		**Department Information**	**Directories**	**Google Searches**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
𝟙.Finance	0.73***	0.84***	0.70***	0.65***	0.77***	0.73***	0.92***	0.56***	0.55***	0.77***	0.93***	0.51***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)	(0.08)	(0.03)
𝟙.Business	0.57***	0.64***	0.54***	0.51***	0.66***	0.57***	0.68***	0.45***	0.34***	0.59***	0.79***	0.45***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)	(0.08)	(0.02)
𝟙.Law	0.45***	0.44***	0.40***	0.43***	0.48***	0.45***	0.51***	0.31***	0.24***	0.51***	0.58***	0.37***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.07)	(0.03)	(0.08)	(0.03)
𝟙.Economics	0.42***	0.46***	0.40***	0.41***	0.46***	0.42***	0.51***	0.30***	0.24***	0.43***	0.62***	0.31***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.04)	(0.02)	(0.08)	(0.02)
𝟙.Computer Science	0.37***	0.40***	0.37***	0.33***	0.32***	0.37***	0.40***	0.31***	0.06*	0.38***	0.51***	0.31***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.08)	(0.02)
𝟙.Engineering	0.32***	0.32***	0.31***	0.32***	0.24***	0.32***	0.35***	0.28***	0.07***	0.35***	0.51***	0.28***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.09)	(0.01)
𝟙.Physics	0.21***	0.20***	0.18***	0.21***	0.13***	0.21***	0.26***	0.13***	-0.03	0.22***	0.49***	0.18***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.08)	(0.01)
𝟙.Biology	0.22***	0.21***	0.20***	0.22***	0.21***	0.22***	0.26***	0.14***	-0.04	0.23***	0.19**	0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.09)	(0.01)
𝟙.Agriculture	0.20***	0.20***	0.20***	0.19***	0.20***	0.20***	0.22***	0.17***	-0.04	0.21***	0.32***	0.18***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.01)	(0.02)	(0.02)	(0.05)	(0.02)	(0.08)	(0.02)
𝟙.Public Administration	0.19***	0.16***	0.18***	0.20***	0.13***	0.20***	0.27***	0.10***	0.04	0.22***	0.27***	0.16***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.04)	(0.03)	(0.10)	(0.01)
𝟙.Psychology	0.17***	0.15***	0.15***	0.18***	0.16***	0.17***	0.22***	0.10***	0.02	0.19***	0.38***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.09)	(0.01)
𝟙.Maths	0.16***	0.17***	0.15***	0.16***	0.14***	0.16***	0.20***	0.09***	-0.03	0.18***	0.45***	0.12***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.08)	(0.01)
𝟙.Education	0.14***	0.13***	0.12***	0.14***	0.11**	0.14***	0.14***	0.09***	0.06	0.15***	0.25***	0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)	(0.01)	(0.07)	(0.01)	(0.08)	(0.01)
𝟙.Social Sciences	0.12***	0.11***	0.11***	0.13***	0.11***	0.12***	0.15***	0.07***	-0.04	0.14***	0.26***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.08)	(0.01)
𝟙.Communication	0.11***	0.09***	0.10***	0.12***	0.08***	0.11***	0.12***	0.05***	-0.09	0.12***	0.24***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.06)	(0.01)	(0.08)	(0.01)
𝟙.Architecture	0.08***	0.07***	0.08***	0.09***	0.09***	0.08***	0.10***	0.08***	-0.33***	0.10***	0.17*	0.07***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.05)	(0.02)	(0.09)	(0.01)
𝟙.Philosophy	0.08***	0.05***	0.06***	0.09***	0.03	0.08***	0.10***	0.02***	-0.07	0.10***	0.19*	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.12)	(0.01)	(0.10)	(0.01)
𝟙.History	0.07***	0.05***	0.05***	0.08***	0.04	0.07***	0.07***	0.03***	0.18*	0.08***	0.26***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.09)	(0.01)	(0.08)	(0.01)
𝟙.English	0.05***	0.04***	0.04***	0.05***	-0.00	0.05***	0.03***	0.02***	-0.20**	0.06***	0.16**	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.09)	(0.01)	(0.08)	(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	859,703	224,420	239,214	370,703	17,213	842,389	430,094	429,609	17,490	452,360	43,207	304,426
R^2	0.64	0.67	0.66	0.53	0.77	0.64	0.58	0.65	0.44	0.67	0.64	0.59

This table presents wage premiums 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 premiums for the full sample of research tenure-track faculty. Columns 2-4 show premiums by academic rank: assistant, associate, and full professors. Columns 5-6 compare premiums across private and public universities. Columns 7-8 display premiums by university classification: R1 universities (doctoral universities with very high research activity) and all others. Column 9 restricts the sample to top scholars ranked in the top 2000 in their field. Columns 10-12 examine premiums by field classification methodology: department information, field directories, and Google automated searches. 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). 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)$_{f,u,y}$							
Student Earnings	**One Year after Graduation**				**Five Years after Graduation**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Median				
Log(Post-Graduation Earnings)$_{f,u,y}$	0.52***	0.44***	0.41***	0.06***	0.67***	0.58***	0.57***	0.08***
	(0.04)	(0.04)	(0.05)	(0.01)	(0.05)	(0.05)	(0.05)	(0.02)
R^2	0.49	0.66	0.66	0.91	0.52	0.66	0.67	0.90
				Panel B. 25th Percentile				
Log(Post-Graduation Earnings)$_{f,u,y}$	0.45***	0.39***	0.32***	0.05***	0.59***	0.50***	0.50***	0.06***
	(0.03)	(0.04)	(0.04)	(0.01)	(0.05)	(0.05)	(0.04)	(0.01)
R^2	0.48	0.66	0.65	0.91	0.49	0.65	0.66	0.90
				Panel C. 75th Percentile				
Log(Post-Graduation Earnings)$_{f,u,y}$	0.57***	0.48***	0.43***	0.06***	0.67***	0.58***	0.53***	0.05***
	(0.04)	(0.04)	(0.05)	(0.01)	(0.04)	(0.05)	(0.05)	(0.01)
R^2	0.50	0.66	0.66	0.91	0.53	0.66	0.67	0.90
Observations	172,827	172,482	172,827	172,327	115,627	115,351	115,627	115,218
Fixed Effects:								
University x Field	-	-	-	Yes	-	-	-	Yes
Field x Year	-	-	Yes	-	-	-	Yes	-
University x Year	-	Yes	-	-	-	Yes	-	-
Wage Format x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rank x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree Level x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regression coefficients from OLS specifications that relate the log of faculty pay in an academic program, proxied by the average faculty pay in the corresponding field and university, to the log of student earnings one and five years after graduation from that program. Student earning outcomes are sourced from the U.S. Census Bureau's Post-Secondary Employment Outcomes (PSEO) dataset as described in Section II. The sample includes 8,561 academic programs across 368 universities, corresponding to 3,700 programs per year on average over the 2020-2022 period. The sample is expanded to cover the three academic ranks. All specifications include academic rank × year, wage format (base pay and total compensation) × year, and degree level (graduate or undergraduate) × year fixed effects. Columns 2 and 6 estimate within-university across-field elasticities by including university × year fixed effects. Columns 3 and 7 estimate within-field across-university elasticities by including field × year fixed effects. Columns 4 and 8 estimate within-academic program across time elasticities by including university × field 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: Instrumental Variable Analysis using Leave-out-Means.

	Log(Faculty Pay)$_{f,u,y}$							
	One Year after Graduation				**Five Years after Graduation**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{PostGraduationEarnings}$	0.61***	0.54***	0.78***	0.01	0.78***	0.72***	1.03***	-0.30
	(0.05)	(0.05)	(0.08)	(0.16)	(0.07)	(0.08)	(0.09)	(1.15)
Observations	171,178	170,872	171,178	170,408	114,465	114,225	114,465	113,844
R^2	0.24	0.21	0.02	0.00	0.31	0.24	0.05	-0.02
Fixed Effects:								
University x Field	-	-	-	Yes	-	-	-	Yes
Field x Year	-	-	Yes	-	-	-	Yes	-
University x Year	-	Yes	-	-	-	Yes	-	-
Wage Format x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rank x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree Level x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Test	144	106	100	0	126	86	127	0

This table reports regression coefficients of our instrumental variable analysis, where we instrument student post-graduation earnings using the leave-out-mean at the *field* × *year* × *state* × *degree level* cell. 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 6. Elasticity of Faculty Pay to Post-Graduation Earnings: First Stage of our Instrumental Variable Analysis using industry-region placements.

	Log(Student Earnings)$_{f,u,y}$							
	One Year after Graduation				**Five Years after Graduation**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument$_{f,u,y}$	1.15***	1.28***	0.62***	0.33***	1.06***	1.07***	0.85***	0.46***
	(0.12)	(0.13)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.08)
Observations	138,794	138,404	138,794	137,977	90,562	90,274	90,562	89,935
R^2	0.51	0.64	0.80	0.98	0.57	0.68	0.78	0.98
Fixed Effects:								
University x Field	-	-	-	Yes	-	-	-	Yes
Field x Year	-	-	Yes	-	-	-	Yes	-
University x Year	-	Yes	-	-	-	Yes	-	-
Wage Format x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rank x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree Level x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Test	100	93	44	14	167	139	126	34

This table reports regression coefficients from the first stage of our instrumental variable analysis. The dependent variable is the log of student post graduation earnings in an academic program and year. The independent variable is our instrument. We construct the instrument variable by combining the student placement data from the PSEO with salary data from the American Community Survey. 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 academic program employed in the corresponding industry-region-year cell, as reported in the PSEO. 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 7. Elasticity of Faculty Pay to Post-Graduation Earnings: Second Stage of our Instrumental Variable Analysis using industry-region placements.

	Log(Faculty Pay)$_{f,u,y}$							
	One Year after Graduation				**Five Years after Graduation**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{PostGraduationEarnings}_{f,u,y}$	0.81***	0.74***	0.85***	0.73***	0.88***	0.90***	0.58***	0.48***
	(0.08)	(0.08)	(0.18)	(0.24)	(0.07)	(0.09)	(0.13)	(0.15)
Observations	138,794	138,404	138,794	137,977	90,562	90,274	90,562	89,935
R^2	0.18	0.14	0.02	-0.09	0.30	0.21	0.15	-0.02
Fixed Effects:								
University x Field	-	-	-	Yes	-	-	-	Yes
Field x Year	-	-	Yes	-	-	-	Yes	-
University x Year	-	Yes	-	-	-	Yes	-	-
Wage Format x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rank x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree Level x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regression second-stage regression coefficients from our instrumental variable analysis. The dependent variable is the log of faculty pay in an academic program, proxied by the average faculty pay in the corresponding field and university. The independent variable is the log of student earnings one and five years after graduation from that program that we instrument using our wage index. 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 8. Mechanism: Heterogeneity in Elasticity

	Log(Faculty Pay)$_{f,u,y}$									
	Demand Channel						Supply Channel			
	Labor Intensity		Master Premium		Donation Intensity		PhD Opportunity Cost		PhD Research Input	
	(1) Low	(2) High	(3) Low	(4) High	(5) Low	(6) High	(7) Low	(8) High	(9) Low	(10) High
					Panel A: OLS Estimations					
$Log(Post-GraduationEarnings)_{f,u,y}$	0.44***	0.63***	0.55***	0.58***	0.52***	0.61***	0.49***	0.62***	0.45***	0.63***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)
Fields × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,472	71,155	30,081	85,546	69,517	46,110	63,960	51,667	45,904	69,723
R^2	0.65	0.68	0.62	0.65	0.63	0.60	0.59	0.60	0.64	0.68
					Panel B: IV-2SLS Estimations					
$Log(Post-GraduationEarnings)_{f,u,y}$	0.74***	0.87***	0.75***	0.85***	0.74***	0.90***	0.76***	0.87***	0.74***	0.87***
	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
Unit × Field Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,944	57,288	22,336	67,896	48,794	41,438	45,664	44,568	33,442	56,790
R^2	0.13	0.15	0.12	0.15	0.11	0.18	0.09	0.18	0.13	0.15

This table reports regression coefficients of the log average annual faculty salary on the log of student post-graduation median earnings (five years post-graduation). Data are sourced from the U.S. Census Bureau's Post-Secondary Employment Outcomes (PSEO). All specifications include academic rank × year, wage format × year, and degree level × year fixed effects. Panel A reports OLS estimates including university × year fixed effects. Panel B reports IV-2SLS estimates including university × field fixed effects, where student earnings are instrumented by the instrument used in Table 7. The sample is split along five dimensions reflecting field specific frictions in demand and supply adjustments. On the demand side, these dimensions include Labor Intensity, Master Premium, and Donation Intensity. On the supply side, these dimensions include PhD opportunity cost, proxied by the PhD premium in the industry, and PhD research input, proxied by the number of PhD co-authors on average. For each dimension, "Low" and "High" subsamples are defined as observations below and above the sample median, respectively. 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 9. Elasticity of Faculty Pay to Research Output

	Log(Faculty Pay)							
	Total Citation Quintiles				H-Index Quintiles			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quintiles	0.08***	0.05***	0.04***	0.02**	0.08***	0.05***	0.03***	0.01
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Quintiles × 𝟙.Finance			0.10***	0.08***			0.09***	0.07***
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Business			0.09***	0.06***			0.09***	0.06***
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Economics			0.07***	0.06***			0.08***	0.07***
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Biology			0.06***	0.04***			0.07***	0.05***
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Psychology			0.05***	0.03***			0.07***	0.04***
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Maths			0.05***	0.04***			0.06***	0.05***
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Physics			0.05***	0.04***			0.06***	0.05***
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.ComputerScience			0.05***	0.02			0.05***	0.03*
			(0.02)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Philosophy			0.04**	0.03			0.04***	0.03**
			(0.02)	(0.02)			(0.02)	(0.02)
Quintiles × 𝟙.PublicAdministration			0.04***	0.02*			0.05***	0.03**
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.SocialSciences			0.03***	0.02**			0.04***	0.03***
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Engineering			0.03**	0.02			0.03***	0.02**
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.History			0.02	0.01			0.03*	0.02*
			(0.01)	(0.01)			(0.02)	(0.01)
Quintiles × 𝟙.Communication			0.02	0.01			0.03*	0.02
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Education			0.01	0.00			0.02**	0.01
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.English			0.01	0.00			0.01	0.01
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Law			-0.00	-0.00			0.01	0.01
			(0.02)	(0.02)			(0.02)	(0.02)
Quintiles × 𝟙.Agriculture			-0.01	0.00			0.00	0.01
			(0.01)	(0.01)			(0.01)	(0.01)
Quintiles × 𝟙.Architecture			-0.01	-0.00			-0.01	-0.00
			(0.01)	(0.01)			(0.01)	(0.02)
Fixed Effects								
University × Year	-	Yes	-	Yes	-	Yes	-	Yes
Field	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rank × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience Quintiles	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wage Format × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83,604	83,557	83,604	83,557	83,604	83,557	83,604	83,557
R^2	0.53	0.61	0.54	0.61	0.53	0.61	0.53	0.61

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 1-4) and H-index (Columns 5-8). Columns 3-4 and 7-8 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, field, and experience quintiles, where experience is measured as years since first publication. Columns 2, 4, 6, and 8 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.