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

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Abstract

A long time series of faculty wages at public and private four-year institutions in the U.S. and Canada reveals a widening dispersion in pay across disciplines, primarily driven by economics and business – and especially finance. Using a shift-share instrument based on persistent university student placement patterns across locations and industries, we uncover a causal relationship between students earnings after graduation and faculty compensation. 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. Fields that are more scalable and profitable – measured by student-to-faculty ratios and university revenues – and with higher frictions in PhD supply exhibit markedly higher elasticity. Our findings suggest that increasing competition within fields, fueld by industry spillovers, is the primary mechanism underlying the widening dispersion in faculty compensation.

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1 Introduction

Returns to education are widely recognized as high and have increased significantly 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 this field-specific heterogeneity in returns to education, and its influence on student choices and outcomes, little is known about its effects on the supply side of education, especially on faculty wages. Recent studies, such as Conzelmann et al. (2023) and Light (2024), explore impacts on course offerings and the number of degrees awarded. However, prior research highlights evidence of increasing variation in faculty wages across academic fields (e.g., Courant and Turner (2019)), raising the following questions: How does faculty pay respond to changes in student future earnings? Does the elasticity varies across fields, driving across field wage differentials? If so, what is the underlying mechanism? Beyond the cost of education, faculty wages may affect its quality, the allocation of talent across fields, and the production of innovation.[3]

To answer these questions, we first assemble a long time series of individual faculty pay across virtually all U.S. and Canada 4-year colleges and universities enrolling more than 100 students. The dataset includes over 200,000 research faculty from 1,500 U.S. and Canadian universities, spanning 1993-2023, and is merged with university-field-rank-year aggregated data from historical archives covering

[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] 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).

1974-1995. To obtain individual data on faculty wages, we first collect name-identified wage data from U.S. public universities through public record 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.[4][5] 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.[6] 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. Using individual wage data from the American Community Survey with information on each individual field of study, we show that the average across-field wage differentials of faculty we observe correlate with student life-time earnings across majors over the 2009-2020 period.

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

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

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

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

how faculty pay responds to student earnings across fields. 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. 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. To address concerns of reverse causality and further exploit the long time dimension of our data, we 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 growing 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 elasticities to student expected 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 elasticity to student earnings across fields and show that they result in competition forces varying across fields. Our findings show that higher levels of student expected earnings drive 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, top universities capture a greater share of total revenues in high-earning fields through increased tuitions 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 novel comprehensive dataset that includes faculty and student wages across universities, years, and fields. 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 Faculty Wages

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 over the longest time period possible, which varies depending on the state 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 also exploit publicly available data when possible, which is often the case online for the years after 2018.

We collected data from 32 U.S. states and two Canadian provinces covering more than 300 universities over the 1993-2023 period. In 2019, these universities enrolled about 2.8 million full time undergraduate students, corresponding to 33% of all the students enrolled in four year programs in the U.S. at this date (IPEDS 2019). This sample includes 11 of the 15 states with the largest university systems in the US, i.e., California, Ohio, Florida, New York, Georgia, Texas, Utah, New Hampshire, Illinois, Arizona, and Michigan. Table A2 in the Internet Appendix lists the states and sample periods that this sample covers.

We extend the sample back to the early 70s using university field level data from historical archives. For over five decades, the National Association of State Universities and Land-Grant Colleges (NASULGC) has conducted salary surveys each year which are compiled by the Office of Institutional Research at Oklahoma State University. These surveys were initiated to make comparisons between Oklahoma State University faculty salaries and faculty salaries from across the nation.

In this study, we use data from surveys from the early 70s.[7]

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.[8]

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 20,000 professors over the 2005-2017 period working across 1,280 universities that we append to our public university dataset.

2.1.3 Academic Fields

A significant challenge to our analysis is 1/ identifying research tenure-track faculty among academic employees and 2/ determining their respective academic fields when the information is missing, which is often the case with data from public information request.

To address this challenge, we first match our faculty wage dataset with authors listed in Scopus.[9] Scopus is one of the leading multidisciplinary citation databases

[7] See for example Scott and Bereman (1992)

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

[9] Because of downloading restrictions, we linked a 50% random sample of academic employees

in the world and offers comprehensive coverage of articles from thousands of peer-reviewed journals, conference proceedings, trade publications, books, and patent records.[10] For every author, Scopus offers information on its research output, including the total number of publications, cumulative citations, and the h-index, which quantifies both the productivity and citation impact of an individual's publications. We classify as research faculty any individual in our public university dataset with a valid match in Scopus and use Scopus' field classification to identify academic fields. Scopus builds this classification using authors' publication history. Given that Scopus categorizes Law within Humanities, we identify law faculty based on the departmental designation, which typically specifies the law school's name.[11]

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 700 U.S. public and private institutions. 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 5,332 Accounting, Finance, Economics, Marketing and Business professors in our faculty wage dataset by linking it with the James Hasselback' directories. Hence, we identify the exact field for 48% of the faculty identified in Scopus as part of the "Econ" or "Business" fields and 1.5% of the initial public university data not merged with Scopus from this step.

Finally, when available, we use online directories of university faculty.

We group subfields and departments into 12 fields as described in Table A1 in the Internet Appendix, including Finance, Economics, and Business. The Finance

to Scopus.

[10]We prefer Scopus over Web of Science due to its broader scope in covering various disciplines and sources.

[11]We refrain from using departmental information to assign academic fields for disciplines other than Law, as department names often encompass multiple fields. Examples include broad labels such as 'Faculty of Arts and Science', 'Economics, Finance, and Entrepreneurship', or 'Business School.'

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

field includes accounting faculty, as they are often part of the same department as Finance faculty and their research agenda and teaching scope largely overlaps. Business encompasses all business-related fields excluding Finance and Accounting, thereby covering marketing, strategy, and operations. The remaining nine fields are Computer Sciences, Engineering, Humanities, Law, Life Sciences, Mathematics, Medicine and Healthcare, Physics, and Social Sciences.

Table 1 provides summary statistics of faculty wages by field, position, university rank, type and location. Our final academic wage dataset comprises over 424,000 faculty-year observations and more than 115,000 professors working across over 1,590 universities in 12 different academic fields from 1993 to 2023.

INSERT TABLE 1 HERE

2.1.4 Representativeness and Internal Consistency

To assess the representativeness of our final wage sample, 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 student financial aid programs. We find that our final sample comprises universities that enroll 82% of all 2019 full-time undergraduate students in four-year colleges, and 80% of all 2019 full-time undergraduate students in Business Programs. Finally, our final sample comprises universities that cover 89% of assistant/associate/full professors working at four-year colleges in the years 2019-2020.

A challenge in accurately quantifying wage heterogeneity across academic fields is establishing a uniform measure of compensation. We address this challenge by focusing on the "base salary," which is available for approximately 75% of the faculty in our data. 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.

For robustness, we also 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. However, the information on total compensation is available for only 40% of our observations.

2.2 Student Wages

2.2.1 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 at the U.S. Census Bureau created this dataset in collaboration with individual post-secondary institutions, higher education systems, and state agencies. These entities provide transcript data to the U.S. Census Bureau, which is then matched with a national database of employment records. The dataset includes information from 478 four-year post-secondary institutions across 28 states, covering the years 2000 to 2019.[14]

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 year 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 Classification of Instructional Programs (CIP) developed by the National Center for Education Statistics.

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

[14] We use the June 2024 release of the dataset.

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.

2.2.2 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

2.3 Other Data

2.3.1 Tuition Data: Amounts and Regulations

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:

$$tuition_{und,f,u} = \overline{tuition_{und,u}} * \frac{tuition_{grad,f,u}}{\overline{tuition_{grad,u}}} \tag{1}$$

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:

$$s_{und,f,u} = \frac{length_{und,f} * degrees_{und,f,u}}{length_{und,f} * degrees_{und,f,u} + length_{grad,f} * degrees_{grad,f,u}} \tag{2}$$

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.

Finally, we use the dataset of tuition freezes and caps from Deming and Walters (2018) extended by Miller and Park (2022) to cover the 1990-2019 period to properly identify the relationship between tuition and professor wages.

2.3.2 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:

$$\ln(w_{i,t}) = \sum_{f=1}^{n} \beta_{field_f} \mu_{field_f} + \mu_{u,t} + \mu_{rank_i} + \mu_{H1B} + \epsilon_{i,t}, \tag{3}$$

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 × 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 60%

wage premium over Humanities, 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, Medicine, and Computer Sciences.

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 Finance, Business, Computer Science and Humanities. 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:

$$\ln(w_i) = \beta_f \mu_f + \mu_u + \mu_p + \mu_{h1b} + \epsilon_i, \tag{4}$$

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:

$$\text{Total Work-life Earnings}_f = \sum_{\tau=23}^{67} \beta_\tau \omega_{\tau,f} \tag{5}$$

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 5 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 5

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:

$$GrowthRate = \frac{x_{last} - x_{first}}{x_{first} * (N-1) * 3} \tag{6}$$

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 6 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 6

4 A Causal Relationship?

We hypothesize that student earning potential causally impacts faculty wage.[15] 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.

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 ex-

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

planatory 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:

$$Z_{f,u,t} = \sum_g \sum_n s_{f,u,g,n} \ln \varpi_{g,n,t}, \tag{7}$$

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 65 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:

$$\ln(w_{i,t}) = \beta \ln(\omega_{f,u,t}) + \mu_{i,t} + \epsilon_{i,t} \tag{8}$$

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. 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. Academic wages appear to be strongly related to both undergraduate and graduate student wages, even when university-by-year, field-by-year and field-by-position fixed effects are included. The economic magnitude is large. With year and position fixed effects, the elasticity is 0.45. As expected, including field fixed effects – given that field accounts for much of the observed variance – significantly reduces the elasticity, but it remains both statistically and economically significant.

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:

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

And our second stage is

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

We report the first stage coefficients in columns 1 to 3, and the second stage coefficients in columns 4 to 6.

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 8 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 8

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

$$\ln(w_{i,t}) = \beta_1 \ln(\omega_{f,u,t}) + \sum_{f=1}^{n} \beta_{2_f} \ln(\omega_{f,u,t}) \mu_{field_f} + \sum_{f=1}^{n} \beta_{field_f} \mu_{field_f} + \mu_t + \mu_p + \epsilon_{i,t} \tag{11}$$

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:

$$\text{Tuition Revenue per Research Faculty}_{f,u} = \frac{\text{students}_f}{\text{faculty}_f} * (s_{und,f,u} tuition_{und,f,u} + (1 - s_{und,f,u}) tuition_{grad,f,u}) \tag{12}$$

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 11 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 11

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:

$$\text{Donation Intensity}_f = \frac{\frac{\text{Sum of all donations}_f}{\text{Sum of all donations}}}{\frac{\text{\# professors}_f}{\text{Total \# research faculty}}} \tag{13}$$

Figure 12 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 12

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.[16] We collect the list of billionaires in the U.S. in 2021 and plots the number of billionaires across industries. Figure A10 in the Internet Appendix indicates that the Finance industry has the highest number of billionaires, close to 600, then followed by Computer Sciences and Manufacturing.

5.3 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.[17]

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

[17] 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

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

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.

the exact friction at play.

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7 Figures

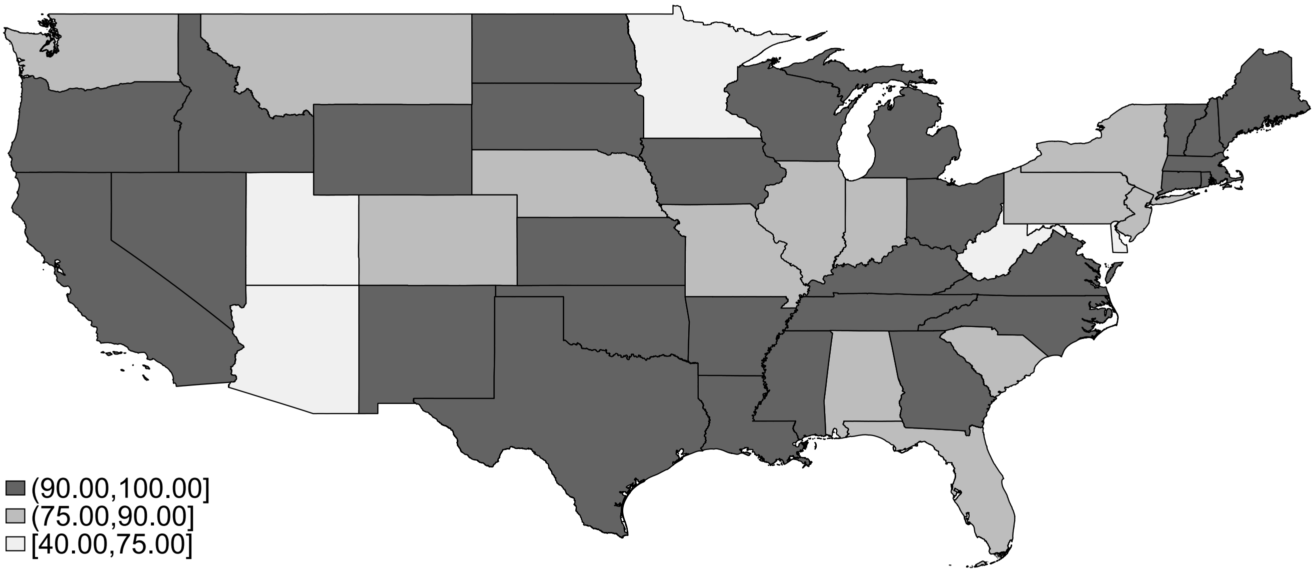

Figure 1. Fraction of Undergraduate Students Represented in the Data across States

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).

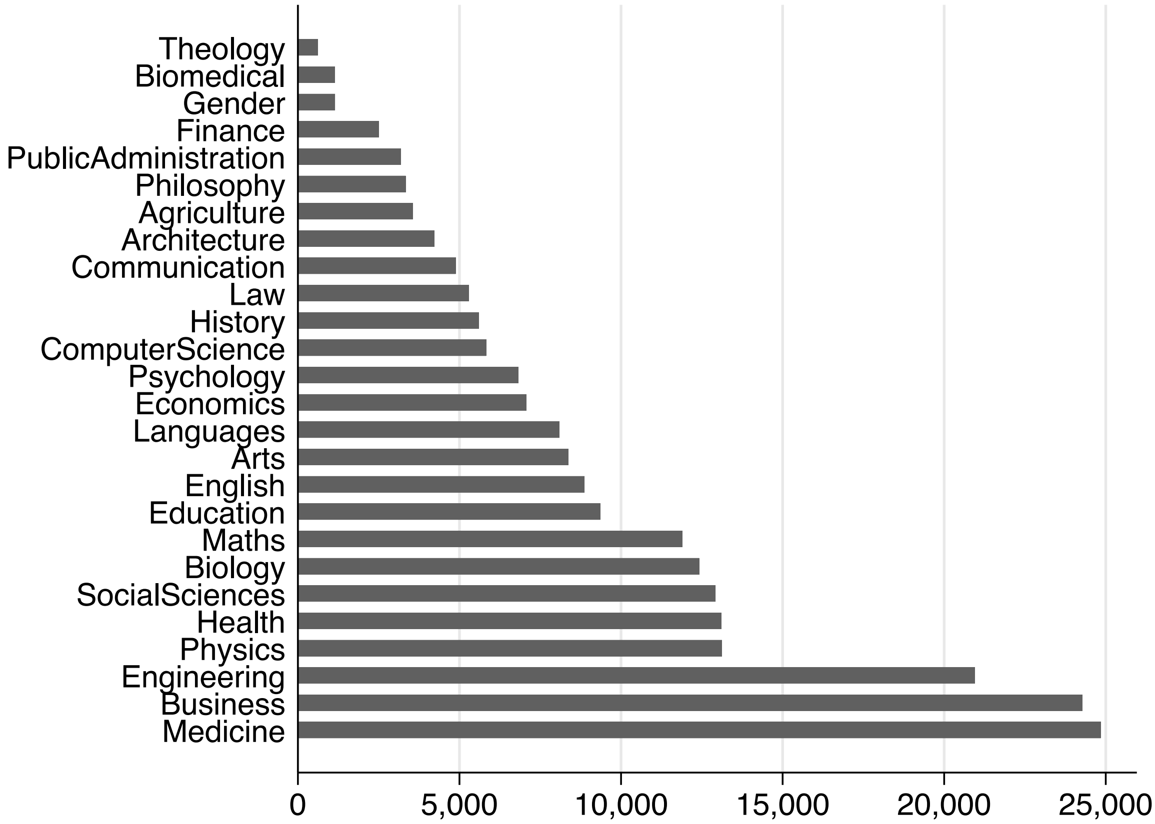

Figure 2. Number of Professors by Field

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.

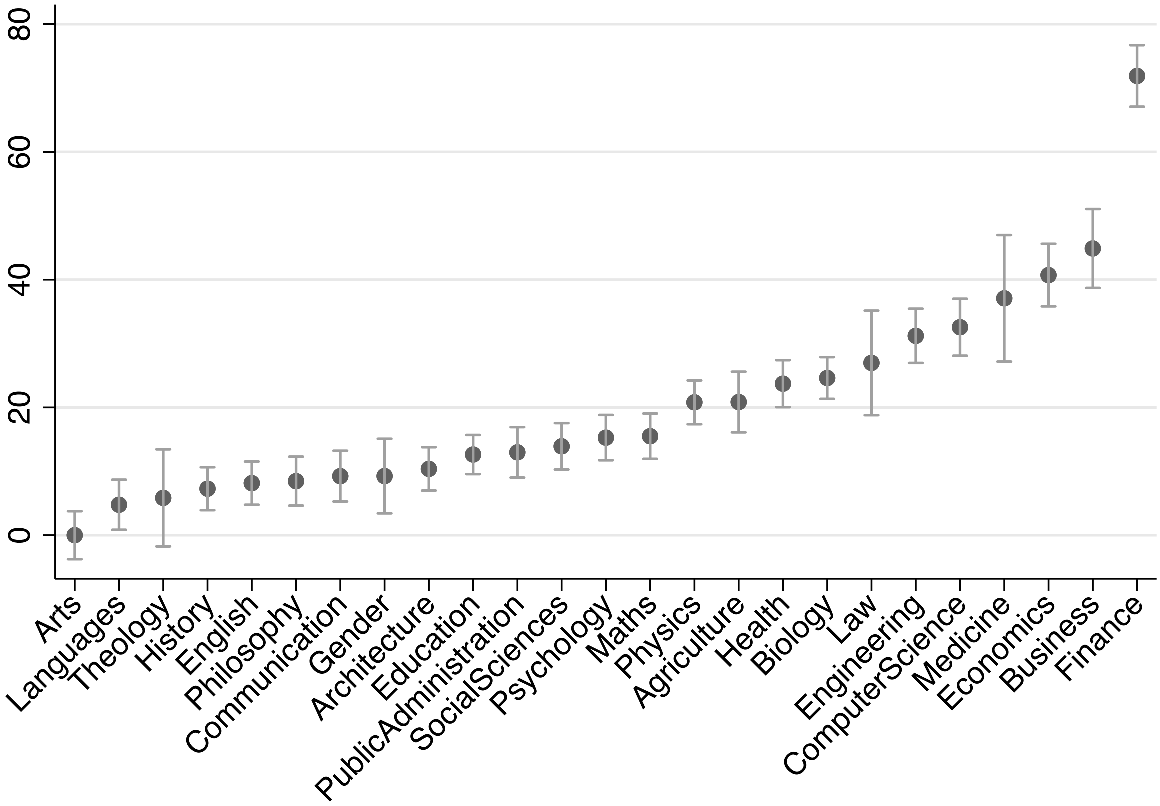

Figure 3. Academic Pay across Fields

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.

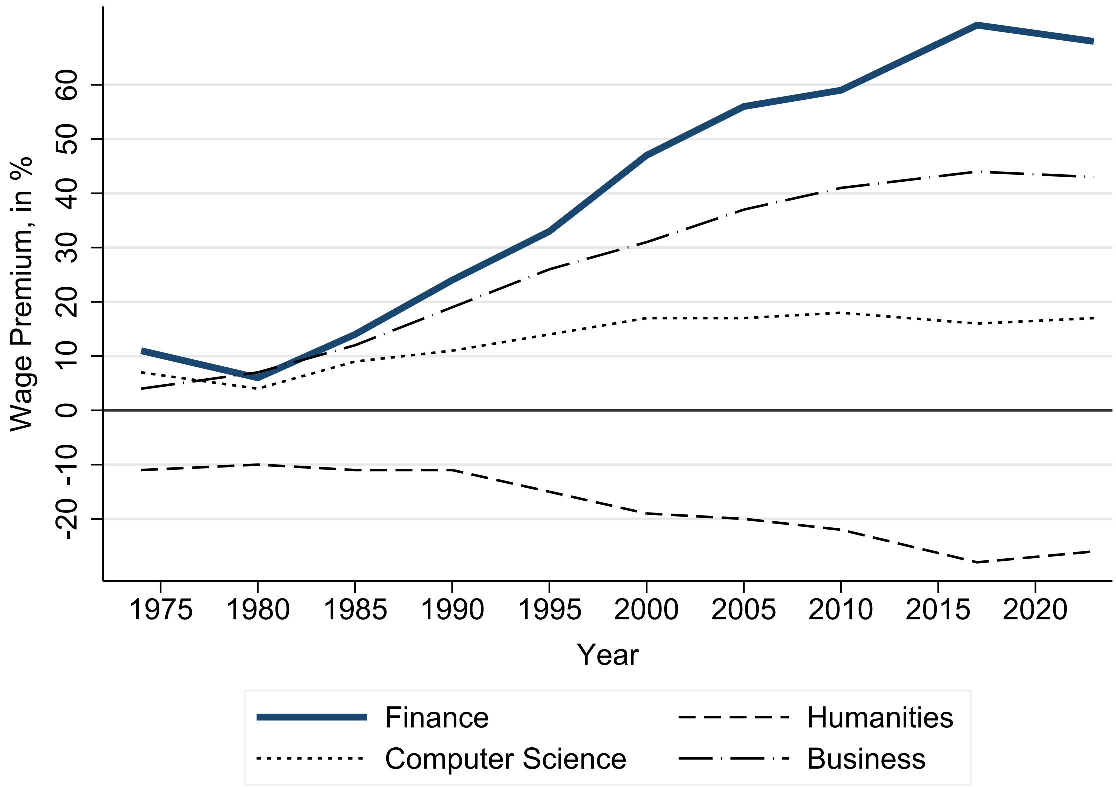

Figure 4. Evolution of Academic Pay across Fields (1974-2023)

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.

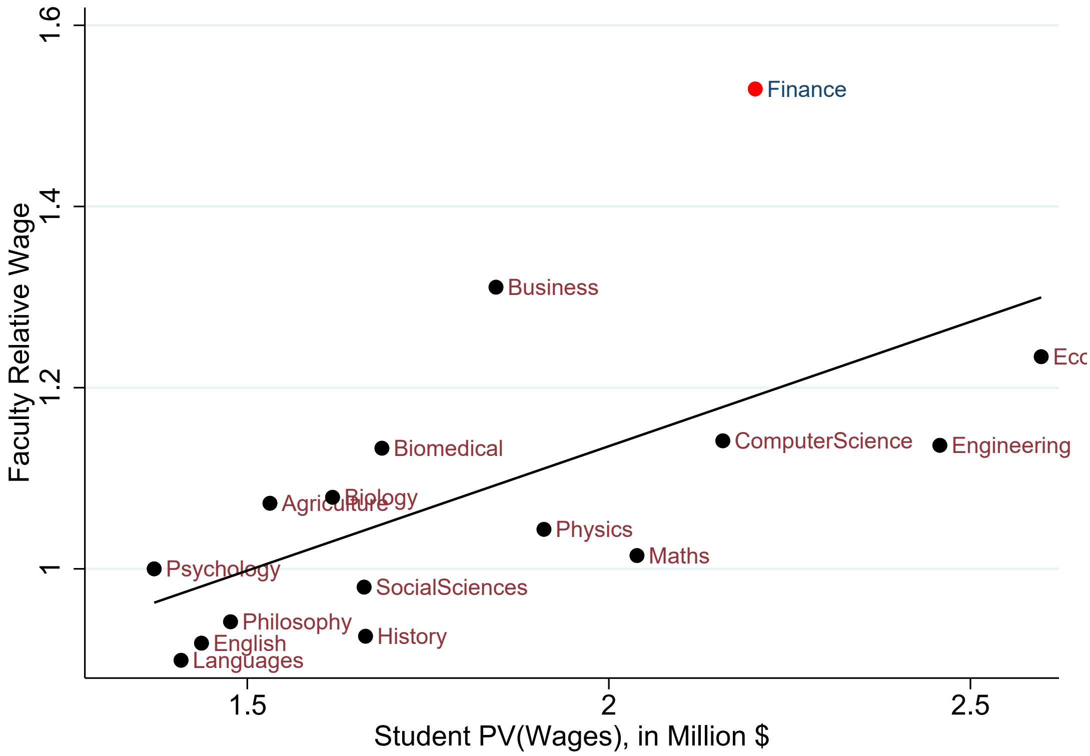

Figure 5. Faculty Wages versus Student Expected Earnings across Fields

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%.

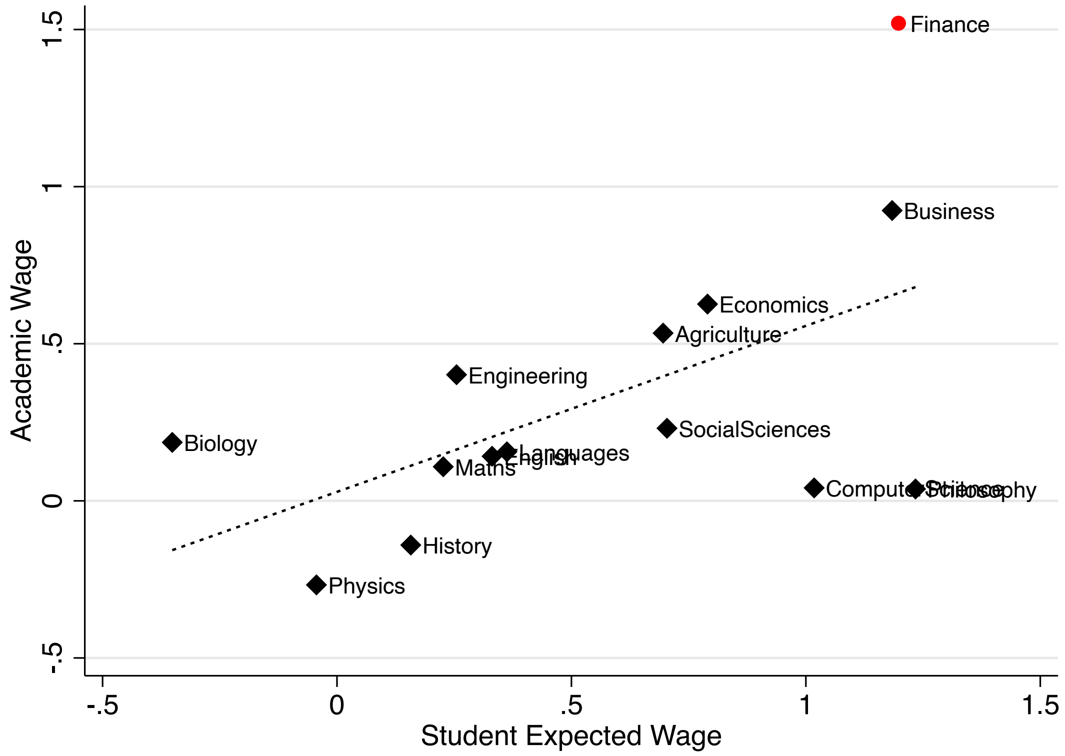

Figure 6. Yearly Growth Rate of Faculty versus Undergraduate Student Future Earnings (2001-2019)

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 .

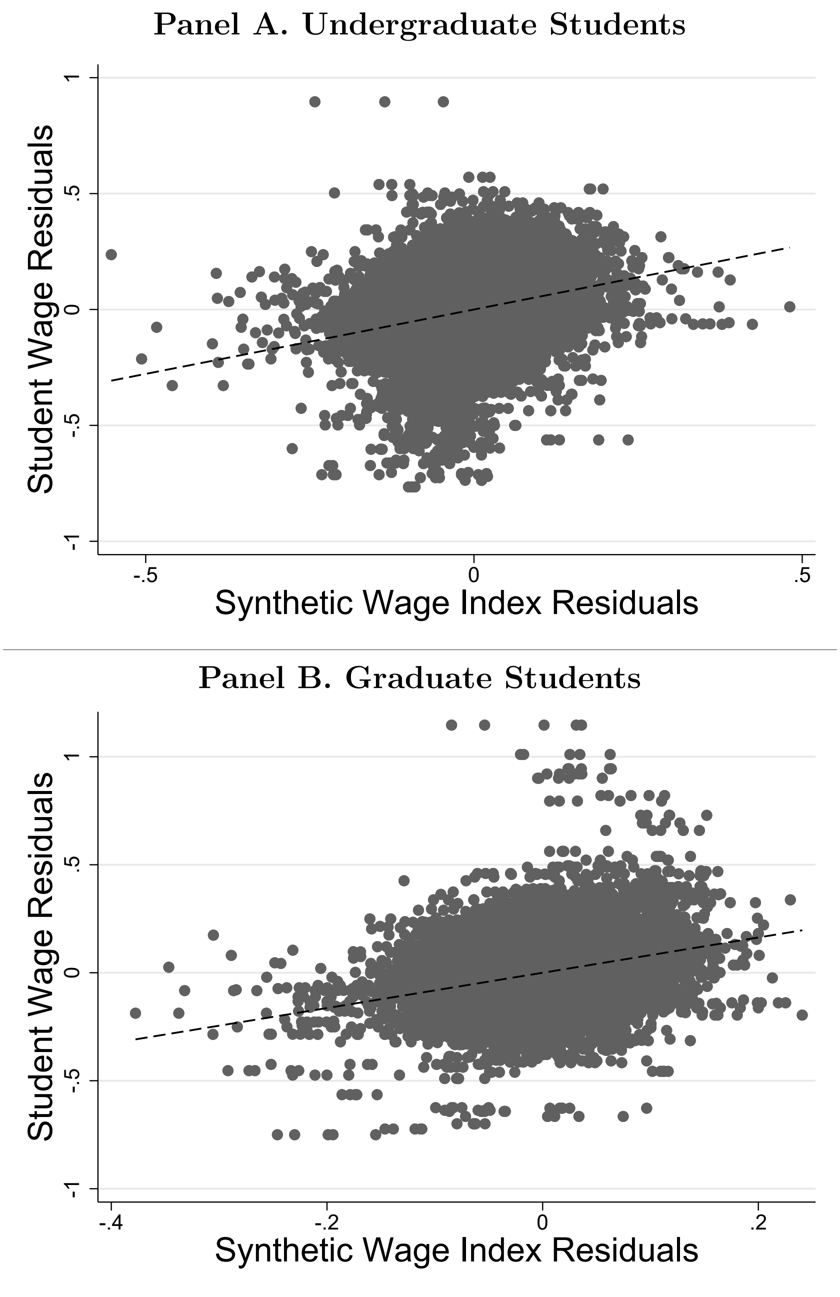

Figure 7. Correlation between Innovations in Student Wages and in Synthetic Wage Index

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.

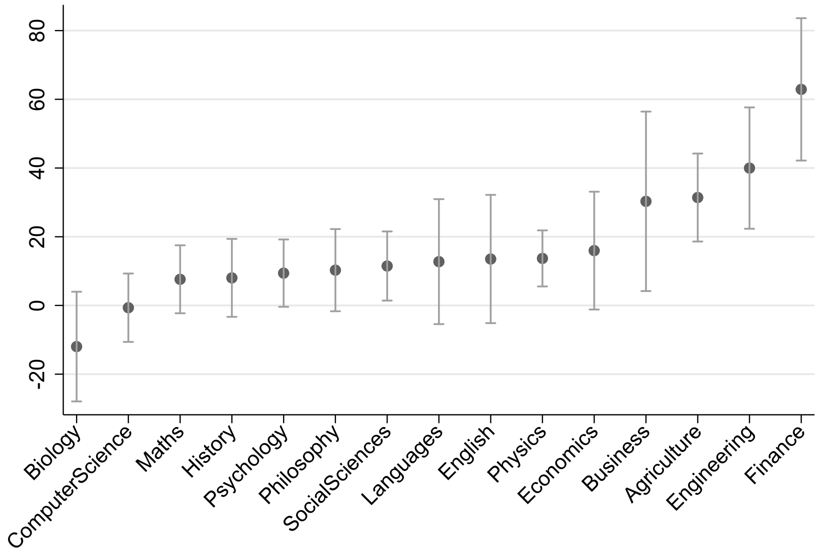

Figure 8. Within Field Elasticities of Faculty Wages to Student Wages across Time

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.

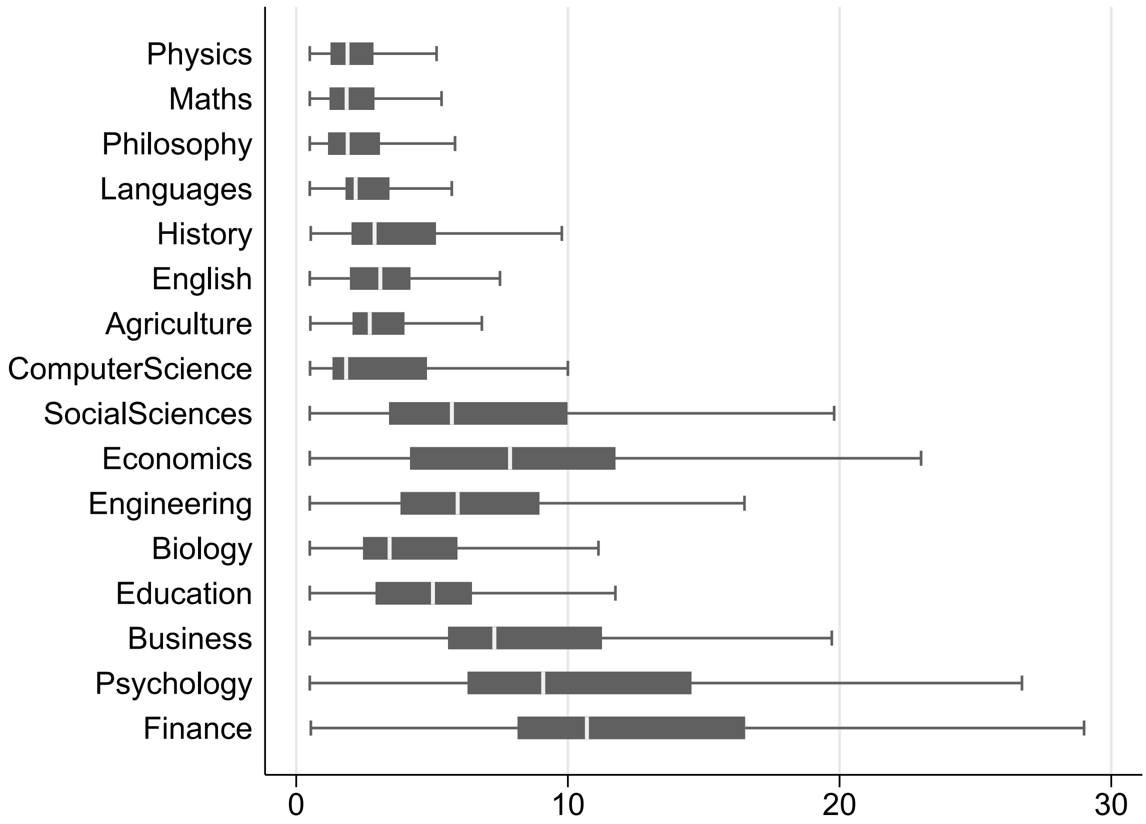

Figure 9. # of Graduating Students per Professor across Fields
This figure presents box plots depicting the distribution of graduating students per professor across fields. Each box plot displays the lower and upper adjacent values, along with the 25th percentile, median, and 75th percentile. The number 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 number of graduating students per professor is calculated at the field-university-year level, with additional weighting based on the number of professors in the department.

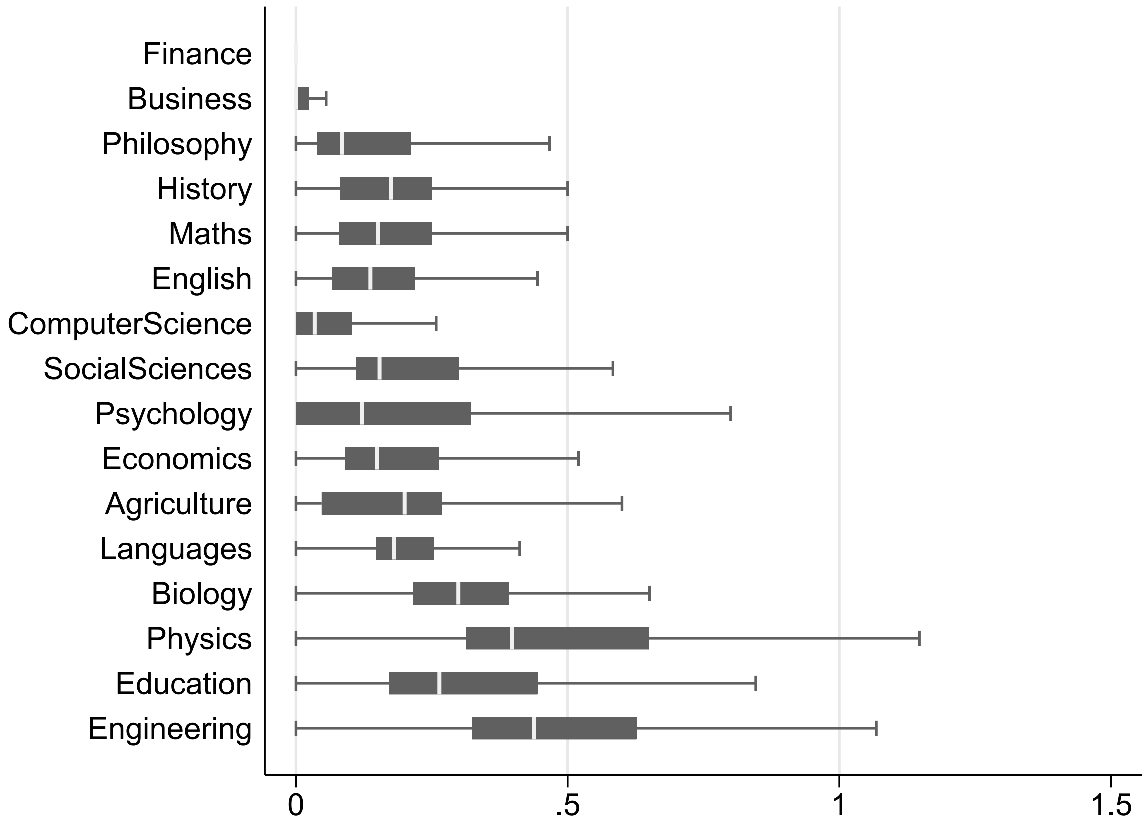

Figure 10. # of PhD Degrees per Professor across Fields
This figure presents box plots depicting the distribution of PhD degrees conferred per professor across fields. Each box plot displays the lower and upper adjacent values, along with the 25th percentile, median, and 75th percentile. The number of professors is based on the sample of academic wages obtained through public record requests, while the number of PhD degrees comes from IPEDS. The number of PhD degrees conferred per professor is calculated at the field-university-year level, with additional weighting based on the number of professors in the department.

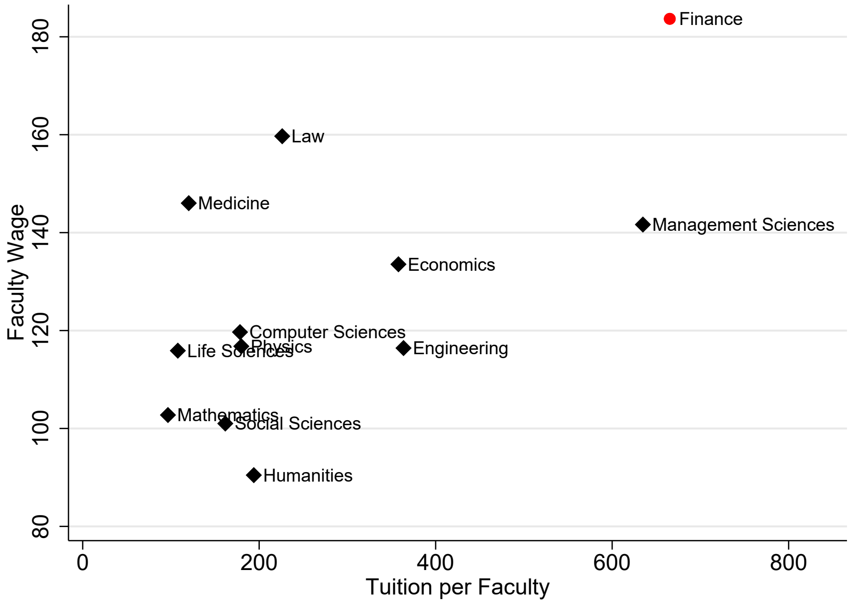

Figure 11. Faculty Wages and Per-Faculty Tuition Revenues across Fields

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.

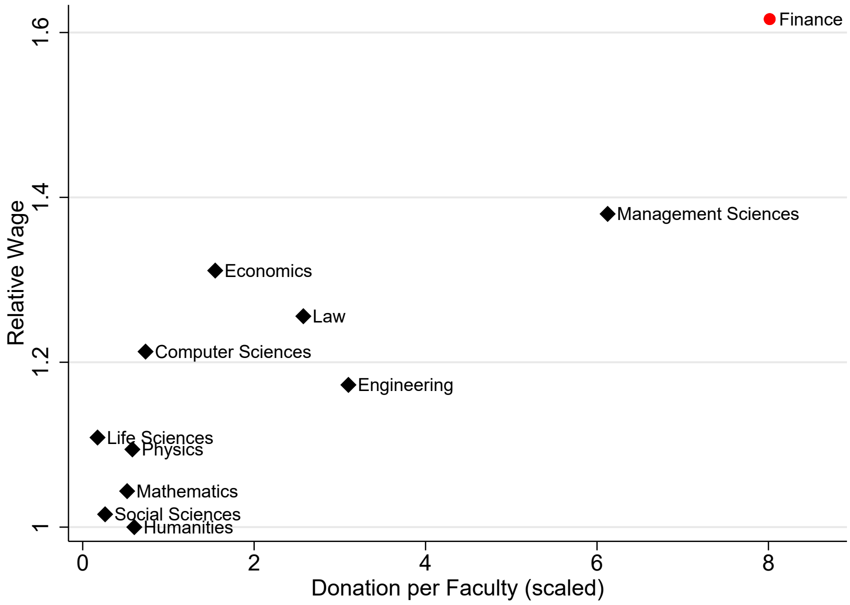

Figure 12. Faculty Wages and Donations across Fields

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.

8 Tables

Table 1. Summary Statistics: Faculty Wages

	Gross Base Salary, in 2010 $						
	Mean	Median	SD	p10	p90	p95	# Obs.
Total Sample	113,260	99,991	52,096	62,312	180,840	218,058	379,123
By Academic Field							
Finance & Accounting	156,075	140,286	63,858	84,302	248,566	283,134	12,473
Law	146,861	137,342	58,778	75,488	230,409	259,605	11,375
Medicine and Health	134,219	114,740	66,764	68,689	232,656	295,275	69,851
Management Sciences	134,684	122,281	54,972	76,749	210,302	246,214	21,772
Economics	130,142	116,600	57,023	71,402	209,705	256,520	11,267
Engineering	113,123	104,578	40,328	70,946	165,600	187,437	31,207
Physics	111,259	102,626	41,842	67,647	164,384	192,217	12,888
Computer Sciences	110,402	101,383	41,365	66,719	165,993	189,772	13,045
Life Sciences	107,319	97,193	42,755	64,476	162,848	190,580	56,079
Mathematics	101,794	91,349	40,737	59,071	157,400	178,712	18,084
Social Sciences	94,864	84,105	37,938	58,970	143,997	168,785	67,847
Humanities	91,077	81,340	35,189	56,120	138,873	156,941	53,235
By Position							
Full Professor	136,547	125,188	53,592	80,528	206,743	247,046	184,179
Associate Professor	95,868	87,348	37,940	62,089	134,607	161,658	96,263
Assistant Professor	87,338	75,506	40,748	55,719	131,738	171,886	94,023
By University Rank							
Top 50	125,680	111,263	53,195	71,197	200,000	230,978	44,106
Below Top 50	111,625	98,513	51,727	61,628	177,257	215,371	335,017
R1	122,195	104,958	57,268	67,717	200,300	243,103	197,041
Non R1	103,592	94,401	43,840	58,647	156,498	183,210	182,082
By University Type							
Public	110,801	95,036	53,212	61,647	181,922	221,007	313,340
Private	124,972	121,684	44,587	70,000	176,695	206,520	65,783

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 424,000 faculty-year observations from over 115,000 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 Scopus, 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.

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)
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. 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)
$Z_{\text{university,field,year}}$	1.92***	2.13***	0.74***	0.09***	0.09***					
	(0.08)	(0.07)	(0.17)	(0.01)	(0.01)					
Log(Student Wages)$_{\text{university,field,year}}$						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 (7). 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. 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)$_{university,field,year}$	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.