Market Forces in Academia: Student Future Earnings and Faculty Pay*

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Abstract

A long-term analysis of faculty wages at public and private four-year institutions in the U.S. and Canada reveals a growing pay dispersion across disciplines, driven primarily by economics, business, and especially finance. Using data on student future earnings across fields and universities, we identify spillover effects from industries to academia, where faculty wages increase with student future earnings. Additionally, we find that the elasticity of faculty pay to student earnings varies significantly across disciplines. Fields that are more scalable – measured by student-to-faculty ratios – and those with greater frictions in PhD supply exhibit higher elasticity. Higher returns to citations in these fields indicate that intensifying within-field competition, fueled by industry spillovers, plays a central role in the widening dispersion in faculty compensation.

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1 Introduction

Returns to education are widely recognized as high and have significantly increased in recent decades. These returns vary largely across fields of study or industries joined by graduates. 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).[1] These field-specific wage differentials persist even after controlling for institution and peer quality (Kirkeboen et al. 2016), and are often larger than the earnings gap between high school and college graduates (Altonji et al. 2012). As a result, the choice of college major has become a crucial determinant of the level, profile, and risk of future earnings.[2]

While a growing literature investigates the influence of heterogeneous returns to education across fields on student choices and outcomes, little is known about its effects on the supply side of education, especially on faculty wage.[3] Beyond university tuitions and costs, faculty wages may affect the quality of education, the allocation of talent across fields, research productivity, and innovation.[4] Prior research highlights evidence of increasing dispersion in faculty wages across academic fields (e.g., Courant and Turner (2019)). Do student future earnings drive an increasing dispersion in faculty pay across academic fields? What is the underlying mechanism?

To answer these questions, we assemble a long time series of individual faculty pay across most research institutions in the U.S. and Canada. The dataset includes over 200,000 research faculty from 1,500 universities, spanning 1993-2023, and is merged with university-field-rank-year aggregated data from historical archives covering 1974-1995. To obtain individual data on faculty wages, we first collect name-identified wage data from U.S. public universities through public record

[1] The large wage differentials across industries have garnered the interest of economists for decades (Krueger and Summers 1988; Gibbons and Katz 1992).

[2] See for example Arcidiacono (2004); Hamermesh and Donald (2008); Altonji et al. (2012); Hastings et al. (2013); Andrews et al. (2017); Andrews and Stange (2019); Hampole (2023); Andrews et al. (2024).

[3] Recent studies, such as Conzelmann et al. (2023) and Light (2024), explore impacts on course offerings and the number of degrees awarded.

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

requests in accordance with the state-level freedom of information laws. We complement this dataset with information on faculty from *private* and other public universities using green card and H1B application data, thereby leveraging the significant share of faculty employed in U.S. universities that are not U.S. citizens. We identify the academic field as defined by the Classification of Instructional Program (CIP) using textual analysis on automatically collected Google search data and existing directories for business school faculty.[5][6] Our final dataset includes more than 740,000 individual observations with faculty department and CIP Code, base salary, total compensation, rank, and university over the 1974-2023 period.

Using our 50-year time series on academic wages, we document a growing dispersion in faculty pay across fields since the 1970s, driven primarily by finance, business, and economics. Over the past five decades, finance professors have seen their wage premium relative to all fields grow from around 5% in the 1970s to over 60% in the 2020s. The wage differential between finance and philosophy professors - 100% - is comparable to the wage gap between humanities faculty and kindergarten teachers.[7] In economics and business, the wage premium has increased from 10% to 30%. By contrast, humanities professors, who earned approximately 10% less than the average in the 1970s, now face a 20% wage penalty. Similarly, while mathematics professors enjoyed a premium in the 1970s, they now experience a 5% discount in the 2020s.

Leveraging individual wage data from the American Community Survey with information on each individual field of study over the 2009-2020 period, we uncover that the wage differentials across-field wage strongly correlate with student life-time earnings across majors. The relationship between academic wages and student future earnings is present across fields, across universities, and across time.

We then employ data on student earnings after graduation across universities and fields, coupled with a shift-share instrument, to investigate empirically whether

[5]We restrict our sample to research tenure track faculty and define "universities" as any post-secondary institutions that award bachelor degrees.

[6]We use the directories constructed by James Hasselbach.

[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.

and how faculty pay responds to student earnings across fields. Our identification strategy aims at addressing concerns over reverse causality, as well paid academics might deliver higher value education that is recognized as so in the labor market. We use data on student future earnings and the industry and location placement across universities and majors from the Post-Secondary Employment Outcomes (PSEO) dataset provided by the U.S. Census Bureau.[8] We further exploit the long time dimension of our data and construct a synthetic wage index for each university and field, based on the industries and geographical areas where the university has historically placed students in that field, along with the wage evolution for those industries and areas. The intuition behind this instrument is that, all else being equal, universities that place students in regions and fields where wages increase more than in other areas will experience a rise in student wages plausibly exogenous to the quality of education they offer.

We first show that a plausibly exogenous increase in student post-graduation wages leads to significantly higher faculty wages. In the cross-section of fields and universities, the elasticity of faculty pay to student future earnings ranges from 50% to 60% in the 2000s. As a result, the widening dispersion in student future earnings over time contributes to the growing heterogeneity in faculty pay across disciplines.

However, the heterogeneity in the elasticity of faculty pay to student earnings plays a more significant role in driving pay differentials across fields than the absolute level of student future earnings. Measuring across-time elasticities *within field* reveals significant heterogeneity in faculty pay response to student future earnings. For instance, the elasticity of faculty pay to student earnings in finance is two to three times higher than in the humanities and has continued to rise since the 1970s. This higher elasticity, combined with the substantial increase in wages within the finance industry, explains the majority of the growth in the finance faculty wage premium over the same period.

We investigate the mechanisms that drive this heterogeneity in faculty pay

[8]This dataset covers 50% of the universities in our sample and provides the median wage one, five, and ten years after graduation across programs and cohorts since 2001, as well as placement numbers.

elasticity to student future earnings across fields and show that it relates to competition forces varying across fields. Our findings show that higher levels of student expected earnings predicts an increase in the number of students per faculty, particularly in fields that are more scalable. Conversely, the ratio of PhD students to faculty declines as student expected earnings rise, creating frictions in the faculty supply. Additionally, universities at the top of the revenue distribution capture a greater share of total revenues in high-earning fields through increased tuition and donations. Together, these factors shape competition forces that vary significantly across fields, contributing to the observed heterogeneity in faculty pay elasticity and the growing dispersion in academic wages.

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

Second, our study contributes to the literature on the determinants of academic wages, such as publications (Katz 1973; Tuckman and Leahey 1975; Swidler and Goldreyer 1998; Garfinkel et al. 2024), citations (Katz 1973; Hamermesh 2018), department performance (De Fraja et al. 2020), seniority (Ransom 1993; Moore et al. 1998; Hilmer and Hilmer 2011), university monopsony power (Ransom 1993; Goolsbee and Syverson 2019), university rank (Kim et al. 2009) and attributes such as race or gender (Gordon et al. 1974; Hoffman 1976), including a more recent focus on finance within business schools (Sherman and Tookes 2022). By focusing on the growing field differentials, this paper proposes a novel mechanism: we show how market forces can account for a wage spillover from the industry to

academia. Our findings also provide evidence consistent with the rationale behind the field differentials documented since the mid-1980s by studies such as Bowen and Schuster (1986), Hearn (1999), and Bellas (1997).

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

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

The paper is organized as follows. Section 2 describes the faculty and student wage data we collected across U.S. and Canadian universities over 50 years. Section 3 provides stylized facts on faculty pay. Section 4 investigates the causal relationship between student earnings and faculty pay. Section 5 discusses the potential channels at play. Section 6 concludes.

2 Data

We build a dataset that includes individual level data on faculty wages, academic fields, and citations, across most U.S. universities and over more than 30 years. To do so, we use wage data obtained through public requests and H1B and green

card applications, as well as a textual analysis algorithm to identify fields through automated Google searches. We merge this dataset with university-field-year information on student wages, number of degrees, tuitions and donations.

2.1 Faculty Wages

We focus our analysis on *research* tenure track faculty, as they are central to university mission and governance through their research, teaching and administrative roles. We define "universities" as any post-secondary institutions that award bachelor or graduate degrees. Hence, we do not include community colleges, which typically grant 2-year degrees.

2.1.1 Public Universities

We collect a comprehensive dataset of research tenure-track faculty wages in public universities by performing public record requests across U.S. states and Canada. State-level freedom of information laws guarantee the right to access records maintained by state agencies. We conduct these requests in the states where (1) post secondary institutions are not exempt from disclosing information; (2) the access right is granted to anyone, and not only to citizens of the state. We request data to states, university systems or single universities, over the longest time period possible, depending on the legal framework relative to the freedom of information laws. The scope of data coverage differs also across states and universities, with some providing information on all university employees, not exclusively on faculty.

We collected data from 48 U.S. states and two Canadian provinces covering 382 universities over the 1993-2023 period. In 2019, these universities enrolled about 2.8 million full time undergraduate students, corresponding to XX% of all the students enrolled in four year programs in the U.S. at this date (IPEDS 2019). Table A2 in the Internet Appendix lists the states and sample periods that this sample covers. We obtain information on each individual's first name, last name, base salary and/or total compensation, and affiliated university. *Base salary* includes the 9-month wage in most cases, while *total compensation* includes the summer stipend, grant wage money, and other variable pay. In most cases, we also

have information on the position and rank. Some universities or states provide information on the department.

2.1.2 Private Universities

We complement our public university dataset with information on faculty from *private* and other public universities using green card and H1B application data, thereby leveraging the large share of faculty employed in U.S. universities that are not U.S. citizens. According to the National Study of Postsecondary Faculty, 17% of academics on tenure track positions but not tenured are not U.S. citizens. The U.S. Department of Labor (DOL) makes the permanent residence and H1B applications publicly available on its Employment and Training Administration webpage.[9] We utilize annual data on green card applications from 2005 to 2015 and on H1B applications from 2010 to 2017.

We build an anonymized dataset of faculty wages, positions and fields using the H1B or green card application data in the following way. H1B or green card application data includes anonymized data on yearly wages, demographics, country of birth, occupation, position and employer identity for all applicants. We identify academic employees as individuals working for a university, as indicated by the name of the employer. Next, we single out research faculty and fields using both the job title and the occupation code from the Bureau of Labor and Statistics.

We arrive at an anonymized wage dataset of more than 26,000 professors over the 2005-2017 period working across 1,460 universities that we append to our public university dataset.

2.1.3 Representativeness

To assess the representativeness of our wage data, we use data from the Integrated Postsecondary Education Data System (IPEDS) on enrolled students and professors across universities and degrees. IPEDS, compiled through annual surveys conducted by the U.S. Department of Education's National Center for Education Statistics, covers all postsecondary institutions that participate in the federal stu-

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

dent financial aid programs. We find that our dataset comprises universities that enroll 84% of all 2019 full-time undergraduate students in four-year colleges. Finally, our dataset comprises universities that cover 89% of assistant/associate/full professors working at four-year colleges in the years 2019-2020.

2.1.4 Historical Data from the early 1970s

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.[10] 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 digitized and analyzed 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 converted the digitized PDF files into tables, extracting average salaries and the number of professors by grouped disciplines, university categories, and faculty ranks. Grouped disciplines correspond to CIP families or fields, while Economics and Finance were collected as separate, non-grouped disciplines. Finally, we used information on the number of professors to adjust wages in grouped disciplines when necessary.[11]

2.2 Academic Fields: Algorithm

A significant challenge to our analysis is determining each faculty's academic fields. To do so, we first define academic fields and map with the departments they include with key words. We then run a textual analysis algorithm to identify these keywords in automated Google search results for each combination of names and affiliation in our data.

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

[11] For example, in Social Sciences, we adjusted average salaries to exclude economics professors.

2.2.1 Field Definition and Key Words

We define fields and departments using the Classification of Instructional Program (CIP) from the U.S. Department of Education's National Center for Education Statistics (NCES). The classification was introduced in 1980 to categorize academic programs by field of study and has subsequently been revised to incorporate alterations in academic disciplines. Under the CIP, each instructional program is assigned a six-digit code: we use the first two digits, which represent the broadest categories of related instructional programs, to identify the **academic field** and the first four digits, which indicate subgroups of programs with similar content and objectives, for department.

Our analysis focuses an 18 academic fields and two departments. We focus on academic fields with graduate studies, and exclude those that account for less than 1% of our data, as well as medicine. We single out the following departments with faculty wages that are more than 20% higher than the field average: finance, accounting, and economics, and merge finance and accounting together as they are included in the same field, Business. These departments display wage patterns that differ significantly from wage patterns associated with their corresponding fields.

To identify departments and fields using our textual analysis algorithm, we map all the 420 departments included in our the 18 fields + 2 departments with key words collected from their descriptions. To illustrate, the department "Electrical, Electronics and Communications Engineering", with CIP code 1410, 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 Textual Analysis Algorithm

Next, we conduct automated Google searches for the 500K unique combinations of first name, last name and university we obtain through the public requests. We collect the three lines of text from the first four search results and use a textual analysis algorithm to identify the position. We keep only observations that include the words "professor" and drop teaching faculty identified with the words "instructor," "adjunct," and "educator," as well as clinical professors to focus on research faculty. We keep only the four search results

To identify the department, our textual analysis algorithm first look for a set of pre-identified word sequence such as "a professor in," "a professor of," "in the department of" in each of the four Google search results and then collect the following word. If this first step does yield any keyword that match with our list, then the next one consists in looking for keywords in the full text. Keywords are categorized by level of precision, such that "hellenic studies" will be identified first, before "humanities," which is less precise and can correspond to different fields. The algorithm allows us to collect key words and identify CIP codes for close to 90% of all names and university combinations that are professors.

For observations from the H1B and Green card data, we use the occupation code that we map to CIP codes using the CIP-SOC Crosswalk, developed collaboratively by the Bureau of Labor Statistics and the National Center for Education Statistics.

2.2.3 Accuracy

We verify the accuracy of our algorithm in two ways.

First, we compare the field with obtain with the one given by some universities in public wage requests.

Second, we match our faculty wage dataset with all the James Hasselback's faculty directories from 1993 to 2023.[12] For over 35 years, James Hasselback has compiled comprehensive information on faculty members in Accounting, Finance, Marketing, Economics, and Management departments across approximately 500

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

U.S. public and private institutions, including XX ones from our sample. For each faculty member, the directory includes details such as their specific field, department affiliation, position, year of PhD completion, and PhD alma mater. We identify 5,600 Accounting, Finance, Economics, Marketing and Business professors in our faculty wage dataset by linking it with the James Hasselback' directories and find that our textual analysis algorithm correctly identifies the fields for 90% of them.

2.2.4 Summary Statistics

Table 1 provides summary statistics of faculty wages by field, position, and university rank. Our final academic wage dataset comprises over 740,000 faculty-year observations and more than 200,000 professors working across over 1,590 universities in 25 different academic fields from 1993 to 2023.

INSERT TABLE 1 HERE

A challenge in accurately quantifying wage heterogeneity across academic fields is establishing a uniform measure of compensation. We address this challenge by disentangling the "base salary," which is available for approximately 75% of the faculty in our data., from "total compensation." The base salary excludes summer stipends and variable pay and is typically paid over an 8, 9, 10, or 11-month period. To standardize the base salary measure across universities, we utilize data from IPEDS, which provides details on the compensation structure of base salaries at each university. Figure A1 in the Internet Appendix illustrates the duration of base salary contracts. Notably, for over 80% of our observations, the base salary is for a 9-month period. Therefore, we standardize our base salary measure to reflect a 9-month contract across all universities.

When the base salary is not available, we exploit information on total compensation. This variable includes the summer stipend as well as grant wage money and other variable pay. For faculty with summer stipend, total compensation is 30% higher on average than the base salary. Our specifications control for the type of compensation, base salary or total compensation and Table XX in the Internet Appendix displays the summary statistics for total compensation.

2.3 Student Wages

2.3.1 University-Field-Year Panel

We utilize the Post-Secondary Employment Outcomes (PSEO) dataset provided by the U.S. Census Bureau to obtain student wage data one year after graduation, disaggregated by universities, fields, and years.[13] The Longitudinal Employer-Household Dynamics program (LEHD) at the U.S. Census Bureau produces this dataset in collaboration with individual post-secondary institutions, higher education systems, and state agencies. Graduation records provided by post-secondary institutions include details such as student identity, degree type, field of study, and graduation date. This information is matched with the LEHD database, which covers more than 96% of U.S. employment. The PSEO dataset includes only graduates with earnings data for at least three quarters of the reference year and annual earnings at or above the full-time federal minimum wage. Spanning the years 2000 to 2019, the dataset incorporates data from 478 four-year post-secondary institutions across 28 states. This analysis is based on the June 2024 release of the dataset.

Our study utilizes the wage information provided by the PSEO dataset, which is available at the university, academic program, and cohort levels for both graduate and undergraduate students. Each cohort spans three years for undergraduate students and five years for graduate students. For confidentiality reasons, the PSEO dataset provides the median wage one and five years post-graduation for each university and academic program within each cohort, as well as the 25th and 75th percentiles. We match academic programs to their respective fields using the CIP code.

We also calculate the PV of the median student wages during the first five years after graduation as follows:

$$\text{Five-Year Student Wage}_{f,u,t} = \sum_{\tau=0}^{4} \beta^{\tau}(\omega_{one,f,u,t} + \frac{\tau}{4}(\omega_{five,f,u,t} - \omega_{one,f,u,t})) \quad (1)$$

where $\omega_{one,f,u,t}$ and $\omega_{five,f,u,t}$ denote the median wages of students in field f at

[13] `https://lehd.ces.census.gov/data/pseo_experimental.html`

university u in year t one year and five years after graduation, respectively. We assume $\beta = 1/(1+3\%)$, accounting for a 3% yearly discount rate.

Panel B in Table 2 provides summary statistics from our dataset on student median wages at university and field levels for undergraduate students with bachelor's degrees. Our dataset includes 3,348 university-field observations, covering 321 universities from our sample and representing 53% of the observations in our faculty wage dataset.

INSERT TABLE 2 HERE

In addition, we use the PSEO employment data, which provides the number of employed graduates by industry and region one year post graduation for each year, university and field. The region classification is based on nine Census divisions, which each cover a few states. In addition, the dataset includes information on the number of graduates that reside in the university's state as well as outside of the state but within the university's Census division.

We match the student wage and employment data by university, academic field, and year.

2.3.2 Life-Time Earnings Across Fields

We complete the PSOE dataset, which focuses on wages one year after graduation, with information on student life-time earnings across fields of study from the American Community Survey over the period 2009-2019. 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.

For our main analysis, we also restrict the sample to individuals with at least a master degree. This criterion results in a sample of approximately 1.7 million individuals. We exploit this data on undergraduate majors to categorize individuals into various fields of study, employing the Classification of Instructional Programs developed by the National Center for Education Statistics.

Panel A in Table 2 provides summary statistics of student wages by academic field. One limitation with the data from the American Community Survey is that it is top coded: Wages in the ACS above 99.5% in a state are replaced with the average wage in this state among all observations above 99.5%. To account for the potential impact of top-coded values on wage statistics by academic field or industry, we follow a strategy similar to Philippon and Reshef (2012) explained in Appendix 3.

INSERT TABLE 2 HERE

2.4 Other Data

2.4.1 Degrees

We supplement the data on student wages with information on degrees conferred from IPEDS. The IPEDS dataset provides annual numbers of bachelor's, master's, and PhD degrees awarded by the CIP code for each post-secondary institution, starting from the 1983-1984 academic year.

In 2001, IPEDS revised its reporting standards for bachelor's and master's degrees, introducing separate data collection for first and second majors instead of a single major. To avoid any discrepancies caused by this change, we use bachelor's and master's degree data only from 2001 onward. We also utilize data on PhD degrees starting from 1983.

2.4.2 Tuition

We collect data on annual graduate tuition for academic programs from Internet resources for the academic year 2023-2024 and use the CIP code to match academic programs to their respective fields. Following that, we calculate the average annual

graduate tuition $tuition_{grad,f,u}$ for each university u and field f and convert it to 2019 prices.

We supplement the graduate tuition data with undergraduate tuition data from IPEDS, which includes baseline undergraduate tuition as well as differential undergraduate tuitions at law and medical school. One limitation of IPEDS undergraduate tuition data is that it does not include information on differential undergraduate tuitions in business and engineering schools. To address this limitation, we calculate the annual undergraduate tuition for Finance, Management Science, and Engineering, assuming that the ratio of undergraduate tuition in these fields to the baseline undergraduate tuition is the same as the ratio of graduate tuition in these fields to the average graduate tuition in all fields, except for Finance, Accounting, Management Science, Engineering, Law, and Medicine:

$$tuition_{und,f,u} = \overline{tuition_{und,u}} * \frac{tuition_{grad,f,u}}{\overline{tuition_{grad,u}}} \tag{2}$$

where $\overline{tuition_{und,u}}$ is the baseline annual undergraduate tuition at university u, which is the same for all fields except Finance, Management Science, Engineering, Law, and Medicine. $\overline{tuition_{grad,u}}$ represents the average graduate tuition at university u calculated using all fields, except for Finance, Accounting, Management Science, Engineering, Law, and Medicine.

We supplement the tuition data with IPEDS data on the number of degrees conferred per field and university. We calculate the share of undergraduate students for each university u and field f as follows:

$$s_{und,f,u} = \frac{length_{und,f} * degrees_{und,f,u}}{length_{und,f} * degrees_{und,f,u} + length_{grad,f} * degrees_{grad,f,u}} \tag{3}$$

where $degrees_{und,f,u}$ and $degrees_{grad,f,u}$ are the total number of bachelor's and master's degrees, respectively, awarded over the period 2015-2020 at university u and matched by the CIP code to field f. $length_{und,f}$ and $length_{grad,f}$ represent the median number of years required to complete bachelor's and master's degrees in field f.

2.4.3 Donations

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 identify the academic fields benefiting from these donations using information on the department receiving the donation. When this information is not available, we run a textual analysis on the description of the purpose of the donation to match it to an academic field. For example, in 2010, the University of South Carolina at Columbia received a pledge of $30 million from William and Lou Kennedy to name and establish the Pharmacy Innovation Center. We use the key word *pharmacy* to identify the corresponding field, i.e. Medicine.

Table A4 in the Internet Appendix provides summary statistics on all donations above $1 million received by universities over the 2005-2018 period. We observe that after Medicine, Finance receives the highest amount of donations.

3 Academic Pay: Stylized Facts

3.1 Heterogeneity in Academic Pay across Fields

Table 1 provides summary statistics of faculty wages by field, position, university rank, type and location. Unconditionally, we observe higher pay in Finance and Accounting, with Law and Medicine also ranking high. Full professors and faculty in high rank universities also earn higher wages.

To further investigate these wage differentials across fields, while controlling for observable characteristics and potential composition effects, we estimate the following specification, using Humanities as the reference field:

$$\ln(w_{i,t}) = \sum_{f=1}^{n} \beta_{field_f} \mu_{field_f} + \mu_{u,t} + \mu_{rank_i} + \mu_{H1B} + \epsilon_{i,t}, \tag{4}$$

where $w_{i,t}$ is the 9-month base salary of faculty i in year t, μ_{field_f} are field

indicator dummies for all fields except humanities. $\mu_{u,t}$ are university $\times$ year fixed effects and μ_{rank_i} are academic rank fixed effects controlling for composition effects across fields. We differentiate assistant, associate and full professors, accounting respectively for 37%, 26% and 38% of our observations. Finally, μ_{H1B} are fixed effects indicating non U.S. citizen, i.e. H1B or green card applicants. Standard errors are double clustered at the university and year levels.

Figure 3 plots the $1 + \beta_{field}$ coefficients across fields along with their 95% confidence intervals. Finance ranks as the highest paying field, offering a 70% wage premium over Arts, which is identified as the lowest paying field. The premium in Finance is also significantly higher compared to related disciplines like Business and Economics. Consistent with our unconditional statistics, other fields with relatively high wages include Law, Engineering, Computer Sciences, and Medicine.

INSERT FIGURE 3

Table 3 displays the coefficient of the same regression using total compensation, including summer support, as dependent variable. Again, the highest paying fields include Finance, Business, Economics, Law and Medicine, with pays that are more than 20% larger than in Humanities.

Finally, we estimate this specification across various sub-samples to explore the distribution of the premium along faculty rank and university characteristics. We find that the faculty wage differentials across fields are higher for assistant (Column 2) and associate professors (Column 3) than for full professors (Column 4). When investigating the premium across university types, it is significantly higher for top 50 universities according to the U.S. News ranking (Column 5), as well as for R1 universities (Column 6), i.e., for universities with very high research activities according to the Carnegie Classification of Institutions of Higher Education. Hence, for top 50 universities, the Finance premium *within university and year* is close to 90%, implying that a finance professor is paid close to twice as a much as a professor in Humanities.

INSERT TABLE 3

Table A3 in the Internet Appendix replicates the same analysis using the 9-month base salary instead of total compensation as dependent variable.

The Finance-academia wage premium we identify is economically large: the wage gap between Finance versus Humanities faculty within top 50 universities is of the same magnitude, at around 100%, as the wage gap between Humanities faculty and kindergarten teachers. We obtain data on kindergarten teacher wages from the Bureau of Labor Statistics, U.S. Department of Labor. In May 2022, the average wage of a kindergarten teacher amounts to $60,490, while the average wage of a Humanities professor in our dataset is $138,000 and Finance faculty's one is $275,000. Compared to what we observe in other high-skill service professions like consulting, banking, or auditing, the impact of field-specific expertise on wages seems considerably more pronounced in academia.

3.2 An Increasing Heterogeneity by Field

We now investigate the evolution of field wage differentials over the longest time period possible. To do so, we utilize the data we have manually collected from the archives of the salary surveys conducted by Oklahoma State University. The survey has collected wage data across academic fields for around 100 state universities and land grant institutions since 1974.

Figure 4 displays the evolution of the "salary factor" across fields over the 1974-2023 period for French, Economics, Maths, Finance, Computer Science, and Engineering. The salary factor is defined as the ratio of average wages in a particular field, across ranks and universities, to the average wage across all fields. The figure shows a growing heterogeneity in faculty wages across fields, particularly after the 2000s, indicating that wage gaps have widened significantly over time.

INSERT FIGURE 4

We observe similar trends using our individual-level data by estimating the following model for each field f within each year:

$$\ln(w_i) = \beta_f \mu_f + \mu_u + \mu_p + \mu_{h1b} + \epsilon_i, \tag{5}$$

where the coefficient β_f measures the premium of field f relatively to the average. μ_u, μ_p, and μ_{h1b} are university, position, and non US citizen fixed effects.

Figure A2 in the Internet Appendix displays the regression coefficients β_f for Finance, Business, Computer Science and Humanities.

3.3 Faculty Wage and Student Future Earnings

We provide evidence of a positive correlation between student future wages and faculty pay across fields, both in levels and in the time series. To do so, we first compute work-life earnings across education fields for graduate students using the following simple formula:

$$\text{Total Work-life Earnings}_f = \sum_{\tau=23}^{67} \beta_\tau \omega_{\tau,f} \tag{6}$$

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.

Figure 6 plots the expected life-time earnings versus faculty relative wage across fields. We observe a correlation of 0.70 between professors' pay and the expected future wages of their master students across fields. As a robustness check, Figure A8 in the Internet Appendix plots the same graph on the sample of undergraduate students only. We observe a positive but smaller correlation of 0.56 between professors' pay and student expected earnings across fields.

INSERT FIGURE 6

This positive correlation extends beyond just levels: changes in academic pay across fields also correlate with changes in student wages.

To calculate changes in student future earnings and academic wages for each university and field, we focus on the median wage data provided by the PSEO at the university, field, and 3-year cohort levels for undergraduate students with a

bachelor degree. We include only those university and field combinations that have observations for at least two cohorts. For each university and field combination, we calculate the growth rates of faculty and student wages over the sample period using the formula:

$$GrowthRate = \frac{x_{last} - x_{first}}{x_{first} * (N-1) * 3} \tag{7}$$

where x_{last} represents the median faculty or student wage for the last cohort in the sample, x_{first} denotes the median faculty or student wages for the first cohort in the sample, and N is the number of cohorts in the sample, that we multiply by 3, the number of years in a cohort. Finally, we obtain the yearly growth rates of faculty or student wages per field by averaging the growth rates computed across universities for each field.

Figure 7 displays the result of this exercise and exhibits the strong link between the growth rate of faculty wage in a field, and the growth in expected student wages.

INSERT FIGURE 7

4 A Causal Relationship?

We hypothesize that student earning potential causally impacts faculty wage.[14] A natural concern when interpreting the cross-sectional and time-series correlation between faculty wages and student expected earnings along that hypothesis is that this relationship may be driven by unobserved variable bias, with latent factors such as university prestige or general labor market trends influencing both variables. A reverse direction of causality should also not be ruled out, as better faculty pay may improve the quality of teaching through selection and incentives, and in turn affect the skills and future earning potential of students.

[14]The next section explores the mechanism that would underlie this causal relationship.

4.1 Identification Strategy

To address these concerns, we pursue a two step approach. First, we implement regression specifications with an increasingly broader set of fixed effects. We aim to control for as many general characteristics as possible and test the robustness of the relationship. Our most constrained specification includes university-by-year, field-by-year, and field-by-position fixed effects, ensuring that common trends at the university or field level, as well as faculty rank composition effects, cannot explain the observed relationship.

The second step in our methodology is to instrument student future earnings in the previous specifications, to exploit plausibly exogenous variation in this explanatory variable to fully rule out unobserved variable bias and reverse causality as potential interpretations. To this end, we construct a synthetic student future wage index at the university times field times year level, based on the industries and the geographical areas where the university historically placed students in that field and the wage evolution for workers in that field in those industries and geographic areas. The intuition behind this instrument is that, all else being equal, schools that place students in industries and areas where wages in their field have increased more will experience a plausibly exogenous rise in their student future earnings.

Like the standard application of the Bartik instrument (Bartik 1991), our instrument relies heavily on industry-area shocks. However, different from classical adaptations of this instrument, we convert these industry-area shocks into institution-major shocks using the mapping described below.

To construct the instrument, we combine data from the PSEO dataset and the American Community Survey. For each field f, university u, and year t, we calculate the institution-major-specific demand as follows:

$$Z_{f,u,t} = \sum_{g} \sum_{n} s_{f,u,g,n} \ln \varpi_{g,n,t}, \tag{8}$$

where $s_{f,u,g,n}$ is the share of graduates from the first cohort reported in the PSEO dataset for field f and university u, who are employed in region g and in

industry n. $\varpi_{g,n,y}$ represents the median wage and salary income for employees aged 40 to 60 years old who live in region g and work in industry n in year t. We compute the instrument for all years except the first cohort in the PSEO dataset.

4.2 Results

We first run the following specification:

$$\ln(w_{i,t}) = \beta \ln(\omega_{f,u,t}) + \mu_{i,t} + \epsilon_{i,t} \tag{9}$$

where $w_{i,t}$ is the yearly gross wage of faculty i in year t, while $\omega_{f,u,t}$ represents the university median future wage for students in field f at university u in year t. $\mu_{i,t}$ are a set of fixed effects. To estimate the elasticity of academic wages to student future wages across fields, we consider university $\times$ year and university $\times$ position fixed effects. The regression specification used to estimate the elasticity across universities includes field $\times$ year and field $\times$ position fixed effects. The fixed effects used to estimate the elasticity over time include field $\times$ position and field $\times$ university. Standard errors are double clustered at the university and year levels.

Table 4 displays the coefficients β, which document the average sensitivity of academic pay to student wages across all fields. Columns 4 and 5 are based on a subsample that includes only observations from before 2006 or after 2014. Academic wages appear to be strongly related to undergraduate student wages in the cross-section of fields and universities, as well as across time. The economic magnitude ranges from 0.33 in column 4, which shows the elasticity over time, to 0.43 in column 2 and 0.66 in column 3, which display the elasticity across fields and universities, respectively.

INSERT TABLE 4

Moving to the instrumental variable analysis, we conduct a 2SLS specification and report the coefficients in Table 5. Our first stage specification is as follows:

$$\ln(\omega_{f,u,t}) = \beta Z_{f,u,t} + \mu_{i,t} + \epsilon_{i,t} \tag{10}$$

And our second stage is

$$\ln(w_{i,t}) = \beta \widehat{\ln(\omega_{f,u,t})} + \mu_{i,t} + \epsilon_{i,t} \tag{11}$$

We report the first stage coefficients in columns 1 to 5, and the second stage coefficients in columns 6 to 10.

INSERT TABLE 5

4.3 Threats to Identification

While our university year fixed effects largely absorb local labor market shocks that are uniform across fields, the main threat to our identification strategy is the potential existence of correlated local demand shocks for academic and graduates in specific fields, as for most universities, a large share of graduates place locally.

5 Economic Mechanism

This section explores how the impact of student future earnings on professor wages contributes to growing disparities in academic pay across fields. We begin by showing that differences in the level of student wages alone do not fully explain the field disparities we observe. Instead, we find that the elasticity of faculty wages to student future earnings varies across fields. Our evidence suggests that this heterogeneous elasticity is driven by differences in student willingness to pay, reflected in tuition and donation levels, as well as variation in professor bargaining power, which we measure by the supply of PhD graduates per professor across fields.

5.1 Heterogeneity in Faculty Wage Elasticity to Student Future Earnings

To investigate the relationship between student future earnings and academic pay, and how it varies across fields, we first plot faculty wages versus student future

earnings across universities within each field. Figure 9 suggests that faculty wages are more sensitive to student future earnings in some fields than others. The X-axis is the median wage *students* enjoy in this university and field one year after graduation, while the Y-axis is the average wage *faculty* enjoy in this same university and field. The positive correlation between faculty and student pay across universities seems higher in three relatively high paying fields: Finance, Computer Sciences, and Economics.

INSERT FIGURE 9

To further investigate this relationship, we estimate the following specification, using Humanities as the reference field:

$$\ln(w_{i,t}) = \beta_1 \ln(\omega_{f,u,t}) + \sum_{f=1}^{n} \beta_{2_f} \ln(\omega_{f,u,t}) \mu_{field_f} + \sum_{f=1}^{n} \beta_{field_f} \mu_{field_f} + \mu_t + \mu_p + \epsilon_{i,t} \quad (12)$$

where $w_{i,t}$ is the yearly gross wage of faculty i in year t, while $\omega_{f,u,t}$ represents the university median student wage in field f, divided by the mean value within each year. μ_{field_f} denote field indicator dummies for all fields except humanities. μ_t and μ_p are year and position fixed effects, respectively. Standard errors are clustered at the field times year levels.

Table 6 displays the coefficients β_1 and β_{2_f}, which document the average sensitivity of academic pay to student wages across all fields and the incremental elasticity in specific fields, respectively. Columns 1 and 3 present the coefficients of the field fixed effects for the samples where undergraduate and graduate student wages are available. Columns 2 and 4 show that controlling for student future earnings reduces the wage disparities across fields, particularly in Engineering and Computer Science. Column 4 indicates that the elasticity of faculty wages to undergraduate student wages is more than three times higher in Economics and Finance than in Humanities. Column 6 additionally demonstrates that academic wages are significantly more sensitive to graduate student wages in Finance than in Humanities. Thus, faculty in certain high-paying fields, such as Finance, capture a larger share of the surplus generated by their students compared to other academic fields.

INSERT TABLE 6

5.2 University Revenues per Faculty

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

5.2.1 Tuition Revenue per Professor

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

$$\text{Tuition Revenue per Research Faculty}_{f,u} =$$
$$\frac{\text{students}_f}{\text{faculty}_f} * (s_{und,f,u} tuition_{und,f,u} + (1 - s_{und,f,u}) tuition_{grad,f,u}) \quad (13)$$

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

Figure 12 first plots the relationship between the average annual tuition revenue per research faculty and academic pay. We observe a positive correlation between tuition revenue per research faculty and faculty relative wage. For example, tuition revenue per research faculty in Finance is more than double that of other fields on average. Consistent with Johnson and Turner (2009), we find that higher tuition revenue per research faculty is driven in part by a higher student-to-professor ratio.

INSERT FIGURE 12

5.2.2 Donations and Endowment Income

Donations are another significant source of revenues for universities both through immediate use and endowment accumulation, which in turn produces income. This source of revenue is particularly important for the high research intensity universities. Thus, as per 2015, the top 10 largest public universities endowments total

USD \$76 bn. We calculate donations per research faculty (scaled) in field f as follows:

$$\text{Donation Intensity}_f = \frac{\frac{\text{Sum of all donations}_f}{\text{Sum of all donations}}}{\frac{\text{\# professors}_f}{\text{Total \# research faculty}}} \tag{14}$$

Figure 13 compares the donation per faculty (scaled) across academic fields. Donation per research faculty is significantly higher in Finance than in other fields, including other business fields.

INSERT FIGURE 13

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

5.2.3 Wage Skewness and Willingness to Pay

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

Finally, we exploit Forbes' dataset on billionaires to get a sense of the skewness of the wage distribution.[15] We collect the list of billionaires in the U.S. in 2021 and plots the number of billionaires across industries. Figure A10 in the Internet Appendix indicates that the Finance industry has the highest number of billionaires, close to 600, then followed by Computer Sciences and Manufacturing.

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

5.3 Supply of PhD Students

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

Figure **??** plots the ratio of PhD graduates per faculty versus the academic placement rate across fields. While the share of PhD graduates joining an academic career amounts to more than 70% in business fields, including finance, it is significantly lower in other academic fields. In addition, the number of Finance PhD graduates per professor is significantly lower than in other fields.[16]

INSERT FIGURE **??**

6 Conclusion

This paper provides new evidence on the growing disparities in faculty wages across academic fields, investigating the role of student future earnings. Using a comprehensive dataset on over 200,000 professors and student wages across U.S. and Canadian universities, we establish a causal relationship between student earnings and faculty wages. We show that beyond student earnings levels, a higher elasticity to student earnings in fields such as finance is fueled by factors like tuition revenues, donations, and bargaining power due to a limited supply of PhD graduates. These findings highlight the role of market forces in shaping academic compensation

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

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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7 Figures

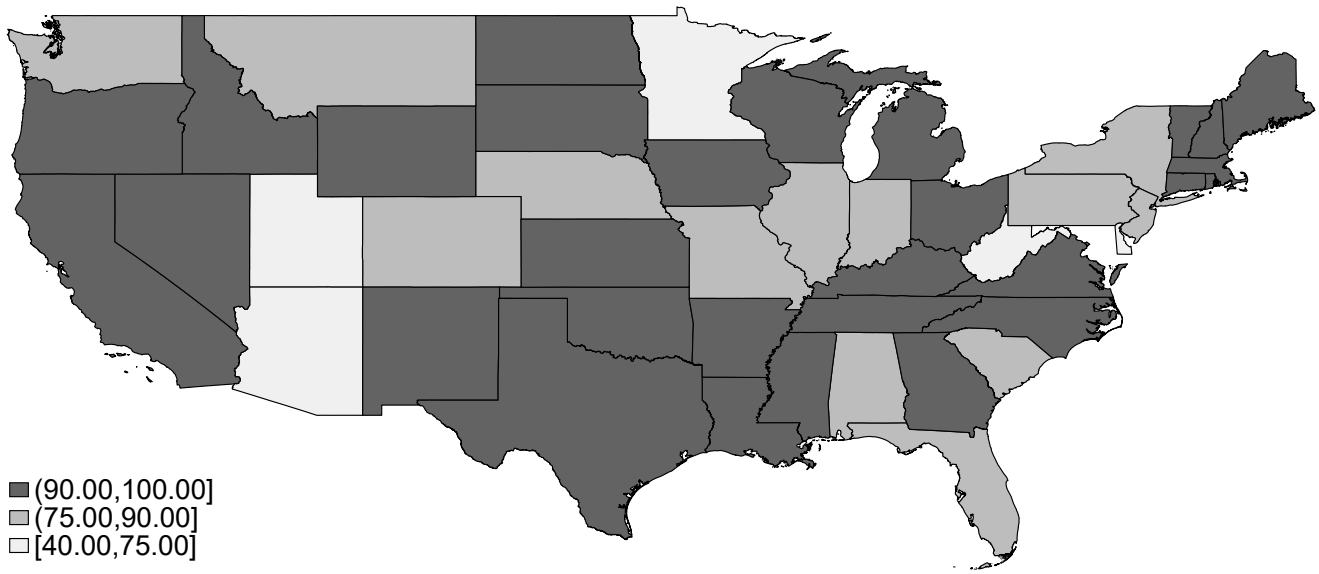


Figure 1. Fraction of Undergraduate Students Represented in the Data across States

This figure displays the fractions of undergraduate students represented by the universities in our sample across states in 2022. The fraction for each state is calculated as the ratio of the total number of bachelor's degrees conferred by the universities in our sample within a state to the total number of bachelor's degrees conferred by all universities in that state. The data on degrees conferred comes from the Integrated Postsecondary Education Data System (IPEDS).

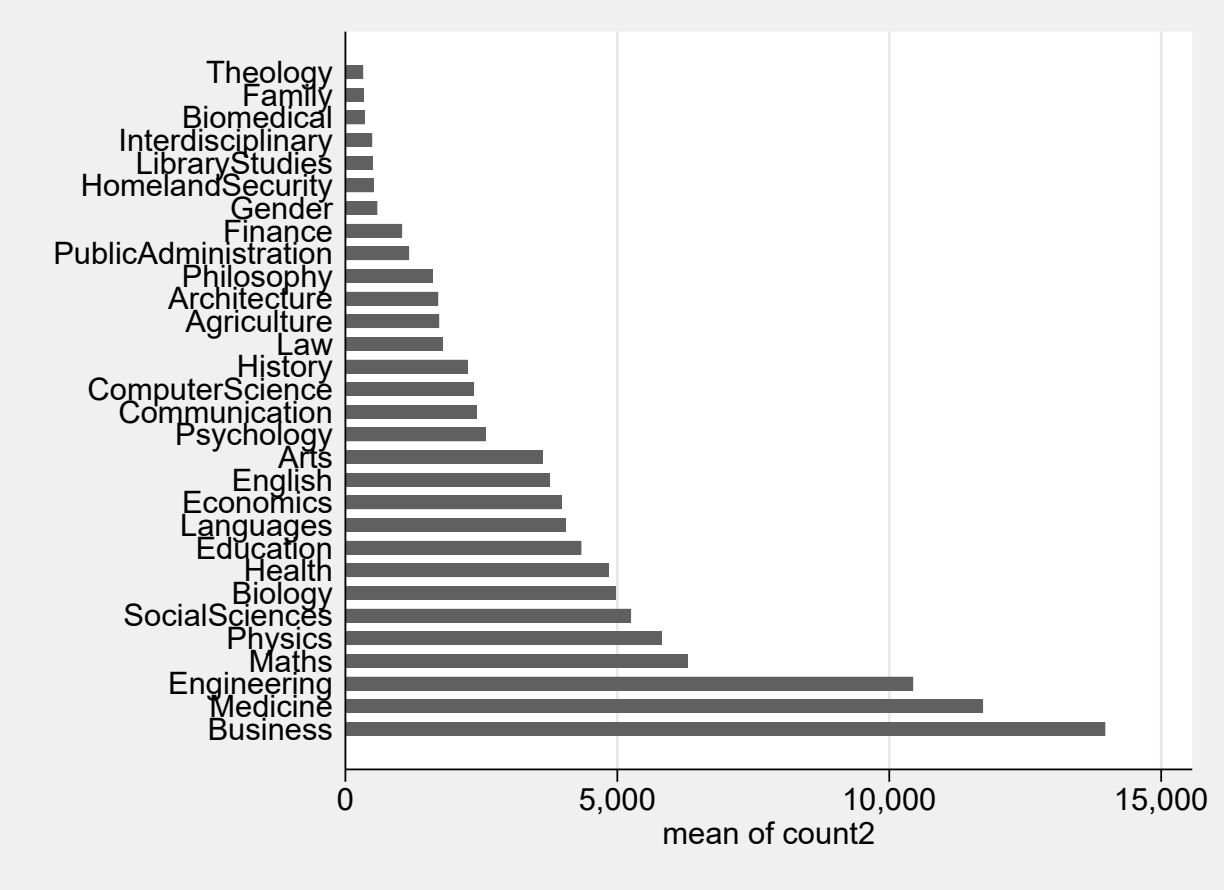


Figure 2. Number of Professors by Field

This figure displays the number of professors by field in our sample of academic wages. The sample includes over 200,000 research faculty from 1,500 U.S. and Canadian universities, spanning 1993-2023. For U.S. and Canadian public universities, we gather faculty wage data through public record requests in compliance with state-level freedom of information laws. We identified academic fields using Google search data, university directories, and the James Hasselback's faculty datasets. We complete this sample with data on faculty salaries in private and other public universities obtained from the U.S. Department of Labor's dataset of green card and H1B applications.

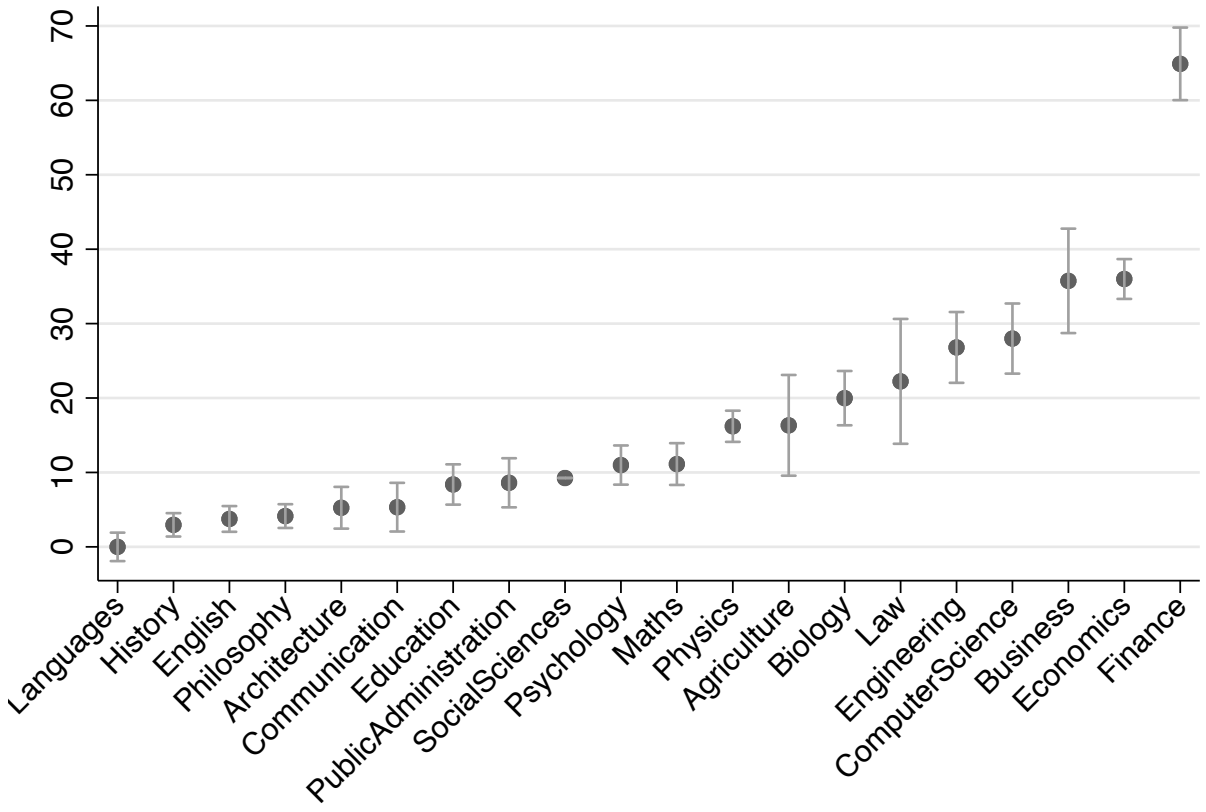


Figure 3. Academic Pay across Fields

This figure displays the wage premium of each academic field relative to Humanities. It plots the coefficient of the field indicator dummies + 1 in OLS regressions in which the dependent variable is the log of the yearly gross wage that corresponds to the 9 month base salary. Each regression also includes university times year and position fixed effects. The bars indicate 95% confidence bounds based on standard errors double clustered at the year and university levels. Our sample is an unbalanced panel consisting of over 740,000 faculty-year observations from over 200,000 research professors at more than 1,590 Canadian and U.S. universities that offer bachelor's degrees, covering the period from 1993 to 2023. For U.S. and Canadian public universities, we gather faculty wage data through public record requests in compliance with state-level freedom of information laws. We identified academic fields using Google search data, university directories, and the James Hasselback's faculty datasets. We complete this sample with data on faculty salaries in private and other public universities obtained from the U.S. Department of Labor's dataset of green card and H1B applications.

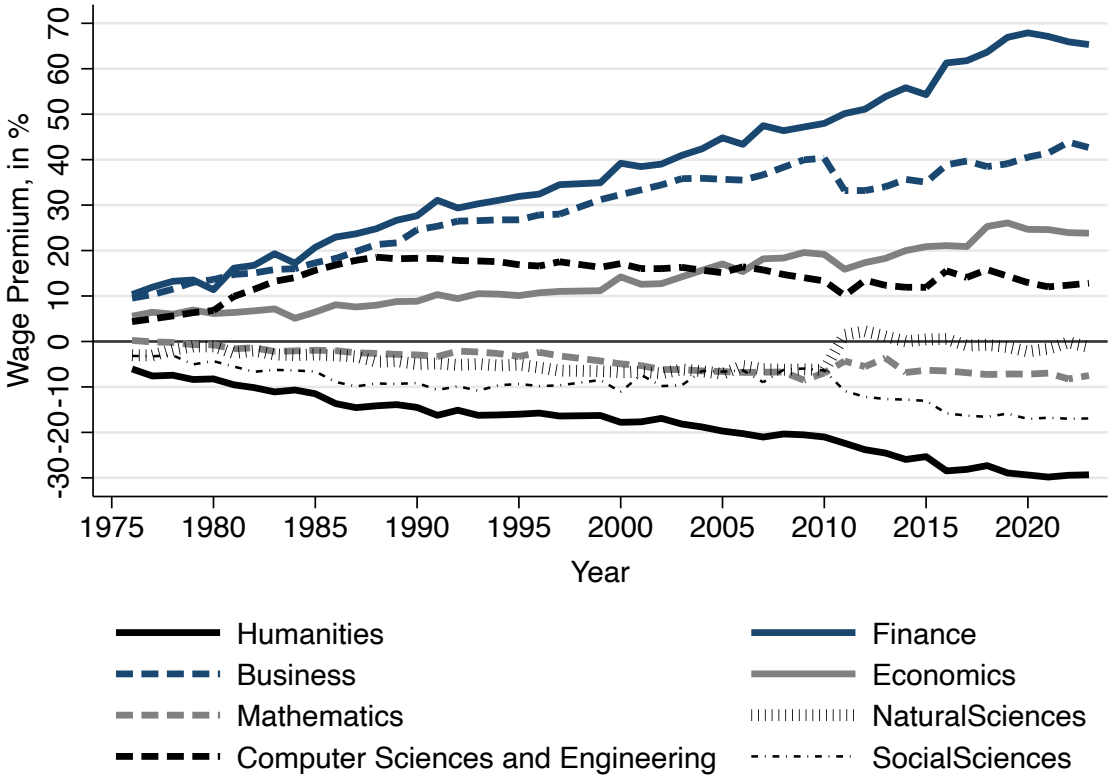


Figure 4. Evolution of Academic Pay across Fields (1974-2023)

This figure plots the evolution of wage premia across academic fields from 1974 to 2023. The lines indicate the ratio of the average salary in the field to the average salary in all fields in each year. The data is from the archives of the Faculty Salary Survey assembled by Oklahoma State University, which covers around 100 institutions belonging to the National Association of State Universities and Land-Grant Colleges.

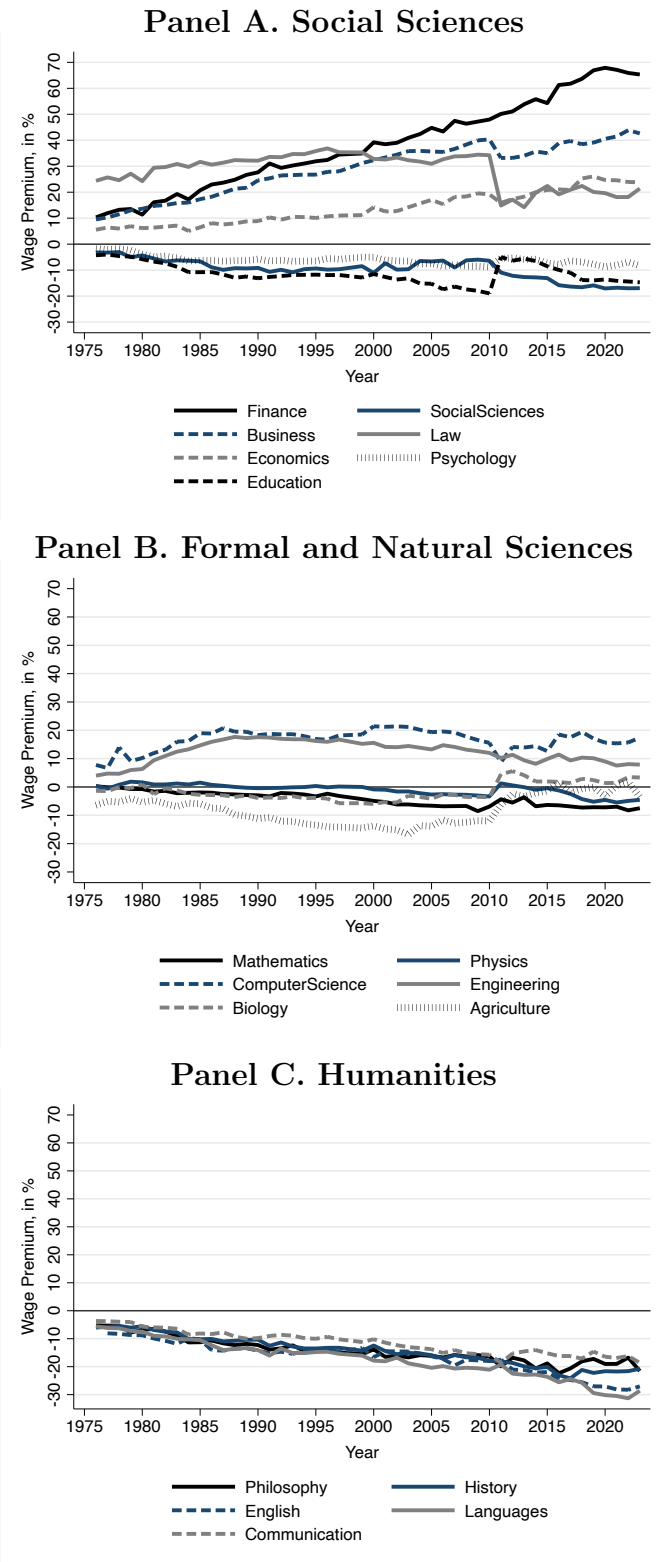


Figure 5. Correlation between Innovations in Student Wages and in Synthetic Wage Index

This figure illustrates the relationship between innovations in student wages and in the synthetic wage index. Student wages are for undergraduate students with bachelor's degree in Panel A and graduate students in Panel B. Innovations in student wages are the residuals from the regression of the logarithm of median student wages on university, field and cohort fixed effects. Innovations in the synthetic wage index are the residuals from the regression of synthetic wage index on university, field and cohort fixed effects. The data on student wages one year post-graduation is derived from the U.S. Census Bureau's Post-Secondary Employment Outcomes dataset, which covers the years 2001 to 2019. The synthetic wage index

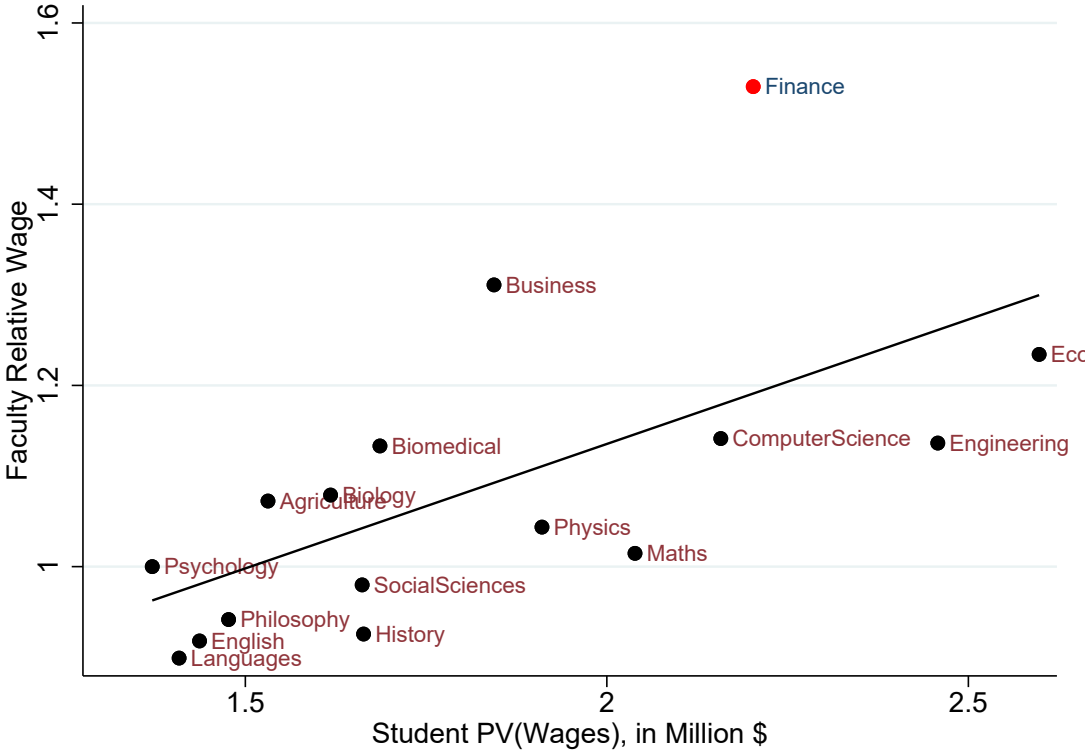


Figure 6. Faculty Wages versus Student Expected Earnings across Fields

This figure illustrates the relationship between the academic wage premium across various academic fields and the present value of students' work-life earnings in those fields. We derived data on students' work earnings from the American Community Survey, which offers individual-level details on wages, demographics, and fields of study, spanning the years 2010 to 2018. For each age group within each field, we calculated the average annual income. The present value of work-life earnings represents the sum of these average incomes from ages 25 to 64, discounted annually at a rate of 3%.

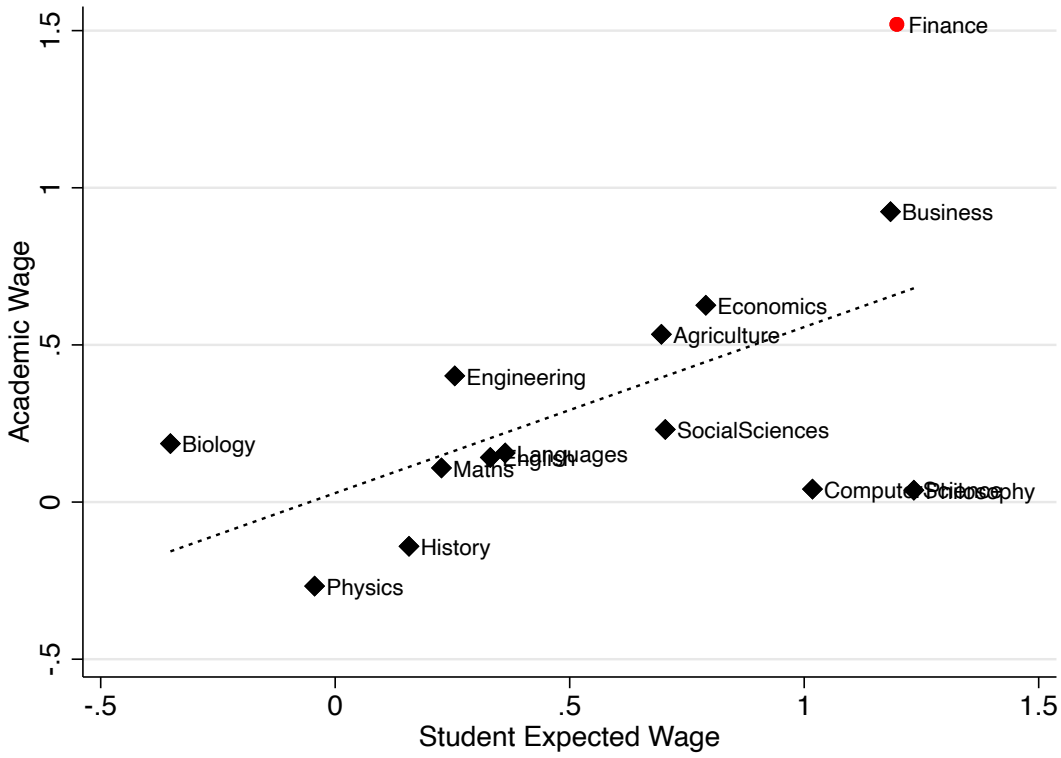


Figure 7. Yearly Growth Rate of Faculty versus Undergraduate Student Future Earnings (2001-2019)

This figure illustrates the relationship between average faculty wage growth rate per cohort and average undergraduate student wage growth rate per cohort. The data on student wages one year post-graduation is derived from the U.S. Census Bureau's Post-Secondary Employment Outcomes dataset, which covers the years 2001 to 2019. These data are matched with our dataset on academic wages by academic field assigned using the CIP code. For each university and field, we compute a yearly growth rate in wages as described in section 3.3 .

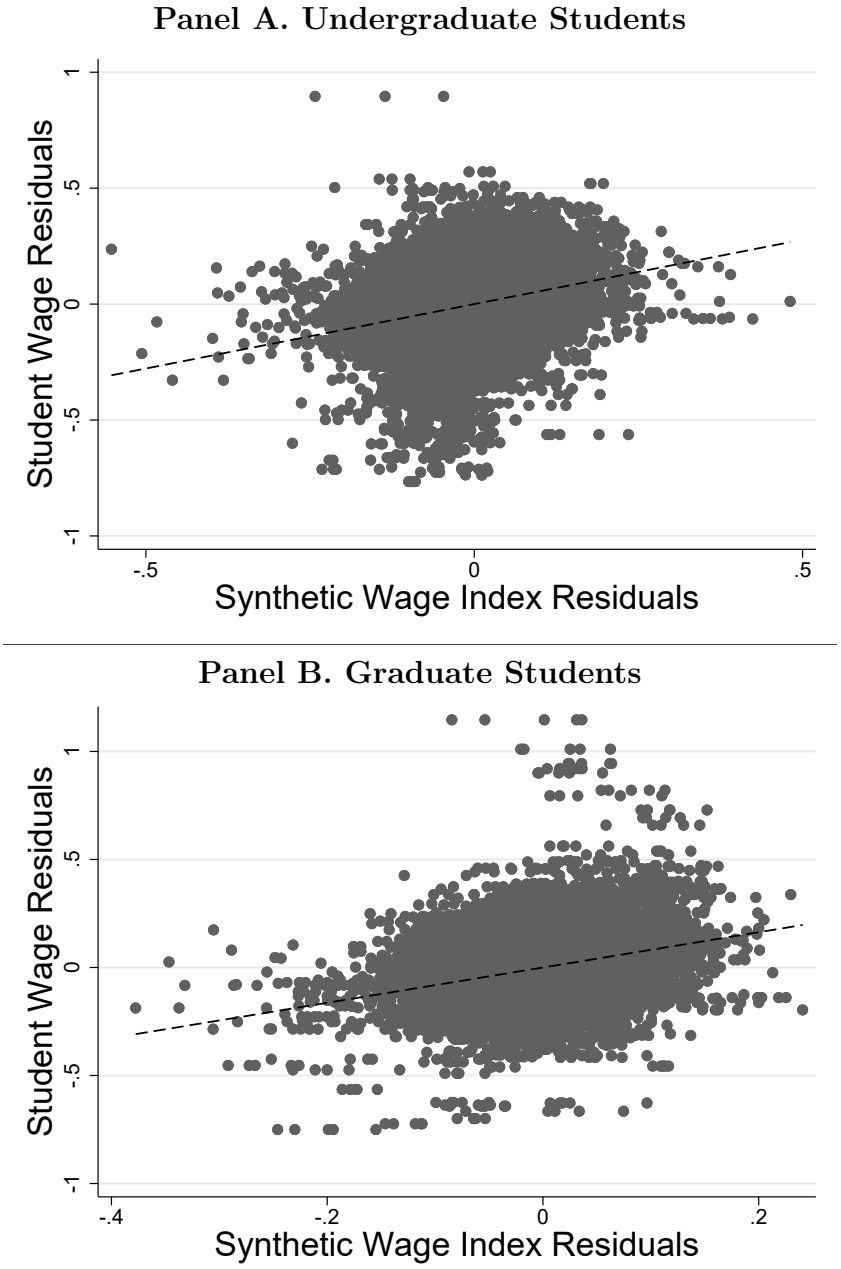


Figure 8. Correlation between Innovations in Student Wages and in Synthetic Wage Index

This figure illustrates the relationship between innovations in student wages and in the synthetic wage index. Student wages are for undergraduate students with bachelor's degree in Panel A and graduate students in Panel B. Innovations in student wages are the residuals from the regression of the logarithm of median student wages on university, field and cohort fixed effects. Innovations in the synthetic wage index are the residuals from the regression of synthetic wage index on university, field and cohort fixed effects. The data on student wages one year post-graduation is derived from the U.S. Census Bureau's Post-Secondary Employment Outcomes dataset, which covers the years 2001 to 2019. The synthetic wage index is constructed using the data on student wages and employment from the Post-Secondary Employment Outcomes dataset and the data on industry wages from the American Community Survey.

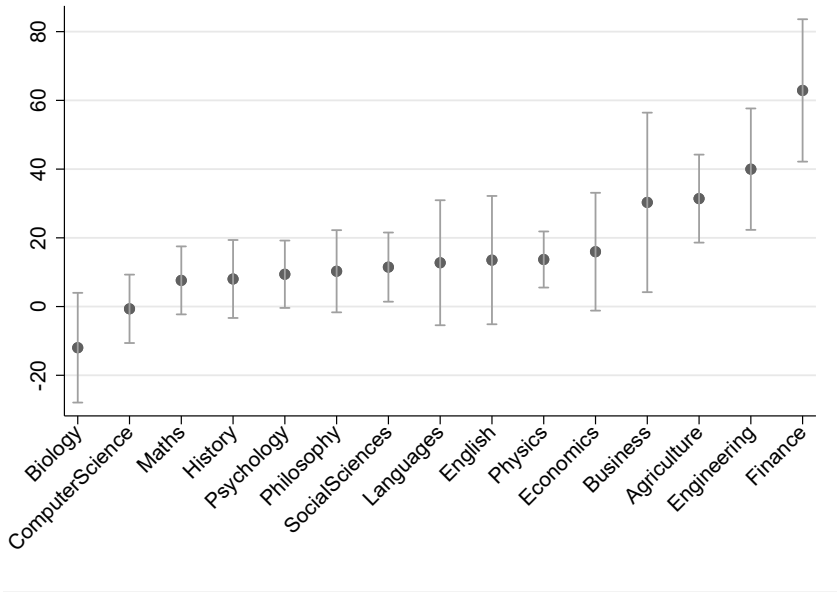


Figure 9. Within Field Elasticities of Faculty Wages to Student Wages across Time

This figure plots within field elasticities of faculty wages to student wages across time. Each elasticity is obtained from the within-field regression of the log of the yearly faculty base salary on the log of the median undergraduate student wage one year after graduation in the same university with university×position and non U.S. citizen 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 sample of academic wages by academic field assigned using the CIP code, university, and year.

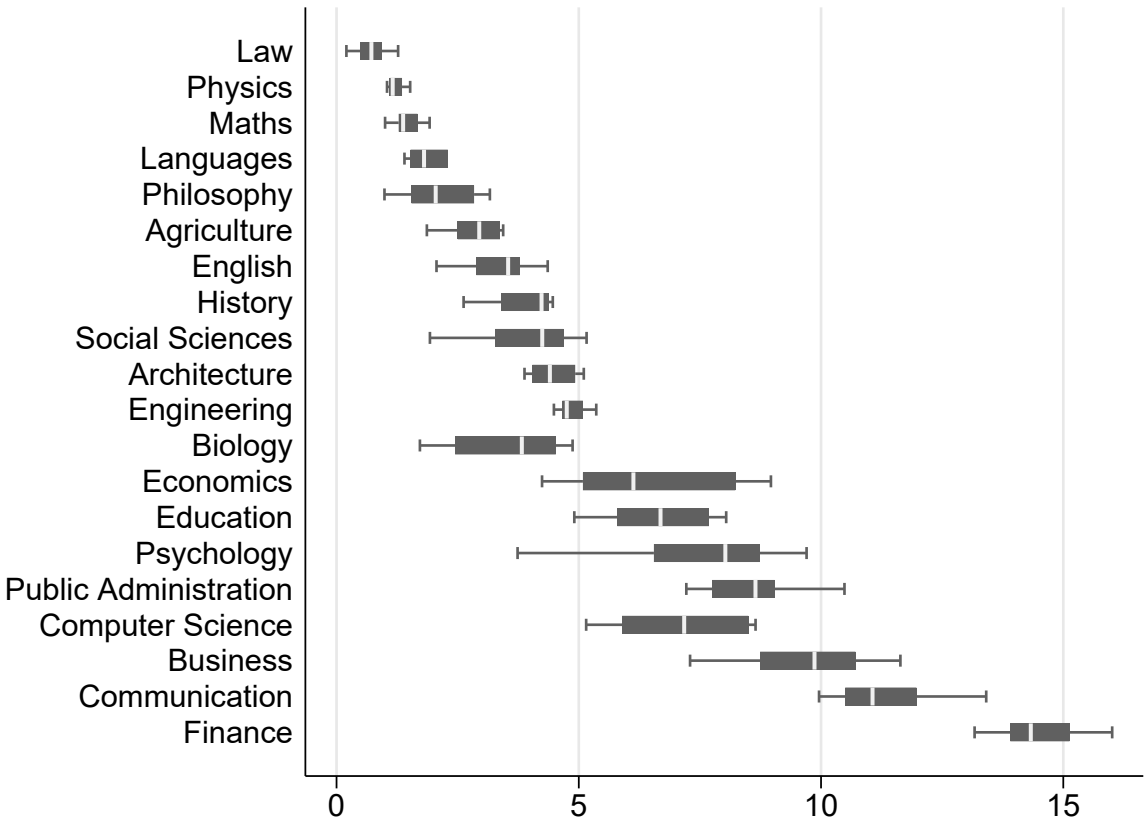


Figure 10. # of Graduating Students per Professor across Fields
This figure displays box plots showing the distribution of graduating students (bachelor's and master's combined) per professor across academic fields. Each box plot displays the lower and upper adjacent values, along with the 25th percentile, median, and 75th percentile. The number of graduating students per professor is calculated at the field-year level using aggregate numbers of professors and degrees for the sample of institutions participating in the Faculty Salary Survey assembled by Oklahoma State University. The total number of professors is obtained from the Faculty Salary Survey, while the total number of degrees awarded at these institutions comes from IPEDS (Integrated Postsecondary Education Data System).

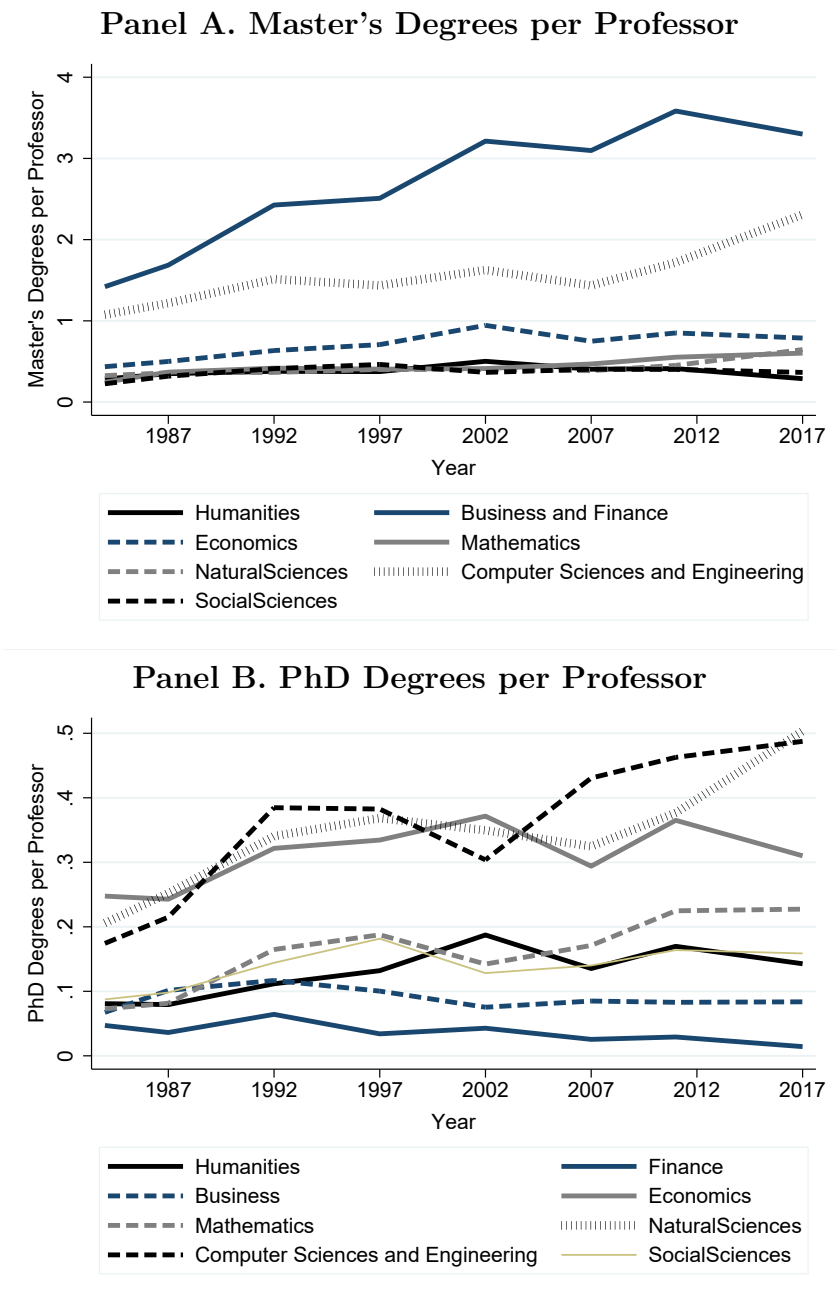


Figure 11. Evolution of the Degree-to-Professor Ratio across Fields (1984-2017)

The figure plots the evolution of the degree-to-professor ratio across academic fields from 1984 to 2017 for master's degrees (Panel A) and PhD degrees (Panel B). The ratios are calculated at the field-year level using aggregate numbers of professors and degrees for the sample of institutions participating in the Faculty Salary Survey assembled by Oklahoma State University. The total number of professors is obtained from the Faculty Salary Survey, while the total number of degrees awarded at these institutions comes from IPEDS (Integrated Postsecondary Education Data System).

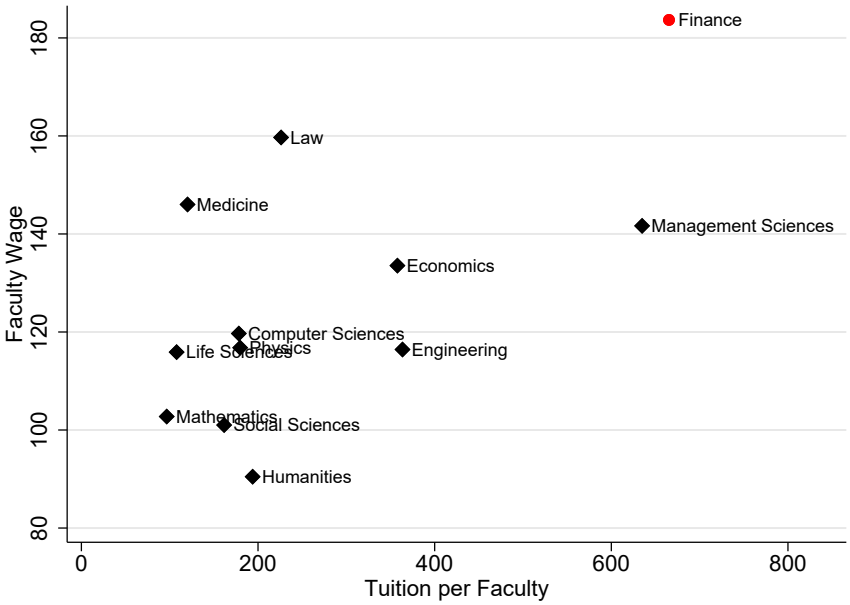


Figure 12. Faculty Wages and Per-Faculty Tuition Revenues across Fields

This figure illustrates the relationship between the average faculty wage and the average annual tuition per research faculty across fields. The average faculty wage for each field is calculated using our sample of professors. We compute the average annual tuition revenue per research faculty as $\frac{\text{students}_f}{\text{faculty}_f} * (s_{und,f,u} tuition_{und,f,u} + (1 - s_{und,f,u}) tuition_{grad,f,u})$, where $\frac{\text{student}_f}{\text{faculty}_f}$ is the average student-to-research faculty ratio in field f based on our sample of universities. $s_{und,f,u}$ represents the share of undergraduate students at university u and field f. $tuition_{und,f,u}$ and $tuition_{grad,f,u}$ are the annual undergraduate and graduate tuition, respectively, at university u and field f. The annual undergraduate tuition $tuition_{und,f,u}$ equals the annual baseline tuition undergraduate tuition at university u for all fields except Finance, Management Science, Engineering, Law, and Medicine. The annual undergraduate tuition for Finance, Management Science, and Engineering is calculated as $tuition_{und,f,u} = \overline{tuition_{und,u}} * \frac{tuition_{grad,f,u}}{\overline{tuition_{grad,u}}}$, where $\overline{tuition_{grad,u}}$ represents the average graduate tuition at university u calculated using all fields, except for Finance, Management Science, Engineering, Law, and Medicine. The numbers are in thousand 2019 dollars.

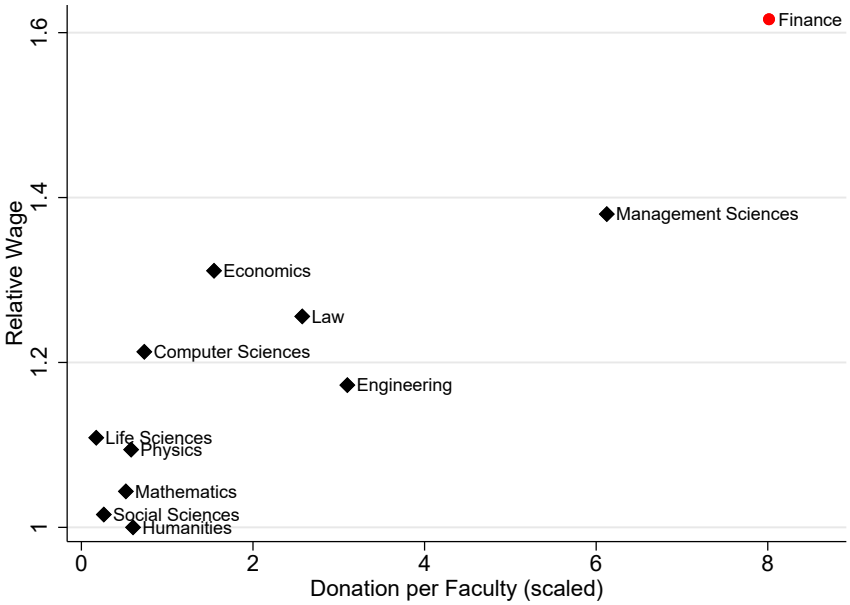


Figure 13. Faculty Wages and Donations across Fields

This figure illustrates the relationship between the academic wage premium and donations. The wage premium for each academic field is the same as in Figure 3. The scaled donation per faculty is the share of donations to a field relative to the share of professors in the field using our data. Donation data comes from the Chronicle of Philanthropy database of charitable gifts and includes information on all donations above $1 million made to U.S. universities in the period 2005-2018.

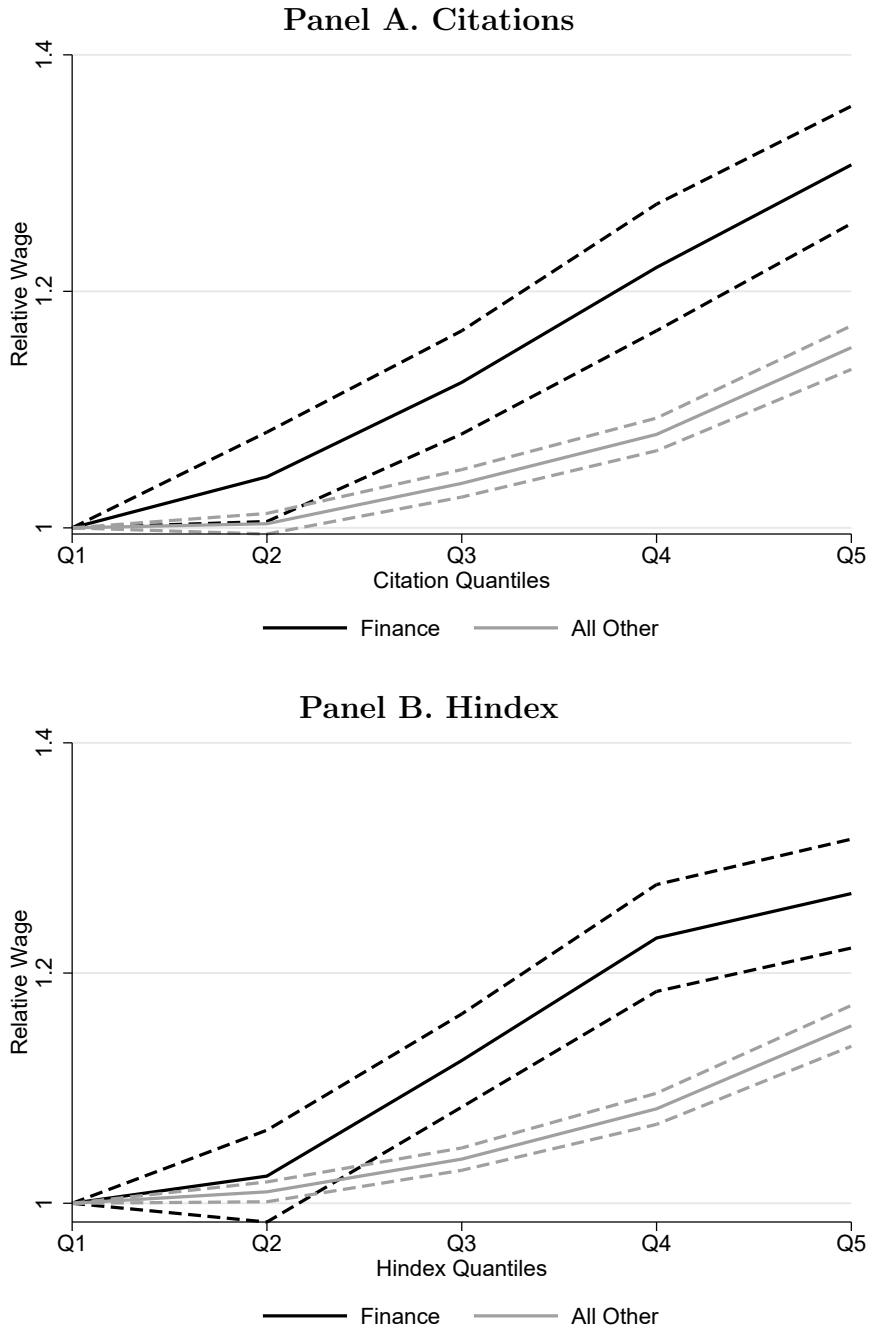


Figure 14. Wage Returns to Research Output

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

8 Tables

Table 1. Summary Statistics: Faculty Wages

	Gross Base Salary, in 2010 $						
	Mean	**Median**	**SD**	**p10**	**p90**	**p95**	**# Obs.**
Total Sample	105,088	94,304	55,335	53,799	168,594	203,500	745,891
By Academic Field							
Finance	158,423	140,875	73,573	82,844	255,298	292,633	9,237
Law	136,291	129,751	70,900	55,797	225,724	259,844	17,290
Medicine	134,531	113,418	91,182	45,794	241,634	299,165	68,483
Business	122,791	113,567	59,647	60,393	196,244	231,479	66,826
Economics	120,702	110,607	54,912	66,760	191,300	235,483	21,465
Biomedical	120,578	109,475	57,016	67,863	190,046	224,959	4,387
Engineering	113,837	106,314	46,948	67,582	170,270	196,689	67,121
Computer Science	112,266	107,688	42,399	66,549	163,325	184,832	22,868
Biology	106,634	97,063	52,048	57,698	164,983	197,676	47,023
Physics	103,768	95,600	45,794	57,847	160,816	188,100	47,779
Health	101,422	94,007	49,418	53,375	158,754	187,094	45,331
Agriculture	97,589	88,423	49,191	54,287	147,886	174,892	10,303
Social Sciences	94,555	87,042	40,865	53,964	144,850	168,618	48,074
Philosophy	94,430	88,174	40,395	52,502	143,961	162,826	11,828
Psychology	94,348	85,834	41,613	54,683	144,048	168,500	25,789
Architecture	94,195	87,531	41,942	54,296	142,089	166,855	14,351
Maths	93,606	84,872	41,671	52,130	147,405	170,100	38,317
Theology	92,387	83,201	43,049	47,487	149,205	170,738	1,744
Public Administration	88,235	80,063	36,546	52,930	134,873	155,005	11,710
Education	87,854	78,567	38,782	50,937	137,679	157,314	27,174
History	87,381	79,884	36,778	50,976	134,347	151,822	21,358
Languages	86,595	78,827	36,732	50,111	133,875	151,627	26,964
English	84,439	75,714	37,089	50,288	130,804	149,433	31,475
Communication	79,832	71,904	36,028	50,259	120,991	139,899	14,445
Arts	77,641	70,866	31,993	47,487	118,643	136,104	28,364
By Position							
Full Professor	127,349	118,373	60,947	66,792	196,567	235,129	344,382
Associate Professor	93,899	87,268	40,580	57,609	134,549	159,643	199,705
Assistant Professor	78,171	70,380	40,682	45,103	119,600	150,509	201,804
By University Rank							
R1	114,946	100,015	63,833	56,734	193,146	231,479	339,222
Non R1	96,864	89,524	45,481	52,671	147,074	170,835	406,669

This table presents summary statistics on faculty wages across various academic fields, positions, university ranks, and types. The reported wages represent the 9-month base salary, exclusive of summer stipends and bonuses. Our sample is an unbalanced panel consisting of over 740,000 faculty-year observations from over 200,000 research professors at more than 1,590 Canadian and U.S. universities that offer bachelor's degrees, covering the period from 1993 to 2023. For U.S. and Canadian public universities, we gather faculty wage data through public record requests in compliance with state-level freedom of information laws. We identified academic fields using textual analysis on automatically collected Google search data and the James Hasselback's faculty datasets. We complete this sample with data on faculty salaries in private and other public universities obtained from the U.S. Department of Labor's dataset of green card and H1B applications.

Table 2. Summary Statistics: Student Future Wages

	Mean	Median	SD	p10	p90	# Obs.
Panel A - Yearly Income Across Education Fields, in 2019 $						
Source: American Community Survey (2010-2018)						
Total Sample	92,675	71,738	81,930	30,218	161,886	1,054,746
By Academic Field						
Finance	142,671	104,243	128,191	40,912	317,071	19,749
Law	104,736	76,637	98,715	28,041	199,271	1,854
Medicine	87,187	77,186	59,267	33,080	141,018	70,111
Management Sciences	110,663	84,746	98,712	33,576	198,478	145,379
Economics	148,151	104,243	140,952	32,730	369,345	22,764
Computer Sciences	117,052	102,547	84,096	41,697	187,637	35,444
Engineering	128,583	108,648	97,552	41,036	212,879	124,146
Life Sciences	87,391	70,621	73,907	27,566	151,152	56,400
Physics	104,414	85,479	86,932	29,312	181,733	30,999
Mathematics	106,297	83,870	94,027	30,867	184,106	20,168
Social Sciences	79,554	63,313	70,360	26,610	136,643	127,552
Humanities	78,839	61,930	73,845	24,547	134,303	104,193
Panel B - 1-year post-Graduation Median Income across Fields AND Universities, in 2019 $						
Source: Post-Secondary Employment Outcomes Dataset (2000-2019)						
Total Sample	37,616	34,254	11,675	25,825	55,158	43,074
By Academic Field						
Business (Including Finance)	38,379	37,258	7,310	30,680	47,092	6,309
Economics	39,612	38,387	6,673	32,235	48,769	1,764
Computer Sciences	49,708	48,928	10,239	37,826	62,012	3,852
Engineering	53,331	54,597	8,563	41,100	62,131	2,898
Life Sciences	28,357	27,811	4,117	23,680	33,860	4,647
Physics	34,580	33,980	6,053	27,627	42,091	2,568
Mathematics	39,866	39,123	7,590	31,065	49,660	2,121
Social Sciences	30,420	29,834	4,074	26,091	35,323	6,144
Humanities	29,538	28,606	5,082	24,068	35,890	5,076

This table provides summary statistics on the median undergraduate student wages one year after graduation across universities and years in Panel A, and industry wages by undergraduate major in Panel B. The data on student wages one year post-graduation is derived from the U.S. Census Bureau's Post-Secondary Employment Outcomes (PSEO) dataset, which covers the years 2000 to 2019. The data for industry wages by undergraduate major are sourced from the American Community Survey, spanning the period from 2010 to 2018. Our sample includes individuals who have obtained at least a master's degree, are under the age of 66, earn a yearly gross wage and salary income exceeding $10,000, and are not employed in post-secondary institutions (excluding industry codes 7870, 7880, and 7890).

Table 3. Faculty Pay Premia versus Humanities - Total Compensation

	All	Assistant	Associate	Full	Top50 US News	R1 Universities
	(1)	(2)	(3)	(4)	(5)	(6)
𝟙_Finance	0.60***	0.75***	0.60***	0.56***	0.91***	0.84***
	(0.05)	(0.07)	(0.06)	(0.03)	(0.03)	(0.03)
𝟙_Business	0.40***	0.51***	0.42***	0.37***	0.57***	0.53***
	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)
𝟙_Economics	0.26***	0.33***	0.32***	0.23***	0.49***	0.41***
	(0.05)	(0.03)	(0.06)	(0.05)	(0.01)	(0.04)
𝟙_Law	0.26***	0.23***	0.23***	0.26***	0.34***	0.33***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)
𝟙_Health	0.23***	0.30***	0.25***	0.21***	0.42***	0.41***
	(0.06)	(0.05)	(0.06)	(0.07)	(0.02)	(0.05)
𝟙_Computer Science	0.22***	0.33***	0.28***	0.16***	0.20***	0.23***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
𝟙_Engineering	0.19***	0.24***	0.20***	0.17***	0.25***	0.26***
	(0.03)	(0.04)	(0.04)	(0.02)	(0.01)	(0.01)
𝟙_Life Sciences	0.13***	0.19***	0.15***	0.12***	0.20***	0.21***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)
𝟙_Physics	0.12***	0.22***	0.15***	0.09***	0.20***	0.19***
	(0.02)	(0.04)	(0.02)	(0.01)	(0.02)	(0.02)
𝟙_Mathematics	0.10***	0.17***	0.11***	0.08***	0.13***	0.15***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.00)	(0.02)
𝟙_Sociology	0.04***	0.08***	0.05***	0.03***	0.07***	0.07***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Fixed Effects						
University × Year	Yes	Yes	Yes	Yes	Yes	Yes
Position	Yes	-	-	-	Yes	Yes
Non U.S. Citizen	Yes	Yes	Yes	Yes	Yes	Yes
Observations	145,853	24,425	34,058	83,756	28,155	51,943
R^2	0.57	0.59	0.57	0.47	0.54	0.54

This table reports wage premia in the main academic fields relative to Humanities across positions and types of university. We estimate OLS regressions, where the dependent variable is the log of total compensation, which includes the summer stipend, as well as grants and bonuses. Column 1 presents wage premia for the whole sample. Other columns show the premia for the following subsamples: assistant professors (Column 2), associate professors (Column 3) and full professors (Column 4). Columns 5 and 6 display the premia for top 50 universities according to the U.S. News MBA Ranking, and doctoral universities with very high research activity according to the Carnegie Classification. Standard errors are doubled clustered at the university and year levels and reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Elasticity of Academic Wages to Undergraduate Student Earnings

	Log(Faculty Pay)				
	All	Across Fields	Across Universities	Across Time	
	(1)	(2)	(3)	(4)	(5)
$\text{Log(Student Wages)}_{\text{university,field,year}}$	0.49***	0.43***	0.66***	0.33***	0.21**
	(0.05)	(0.03)	(0.09)	(0.08)	(0.08)
Fixed Effects:					
Year	Yes	-	-	-	Yes
University × Year	-	Yes	-	-	-
University × Position	-	Yes	-	-	-
Field × Year	-	-	Yes	-	-
Field × Position	-	-	Yes	Yes	Yes
Field × University	-	-	-	Yes	Yes
Observations	109,736	109,404	109,735	35,265	35,265
R^2	0.29	0.45	0.45	0.56	0.56

This table reports regressions of the log of the yearly faculty base salary on the log of the median undergraduate student wage one year after graduation in the same university and field. 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 sample of academic wages by academic field assigned using the CIP code, university, and year. Columns 4 and 5 are based on a subsample that includes only observations from before 2006 or after 2014. Standard errors are double clustered at the university and year levels and reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Elasticity of Academic Wages to Undergraduate Student Earnings: Instrumental Variable Analysis

	First Stage Log(Expected Student Wages)					Second Stage Log(Faculty Pay)				
	All	Across Fields	Across Universities	Across Time		All	Across Fields	Across Universities	Across Time	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Z_{university,field,year}$	1.92***	2.13***	0.74***	0.09***	0.09***					
	(0.08)	(0.07)	(0.17)	(0.01)	(0.01)					
Log(Student Wages)$_{university,field,year}$						0.52***	0.44***	0.76***	1.81**	3.28***
						(0.06)	(0.04)	(0.23)	(0.81)	(1.25)
Fixed Effects:										
Year	Yes	-	-	-	Yes	Yes	-	-	-	Yes
University × Year	-	Yes	-	-	-	-	Yes	-	-	-
University × Position	-	Yes	-	-	-	-	Yes	-	-	-
Field × Year	-	-	Yes	-	-	-	-	Yes	-	-
Field × Position	-	-	Yes	Yes	Yes	-	-	Yes	Yes	Yes
Field × University	-	-	-	Yes	Yes	-	-	-	Yes	Yes
Observations	119,681	119,350	119,680	54,428	54,428	119,681	119,350	119,680	54,428	54,428
R^2	0.65	0.85	0.86	1.00	1.00					
F statistics	575	803	19	354	216					

This table displays the results of the instrumental variable analysis, in which the median undergraduate student wage one year after graduation is instrumented by the synthetic wage index calculated in equation (8). Columns (1)-(5) report the results for the first stage regressions, while Columns (6)-(10) demonstrate the results for the second stage regressions. The synthetic wage index is constructed using the data on student wages and employment from the Post-Secondary Employment Outcomes dataset and the data on industry wages from the American Community Survey. We match these data with our sample of academic wages by academic field assigned using the CIP code, university, and year. Columns 4 and 5 are based on a subsample that includes only observations from before 2006 or after 2014. Standard errors are double clustered at the university and year levels and are reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Elasticity of Academic Wages to Student Earnings: Heterogeneity across Fields

	Log(Faculty Base Salary)					
	Undergraduate Students			**Graduate Students**		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Student Wages)		0.39***	0.15***		0.21***	-0.19***
		(0.03)	(0.05)		(0.03)	(0.04)
$\mathbb{1}_{\text{Engineering}} \times$ Log(Student Wages)			0.46***			0.69***
			(0.06)			(0.05)
$\mathbb{1}_{\text{Computer Science}} \times$ Log(Student Wages)			0.27***			0.45***
			(0.06)			(0.05)
$\mathbb{1}_{\text{Economics}} \times$ Log(Student Wages)			0.52***			
			(0.08)			
$\mathbb{1}_{\text{Finance}} \times$ Log(Student Wages)			1.05***			1.01***
			(0.10)			(0.08)
$\mathbb{1}_{\text{Engineering}}$	0.29***	0.03	0.00	0.30***	0.18***	0.28***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
$\mathbb{1}_{\text{Computer Science}}$	0.28***	0.02	0.07***	0.32***	0.15***	0.29***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)
$\mathbb{1}_{\text{Economics}}$	0.44***	0.32***	0.36***			
	(0.01)	(0.01)	(0.01)			
$\mathbb{1}_{\text{Finance}}$	0.56***	0.44***	0.43***	0.58***	0.46***	0.51***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
Fixed Effects:						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Position	Yes	Yes	Yes	Yes	Yes	Yes
Non U.S. Citizen FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162,898	162,898	162,898	162,762	162,762	162,762
R^2	0.36	0.38	0.39	0.37	0.38	0.39

This table displays the results of a regression of the log of the yearly faculty base salary on the log of the median student wage, field dummies, and the interaction of field dummies with the log of the median student wages for Engineering, Computer Science, Economics, and Finance. The reference field is Humanities. The median student wage is the lagged median student wage one year after graduation in the same university and field. The median student wage is for undergraduate students in Columns 1 to 3 and master's students in Columns 4 to 6. Standard errors are clustered at the field times year levels and reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Elasticity of Graduating Students per Professor to Undergraduate Student Earnings

	Log(Degrees per Prof)				
	All	Across Fields	Across Universities	Across Time	
	(1)	(2)	(3)	(4)	(5)
Log(Student Wages)$_{\text{university,field,year}}$	0.50***	0.99***	0.20***	0.44***	0.22***
	(0.19)	(0.02)	(0.01)	(0.05)	(0.06)
Fixed Effects:					
Year	Yes	-	-	-	Yes
University × Year	-	Yes	-	-	-
Field × Year	-	-	Yes	-	-
Field × University	-	-	-	Yes	Yes
Observations	76,364	76,363	76,348	76,358	76,358
R^2	0.08	0.47	0.37	0.92	0.92

This table reports regressions of the log of graduating students per professor on the median undergraduate student wage one year after graduation in the same university and field. The number of professors is based on the sample of academic wages obtained through public record requests, while the number of graduating students is the total number of bachelor's and master's degrees conferred from IPEDS. 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 data on the numbers of professors and graduating students by academic field assigned using the CIP code, university, and year. Standard errors are double clustered at the university and year levels and are reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Elasticity of PhD Degrees per Professor to Undergraduate Student Earnings

	Log(Degrees per Prof)				
	All	Across Fields	Across Universities	Across Time	
	(1)	(2)	(3)	(4)	(5)
Log(Student Wages)$_{\text{university,field,year}}$	0.73***	-0.12***	1.34***	-0.12*	-0.73***
	(0.01)	(0.02)	(0.04)	(0.05)	(0.09)
Fixed Effects:					
Year	Yes	-	-	-	Yes
University × Year	-	Yes	-	-	-
Field × Year	-	-	Yes	-	-
Field × University	-	-	-	Yes	Yes
Observations	53,137	53,137	53,137	53,136	53,136
R^2	0.05	0.50	0.35	0.86	0.86

This table reports regressions of the log of PhD degrees conferred per professor on the log of the median undergraduate student wage one year after graduation in the same university and field. The number of professors is based on the sample of academic wages obtained through public record requests, while the number of PhD degrees comes from IPEDS. 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 data on the numbers of professors and PhD degrees by academic field assigned using the CIP code, university, and year. Standard errors are double clustered at the university and year levels and are reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Elasticity of Academic Wages to Research Output

	Log(Faculty Pay)				
Research Impact Measure		Citations	H-index	Citations	
	(1)	(2)	(3)	(4)	(5)
𝟙_Finance	0.47***	0.30***	0.36***	0.49***	0.32***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Quintiles		0.07***	0.07***	0.07***	0.06***
		(0.01)	(0.01)	(0.01)	(0.01)
Quintiles×𝟙.Finance		0.05***	0.04***		0.06***
		(0.01)	(0.01)		(0.01)
𝟙_Economics				0.19***	0.07**
				(0.02)	(0.03)
Quintiles×𝟙.Economics					0.04***
					(0.01)
𝟙_Business				0.28***	0.15***
				(0.02)	(0.03)
Quintiles×𝟙.Business					0.05***
					(0.01)
Fixed Effects					
Position × Year FE	Yes	Yes	Yes	Yes	Yes
Experience Quintiles	Yes	Yes	Yes	Yes	Yes
Observations	100,721	100,721	100,721	100,721	100,721
R^2	0.32	0.38	0.38	0.42	0.43

This table reports the coefficients of OLS regressions, where the dependent variable is the log of faculty base salary. Columns 2 and 3 interact citation and h-index quintiles, respectively, with a finance dummy. These quintile measures of research impact are calculated within field and academic rank. Data are from the merge of our academic wage database with Scopus and include 100,721 faculty year observations representing 24,039 professors across 212 public universities. Columns 4 and 5 reproduce the analysis adding dummies for Economics and Business. Standard errors are clustered at the university and year levels and reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.