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

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October 1, 2024

**Abstract**

Using data from over 115,000 university professors across public and private universities in the U.S. and Canada, we document significant and growing wage disparities among faculty. These disparities are largely driven by the cross-section of academic fields and their corresponding student future earnings. By employing a shift-share instrument based on persistent student placement patterns, we provide robust evidence of a causal relationship between student future earnings and faculty compensation, finding an elasticity of faculty compensation to student earnings after graduation in the [0.3 – 0.4] range. The elasticity of faculty wages to student earnings varies substantially across fields, being more than three times higher in Economics and Finance than in Humanities. We interpret these empirical facts as consistent with a mechanism where tuition and donation revenues per faculty, as well as faculty bargaining power, vary significantly across fields.

*JEL classification:* J31, I23

*Keywords:* Faculty Compensation, Labor Markets, Academic Fields, Universities

*We gratefully acknowledge helpful comments and suggestions from Ilona Babenko (EFA discussant), Alex Edmans, Vincent Glode (AFA discussant), Thomas Lemieux, Bill Schwert, Mila Sherman (discussant), and Elena Simintzi, as well as seminar and conference participants at the 2024 AFA, the FSU SunTrust Beach Virtual Conference, the EFA 2022 annual meeting and the 2022 Paris December Finance Meeting. We thank Shishir Aravindan, Akhil Choraria, Botir Kobilov, Nasha Lou, and Dolly Yu for excellent research assistance. Errors are ours only.

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# 1 Introduction

Returns to education are widely recognized as high and have increased significantly in recent decades. However, these high average returns mask important heterogeneity 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, which constitute the largest component of higher education expenditures.[3] In addition to the cost of education, academic wages also affect its quality, the allocation of talent across fields, and the production of innovation. Prior literature has long pointed to aggregate survey evidence documenting growing wage disparities across academic fields (e.g., Courant and Turner (2019)). Therefore, our study seeks to connect this increasing heterogeneity to the broader evolution of the labor markets by answering the following questions: Do higher student future earnings lead to higher faculty wages? If so, what mechanism(s) drive this relationship? And to what extent do these labor market dynamics contribute to widening wage disparities across academic fields?

To answer these questions, we first assemble a novel and comprehensive dataset of individual faculty pay and student future earnings across universities, years,

[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 and wages accounted for an average of 62% of instructional expenditures at four-year postsecondary institutions, according to the Integrated Postsecondary Education Data System (IPEDS).

and fields. The dataset includes over 115,000 research faculty from 1,590 U.S. and Canadian universities spanning the 1993-2023 period, and it provides coverage for more than 60% of all full-time undergraduate students enrolled in four-year colleges in 2019. To obtain faculty wages, we first collect name-identified wage data from U.S. public universities across 32 states 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 using field or publication history from Scopus, faculty directories assembled by James Hasselback, and textual analysis of automatically collected Google search data.[4] We merge this dataset with data on median student wages at the university, year, and field level from the Post-Secondary Employment Outcomes (PSEO) dataset provided by the U.S. Census Bureau.

Armed with this novel dataset, we provide three key stylized facts that highlight the heterogeneity in faculty wage across fields and their relationship to student labor market outcomes. Controlling for year, university and position fixed effects, we first document faculty wage differentials across academic fields. In particular, finance professors enjoy a wage premium averaging over 60% after 2015. This premium is economically large: the wage gap between Finance versus Humanities faculty, which amounts to around 100% within top 50 universities, is comparable to the wage gap between Humanities faculty and kindergarten teachers.[5] Second, using archival data covering around 100 state universities, we show that these wage differentials have increased significantly since 1974. Third, we find a positive correlation between faculty pay and the expected lifetime earnings of graduates across fields. This positive correlation extends beyond levels: changes in academic pay across fields also correlate with changes in student future earnings, further linking faculty compensation to student labor market outcomes.

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

[5]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.

In light of these stylized facts, we present evidence supporting a causal relationship between student labor market outcomes and faculty wages. A natural concern 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. To address this concern and gain identification, we progressively introduce fixed effects in a regression of faculty wages on student wages, aiming to control for as many confounding factors as possible. 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 between faculty pay and student wages.

Reinforcing the causal interpretation calls for a source of plausibly exogenous variation in post-graduation student wages at the school-by-field level. To this end, 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, fields that place students in industries and areas where wages have increased more significantly will experience a plausibly exogenous rise in student wages. To reinforce our instrument, we use wage data from workers aged 40 or above, as this population is less likely to be affected by changes in universities. This methodology provides a strong instrument, accommodating the inclusion of a large set of fixed effects. We document that a plausibly exogenous increase in student post-graduation wages translates into significantly higher faculty wages. Overall, our empirical findings support a causal interpretation of the relationship between student labor market outcomes and faculty wages.

Finally, we investigate the mechanisms through which student wages contribute to the growing disparities in professor pay across fields. We first show that, beyond the level of student future earnings, the heterogeneous elasticity of professor pay to these earnings plays a significant role in these disparities. For instance, we find that faculty wage elasticity to student future earnings is more than three times higher

in Economics and Finance than in Humanities. When exploring potential drivers of this elasticity, we find evidence that student wages spill over into faculty wages through tuition revenues and donations. Lastly, we find that higher bargaining power may also contribute to this higher elasticity in high paying fields, as the pool of PhD graduates is more limited in these fields.

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.[6]

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

### 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.[7]

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.[8] Scopus is one of the leading multidisciplinary citation databases in the world and offers comprehensive coverage of articles from thousands of peer-reviewed journals, conference proceedings, trade publications, books, and patent

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

[8]Because of downloading restrictions, we linked a 50% random sample of academic employees to Scopus.

records.[9] 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.[10]

Second, we match our faculty wage dataset with all the James Hasselback's faculty directories from 1993 to 2023.[11] 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 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,

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

[10] 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.'

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

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.[12] 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 460 four-year post-secondary institutions across 25 states, covering the years 2001 to 2019.[13]

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.

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 1,642 university-field observations, covering

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

[13] These statistics are based on data released in January 2024.

312 universities from our sample and representing 46% 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 $t$, $\mu_{field_f}$ are field indicator dummies for all fields except humanities. $\mu_{u,t}$ are university $\times$ year fixed effects and $\mu_{rank_i}$ 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, $\mu_{H1B}$ 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 1 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 1

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 2 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 2

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 $\beta_f$ measures the premium of field $f$ relatively to the average. $\mu_u$, $\mu_p$, and $\mu_{h1b}$ are university, position, and non US citizen fixed effects.

Figure A2 in the Internet Appendix displays the regression coefficients $\beta_f$ 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 $\tau$ 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 $\tau$ cell.

Figure 3 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 3

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 4 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 4

# 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.

## 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 level, based on the industries and the geographical areas where the university historically placed students in that field and

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

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 $f$, and $\mu_{i,t}$ are a set of fixed effects. Standard errors are double clustered at the university and year levels.

Table 4 displays the coefficients $\beta$, 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

including university times year, field times year and field times position fixed effects. The economic magnitude is large. With year and position fixed effect, the elasticity is of 0.45. As expected given that this dimension accounts for much of the observed variance, including field fixed effects 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 6 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 6

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

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

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. $\mu_{field_f}$ denote field indicator dummies for all fields except humanities. $\mu_t$ and $\mu_p$ are year and position fixed effects, respectively. Standard errors are clustered at the field times year levels.

Table 6 displays the coefficients $\beta_1$ and $\beta_{2_f}$, 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 7 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 7

We further investigate the relationship between tuition revenue and faculty pay using changes in tuition regulations. Based on Deming and Walters (2018), we consider a reduced form of the instrumental variable model in which tuition revenues are instrumented by the implementation of tuition freezes and caps across states in public universities from 1990 to 2019. Specifically, we estimate the following specification:

$$\ln(w_{i,t}) = \beta_1 \mu_{finance} + \beta_2 \mathbb{1}_{\text{Freeze/Cap}} + \beta_3 \mu_{finance} \mathbb{1}_{\text{Freeze/Cap}} + \mu_u + \mu_t + \mu_{H1B} + \epsilon_{i,t} \quad (13)$$

where $w_{i,t}$ is the 9-month base salary of faculty $i$ in year $t$, while $\mu_{finance}$ represents a field indicator variable for Finance. $\mathbb{1}_{\text{Freeze/Cap}}$ is an indicator variable for tuition freezes and caps, which equals 1 if there is a tuition freeze or cap on undergraduate tuition at public four-year universities in a state and 0 otherwise. We only consider tuition freezes and caps that affect undergraduate tuition at all public four-year universities in a state, excluding those that affect only some but not all of a state's public four-year universities. $\mu_u$ and $\mu_t$ are university and year fixed effects, respectively. $\mu_{H1B}$ represent 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.

INSERT TABLE 8

Table 8 displays the results. Academic wages are lower in universities and years with a tuition cap, as shown in Column 1. Column 2 interacts our instrument with a dummy for each main field. We find that the sensitivity of academic

wages to tuition revenues is higher in Finance and Business. Finally, Column 3 indicates that the elasticity increases with the share of undergraduate students in the same university and field, consistent with tuition caps and freezes affecting only undergraduate tuitions.

### 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 8 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 8

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.

### 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 9 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 9

## 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 com-

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

[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.

prehensive dataset on over 115,000 professors and student wages across U.S. and Canadian universities, we establish a causal relationship between student earnings and faculty wages. We show that beyond student earnings levels, a higher elasticity to student earnings in fields such as finance is fueled by factors like tuition revenues, donations, and bargaining power due to a limited supply of PhD graduates. These findings highlight the role of market forces in shaping academic compensation

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

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# 7 Figures

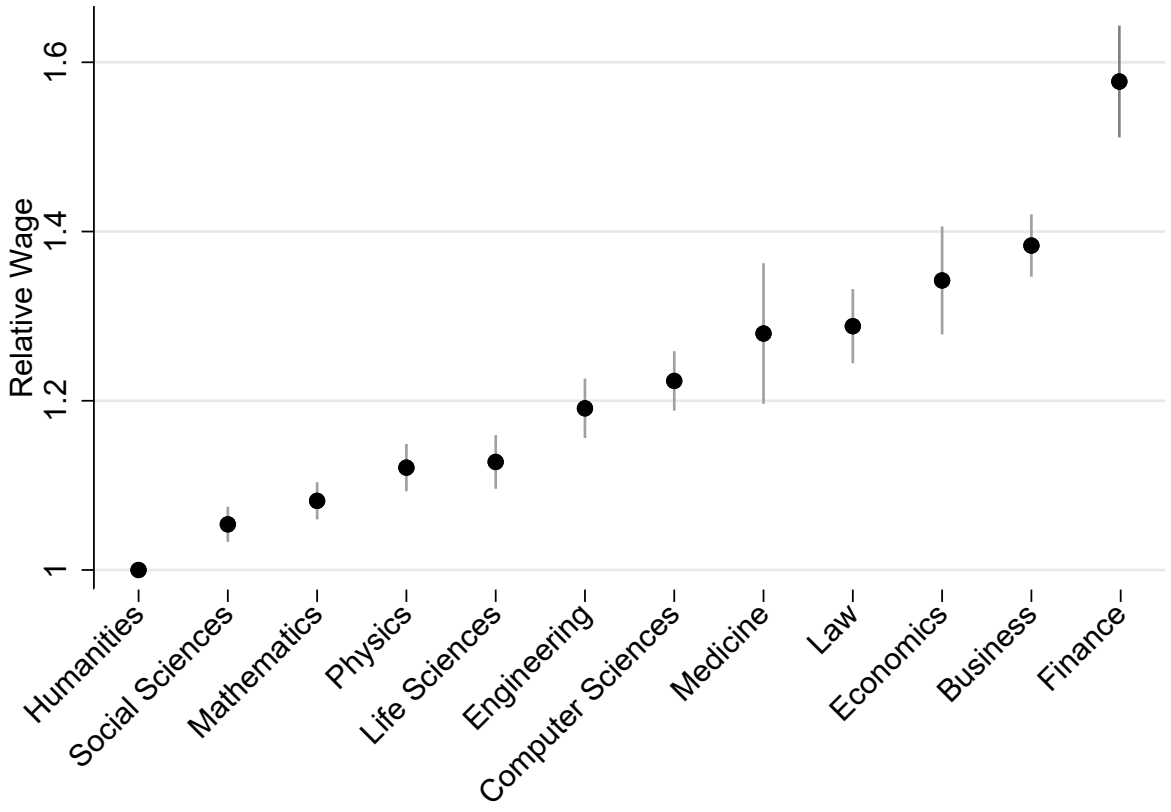



**Figure 1. Academic Pay across Fields**

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 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.

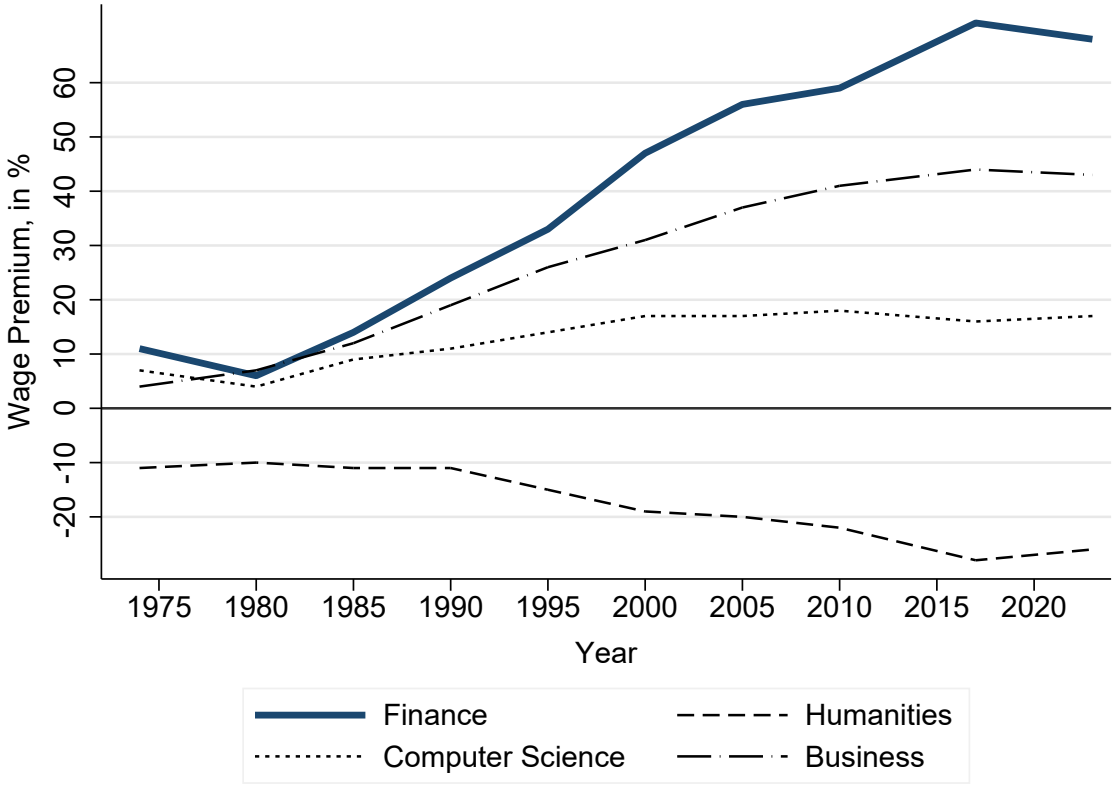



**Figure 2. Evolution of Academic Pay across Fields (1974-2023)**

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.

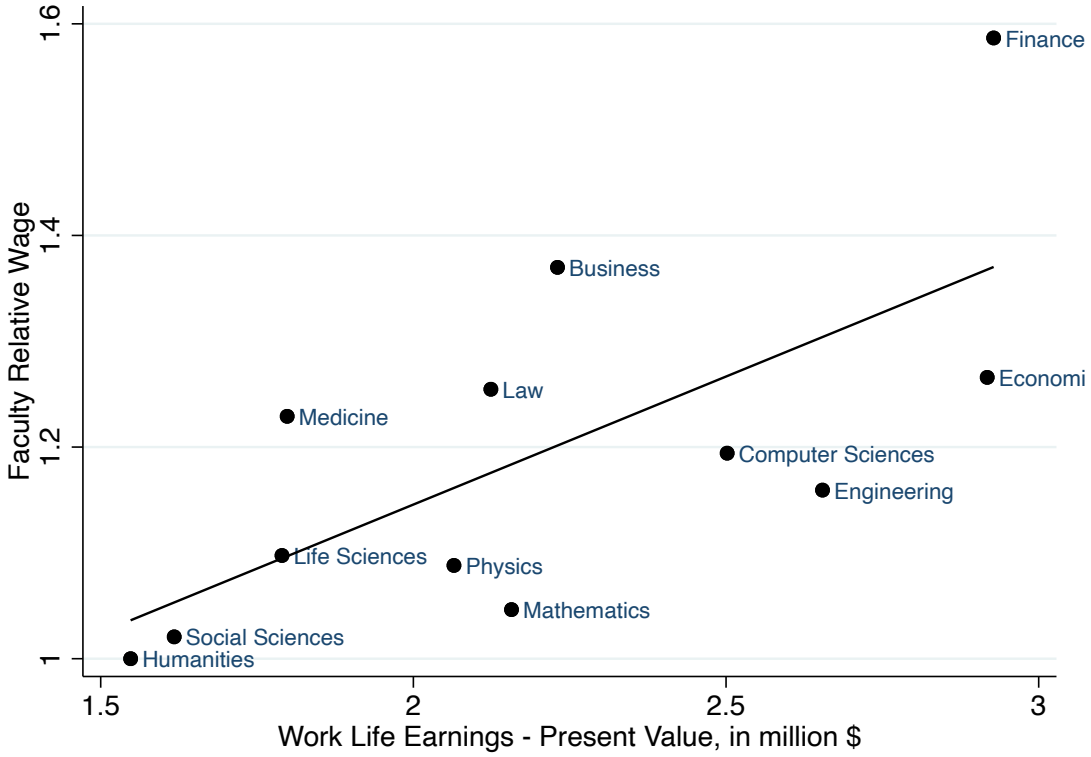



**Figure 3. Faculty Wages versus Student Expected Earnings across Fields**

This figure illustrates the relationship between the academic wage premium across various academic fields and the present value of graduate 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%.

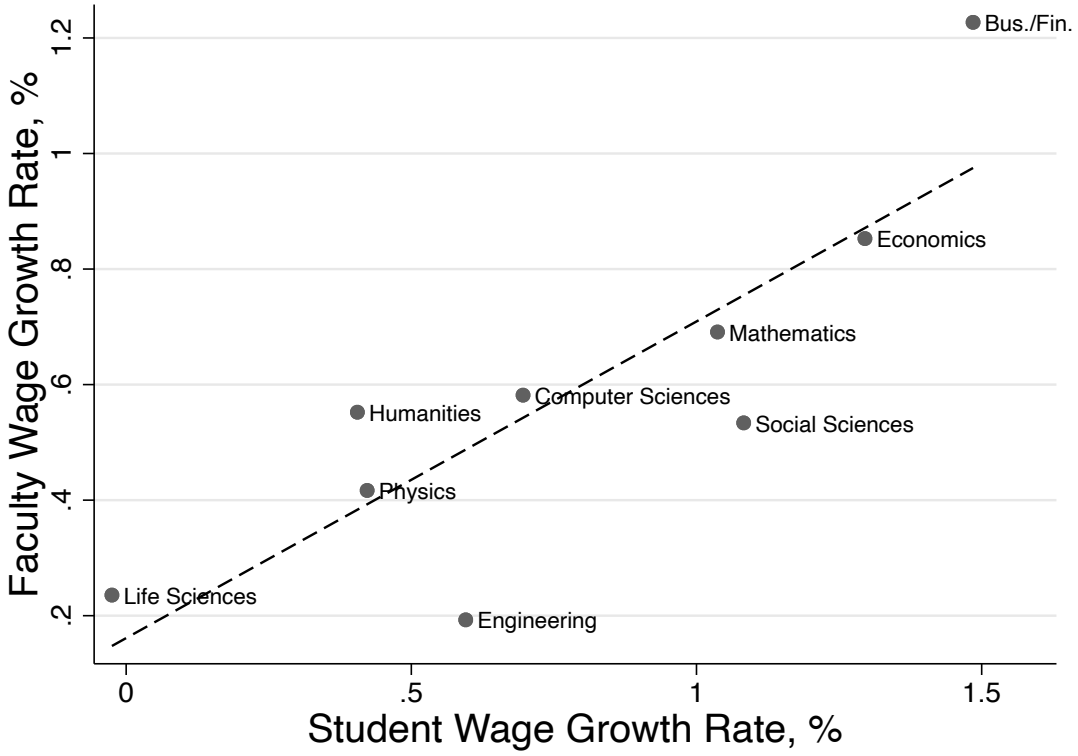



**Figure 4. Yearly Growth Rate of Faculty versus Undergraduate Student Future Earnings (2001-2019)**

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 .

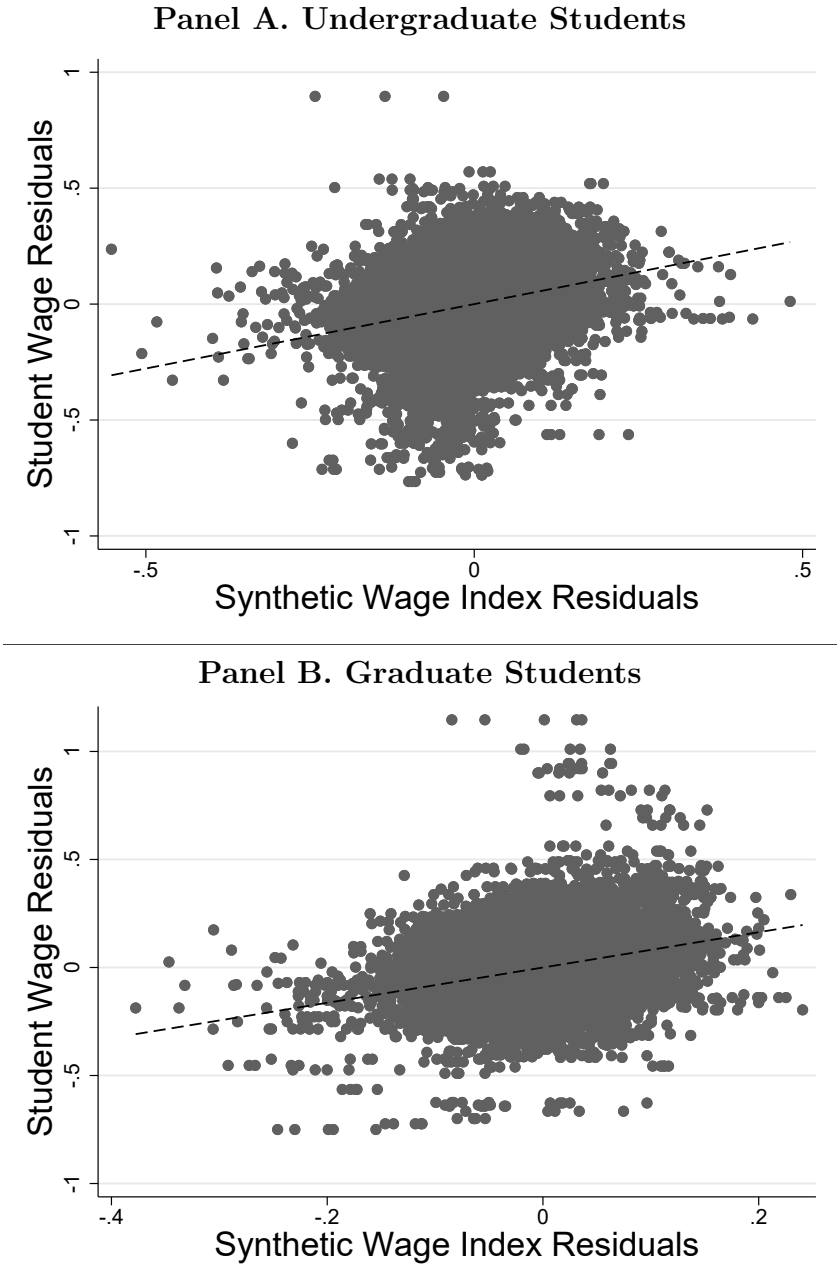



**Figure 5. Correlation between Innovations in Student Wages and in Synthetic Wage Index**

This figure demonstrates 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.

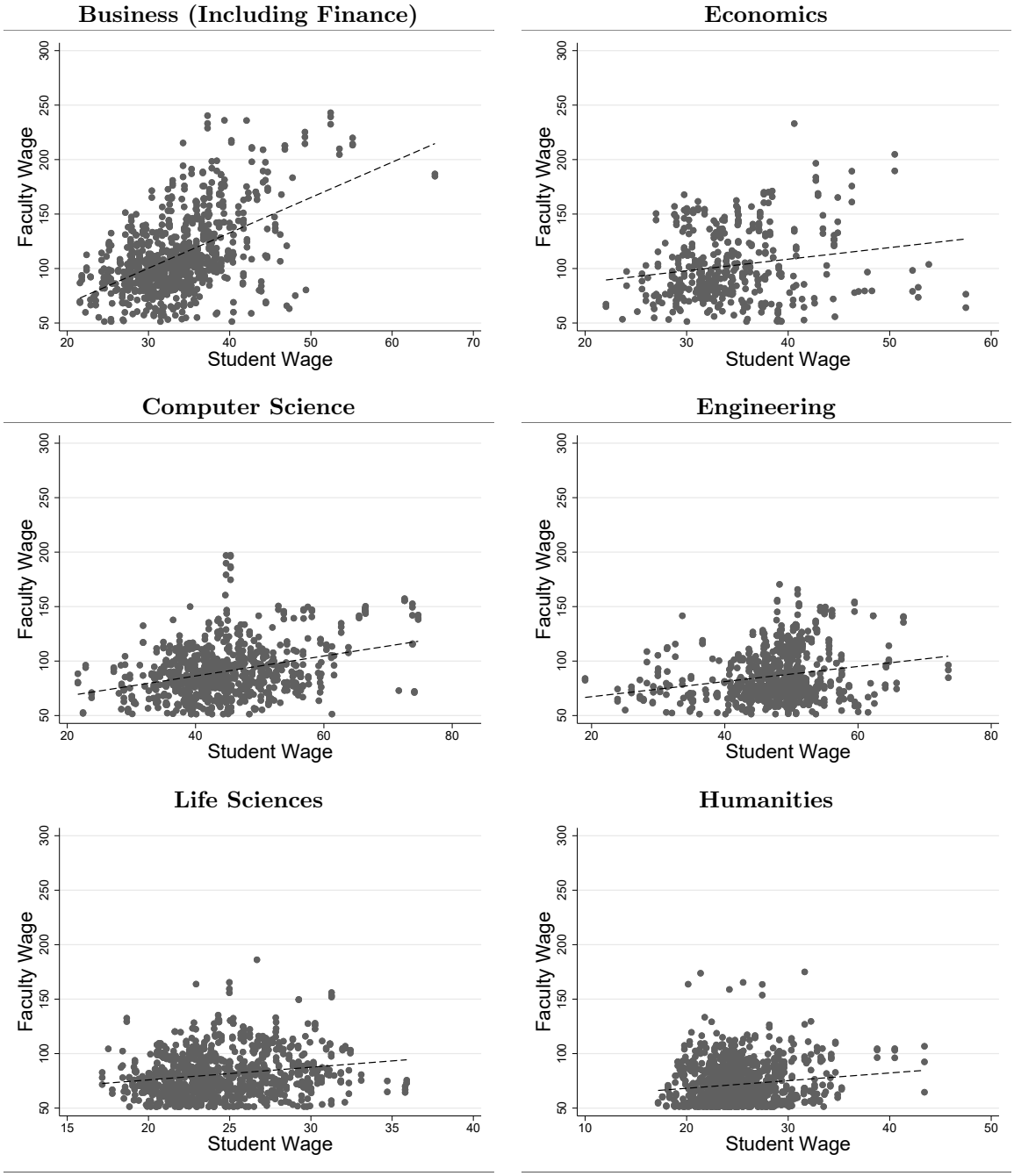



**Figure 6. Elasticity of Faculty Wages to Student Wages across Fields**
This figure illustrates the relationship between faculty pay and their student wages across universities in the Business, Economics, Computer Sciences, Engineering, Life Sciences and Humanity fields. Each dot on the graph represents one university and year. The horizontal axis represents the median student wage in one university, field and year, while the vertical axis represents the average faculty in this same university, field, and year. The university-field student wage data comes from PSOE.

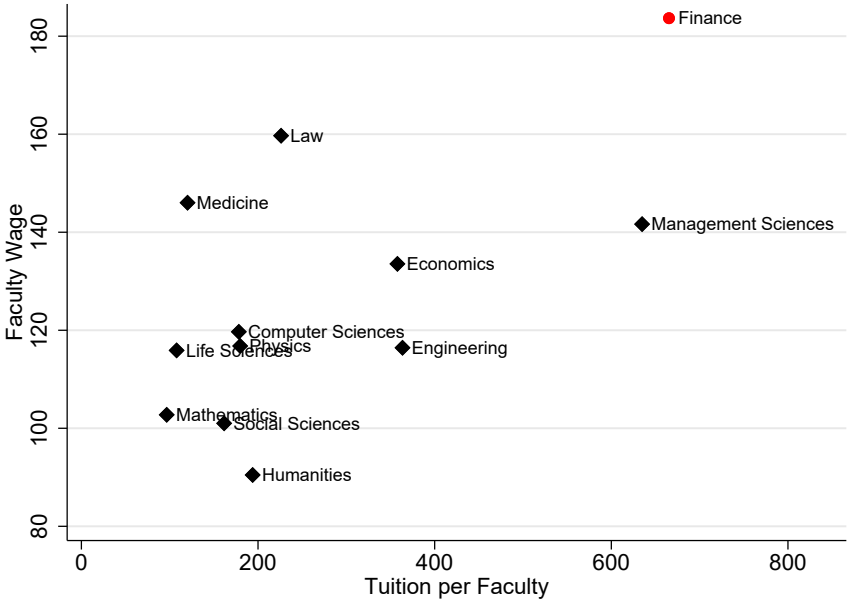



**Figure 7. Faculty Wages and Per-Faculty Tuition Revenues across Fields**

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.

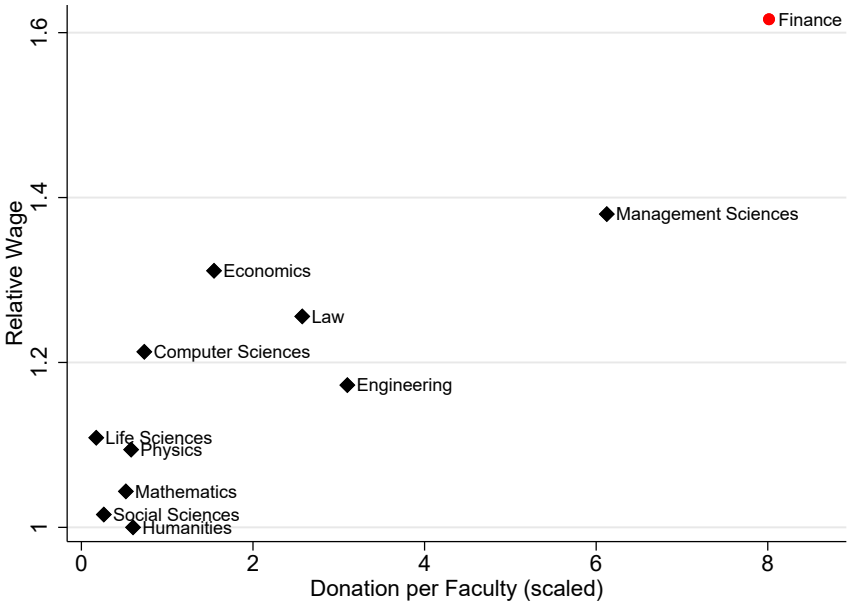



**Figure 8. Faculty Wages and Donations across Fields**

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 1. 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.

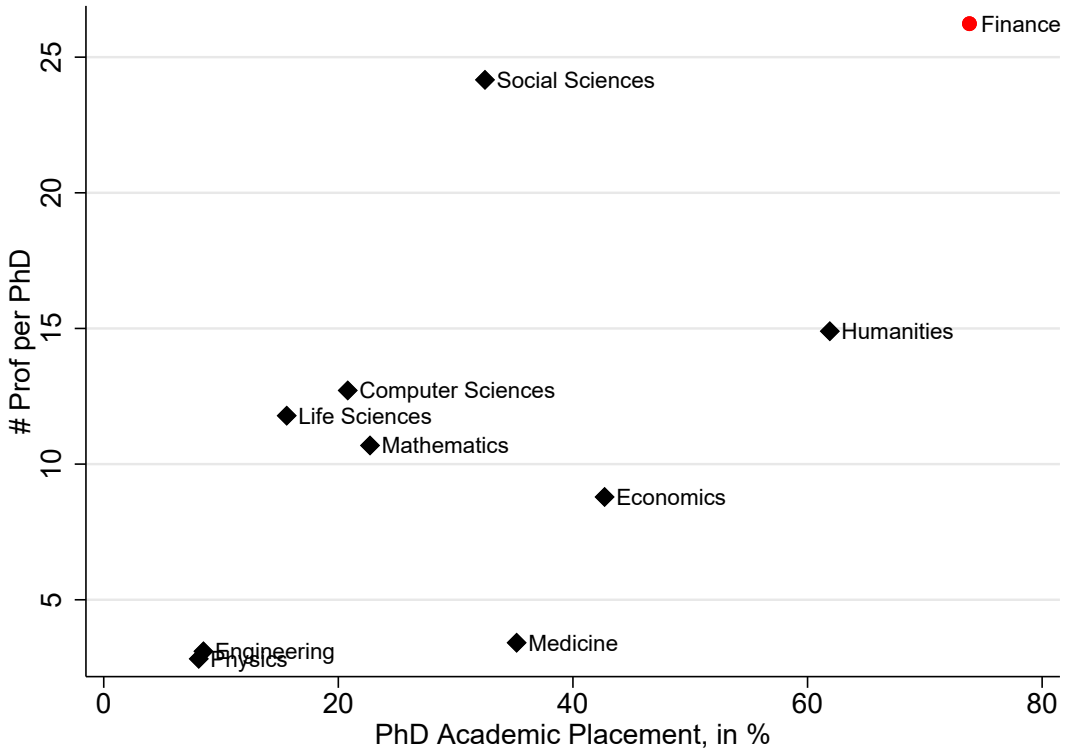



**Figure 9. Supply of PhDs across Fields**

This figure displays the ratio of PhD graduates to faculty versus the academic placement rate. The ratio of PhD graduates to professors for each field equals the total number of PhD graduates in this field divided by the total number of professors in this field included in our main sample. The data on the number of PhD graduates is from IPEDS. We take the yearly average of the number of PhD degrees granted across academic fields over our sample period (2010-2018). The academic placement rate across fields comes 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.

# 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 - 1-year post-Graduation Median Income across Fields AND Universities, in 2019 $** | | | | | | |
| *Source: Post-Secondary Employment Outcomes Dataset (2001-2019)* | | | | | | |
| **Total Sample** | 39,439 | 35,916 | 12,239 | 27,061 | 57,940 | 39,486 |
| Business (Including Finance) | 40,094 | 38,928 | 7,527 | 32,248 | 49,072 | 5,748 |
| Economics | 41,634 | 40,341 | 6,949 | 33,859 | 51,069 | 1,632 |
| Computer Sciences | 51,938 | 51,226 | 10,438 | 39,703 | 64,867 | 3,543 |
| Engineering | 56,248 | 57,683 | 8,974 | 43,538 | 65,378 | 2,664 |
| Life Sciences | 29,812 | 29,211 | 4,351 | 24,985 | 35,625 | 4,316 |
| Physics | 36,316 | 35,706 | 6,424 | 28,907 | 44,212 | 2,361 |
| Mathematics | 41,730 | 40,763 | 7,930 | 32,630 | 51,999 | 1,929 |
| Social Sciences | 31,939 | 31,302 | 4,347 | 27,362 | 37,141 | 5,614 |
| Humanities | 30,873 | 29,975 | 5,188 | 25,174 | 37,476 | 4,620 |
| **Panel B - 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 |

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 2001 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 Student Future Earnings

| | Log(Faculty Base Salary) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Panel A: Undergraduate Students** | | | | |
| Log(Student Wages)$_{\text{university,field,year}}$ | 0.45*** | 0.39*** | 0.13*** | 0.11*** |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| Controls: see Panel C | | | | |
| Observations | 103,854 | 103,853 | 103,631 | 103,631 |
| $R^2$ | 0.52 | 0.52 | 0.52 | 0.53 |
| **Panel B: Graduate Students** | | | | |
| Log(Student Wages)$_{\text{university,field,year}}$ | 0.50*** | 0.51*** | 0.15*** | 0.16*** |
| | (0.03) | (0.04) | (0.03) | (0.03) |
| Controls: see Panel C | | | | |
| Observations | 57,699 | 57,585 | 57,585 | 57,585 |
| $R^2$ | 0.35 | 0.44 | 0.50 | 0.52 |
| **Panel C: Controls** | | | | |
| *Fixed Effects:* | | | | |
| Year | Yes | - | - | - |
| University × Year | - | Yes | Yes | Yes |
| Field | - | - | Yes | - |
| Field × Year | - | - | - | Yes |
| Position | Yes | Yes | Yes | - |
| Field × Position | - | - | - | Yes |

This table reports regressions of the yearly faculty base salary on the median student wage. The median student wage is the lagged median student wage one year after graduation in the same university and field. The median wage is for undergraduate and graduate students in Panels A and B, respectively. Panel C lists the controls used in the regressions reported in Panels A and B. 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 lagged median student wage one year after graduation is calculated as the average of the lagged median student earnings one year after graduation across CIP codes related to the same academic field and is matched with out dataset on academic wages by academic field and year. Standard errors are clustered at the field times year level 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 Student Wages: Instrumental Variable Panel Analysis**

| | First Stage Log(Student Wage) | | | Second Stage Log(Faculty Base Salary) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: Undergraduate Students** | | | | | | |
| $\text{Instrument}_{\text{university,field,year}}$ | 0.69*** | 0.81*** | 0.81*** | | | |
| | (0.10) | (0.11) | (0.11) | | | |
| $\text{Log(Student Wages)}_{\text{university,field,year}}$ | | | | 0.31*** | 0.32*** | 0.30*** |
| | | | | (0.09) | (0.08) | (0.07) |
| Controls: see Panel C | | | | | | |
| Observations | 136,671 | 136,456 | 136,456 | 136,671 | 136,456 | 136,456 |
| $R^2$ | 0.85 | 0.88 | 0.88 | | | |
| $F$ statistics | 52 | 58 | 58 | | | |
| **Panel B: Graduate Students** | | | | | | |
| $\text{Instrument}_{\text{university,field,year}}$ | 0.46*** | 0.58*** | 0.58*** | | | |
| | (0.08) | (0.09) | (0.09) | | | |
| $\text{Log(Student Wages)}_{\text{university,field,year}}$ | | | | 0.52*** | 0.43*** | 0.37*** |
| | | | | (0.17) | (0.12) | (0.11) |
| Controls: see Panel C | | | | | | |
| Observations | 136,257 | 136,091 | 136,091 | 136,257 | 136,091 | 136,091 |
| $R^2$ | 0.77 | 0.80 | 0.80 | | | |
| $F$ statistics | 27 | 34 | 34 | | | |
| **Panel C: Controls** | | | | | | |
| *Fixed Effects* | | | | | | |
| University | Yes | - | - | Yes | - | - |
| Field | Yes | - | - | Yes | - | - |
| Year | Yes | - | - | Yes | - | - |
| Position | Yes | Yes | - | Yes | Yes | - |
| Field × Year | - | Yes | Yes | - | Yes | Yes |
| University × Year | - | Yes | Yes | - | Yes | Yes |
| Field × Position | - | - | Yes | - | - | Yes |

This table displays the results of the instrumental variable analysis, in which the median student wage is instrumented by the synthetic wage index calculated in equation (7). The median student wage is the lagged median student wage one year after graduation for bachelor's and master's students in Panels A and B, respectively. Columns (1)-(3) report the results for the first stage regressions, while Columns (4)-(6) demonstrate the results for the second stage regressions. Panel C lists the controls used in the regressions reported in Panels A and B. 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 dataset on academic wages by academic field assigned using the CIP code. Standard errors are clustered at the field times year level and reported in parentheses. Standard errors are double clustered at the field times year level and 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 Wages: Heterogeneity across Fields**

| | Log(Faculty Base Salary) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbb{1}_{\text{Engineering}}$ | 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) |
| 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) |
| *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 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. Summary Statistics: Tuition Revenue**

| | Mean | Median | SD | p10 | p90 | p95 | # Obs. |
|---|---|---|---|---|---|---|---|
| **Panel A - Annual Graduate Tuition, in 2019 $** | | | | | | | |
| *Source: Internet Sources* | | | | | | | |
| ***By Academic Field*** | | | | | | | |
| Finance & Accounting | 30,049 | 26,156 | 16,610 | 12,586 | 52,236 | 64,148 | 462 |
| Law | 31,353 | 28,015 | 15,823 | 12,598 | 54,594 | 61,895 | 210 |
| Medicine and Health | 26,638 | 24,736 | 12,735 | 12,886 | 43,609 | 51,153 | 565 |
| Management Sciences | 27,658 | 25,341 | 14,622 | 11,146 | 49,374 | 58,382 | 468 |
| Economics | 30,606 | 28,926 | 13,911 | 15,227 | 51,391 | 60,675 | 153 |
| Computer Sciences | 27,863 | 26,147 | 13,355 | 12,705 | 46,390 | 53,227 | 416 |
| Engineering | 28,850 | 27,426 | 13,559 | 13,248 | 48,039 | 56,221 | 322 |
| Life Sciences | 26,918 | 24,990 | 13,096 | 12,979 | 44,029 | 54,575 | 404 |
| Physics | 29,608 | 28,625 | 13,078 | 13,695 | 50,943 | 55,526 | 219 |
| Mathematics | 27,135 | 25,031 | 13,607 | 12,784 | 44,965 | 56,954 | 293 |
| Social Sciences | 25,614 | 23,663 | 12,446 | 12,015 | 43,223 | 50,793 | 539 |
| Humanities | 24,229 | 22,031 | 12,379 | 10,689 | 40,780 | 48,687 | 478 |
| **Panel B - Share of Undergraduate Students, %** | | | | | | | |
| *Source: IPEDS* | | | | | | | |
| ***By Academic Field*** | | | | | | | |
| Business (Including Finance) | 86 | 89 | 11 | 74 | 97 | 100 | 220 |
| Economics | 93 | 99 | 16 | 81 | 100 | 100 | 145 |
| Law | 36 | 0 | 47 | 0 | 100 | 100 | 54 |
| Medicine and Health | 81 | 87 | 23 | 62 | 100 | 100 | 214 |
| Computer Sciences | 84 | 88 | 19 | 59 | 100 | 100 | 217 |
| Engineering | 85 | 88 | 18 | 68 | 100 | 100 | 165 |
| Life Sciences | 93 | 96 | 14 | 88 | 100 | 100 | 234 |
| Physics | 89 | 91 | 11 | 76 | 100 | 100 | 183 |
| Mathematics | 88 | 88 | 12 | 73 | 100 | 100 | 208 |
| Social Sciences | 83 | 85 | 11 | 70 | 95 | 98 | 234 |
| Humanities | 93 | 95 | 7 | 85 | 100 | 100 | 226 |

This table provides summary statistics by academic field for annual graduate tuition in Panel A and the share of undergraduate students in Panel B. We collect data on annual graduate tuition for academic programs from Internet sources 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 for each university and field and convert it to 2019 prices. We compute the share of undergraduate students for each university and field as $s_{und,f,u} = \frac{length_{und,f} * degrees_{und,f,u}}{length_{und,f} * degrees_{und,f,u} + length_{grad,f} * degrees_{grad,f,u}}$, 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 $f$. The data on the total number of bachelor's and master's degrees comes from IPEDS.

**Table 8. Effect of Tuition Freezes and Caps on Academic Wages**

| | Log(Academic Wage)$_{i,y}$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\mathbb{1}_{\text{Freeze/Cap}}$ | -0.02* | -0.01 | -0.02 |
| | (0.01) | (0.01) | (0.02) |
| $\mathbb{1}_{\text{Finance}}$ | 0.48*** | 0.51*** | 0.47*** |
| | (0.02) | (0.03) | (0.02) |
| $\mathbb{1}_{\text{Finance}} \times \mathbb{1}_{\text{Freeze/Cap}}$ | -0.18** | -0.18** | -0.27*** |
| | (0.07) | (0.07) | (0.05) |
| $\mathbb{1}_{\text{Computer Science}}$ | | 0.10*** | |
| | | (0.02) | |
| $\mathbb{1}_{\text{Computer Science}} \times \mathbb{1}_{\text{Freeze/Cap}}$ | | -0.07* | |
| | | (0.04) | |
| $\mathbb{1}_{\text{Economics}}$ | | 0.23*** | |
| | | (0.02) | |
| $\mathbb{1}_{\text{Economics}} \times \mathbb{1}_{\text{Freeze/Cap}}$ | | -0.10* | |
| | | (0.06) | |
| $\mathbb{1}_{\text{Business}}$ | | 0.29*** | |
| | | (0.02) | |
| $\mathbb{1}_{\text{Business}} \times \mathbb{1}_{\text{Freeze/Cap}}$ | | -0.12*** | |
| | | (0.04) | |
| $\text{S}_{\text{undergraduate}}$ | | | -0.37*** |
| | | | (0.03) |
| $\text{S}_{\text{undergraduate}} \times \mathbb{1}_{\text{Freeze/Cap}}$ | | | 0.02 |
| | | | (0.17) |
| $\text{S}_{\text{undergraduate}} \times \mathbb{1}_{\text{Finance}}$ | | | -0.08 |
| | | | (0.13) |
| $\text{S}_{\text{undergraduate}} \times \mathbb{1}_{\text{Finance}} \times \mathbb{1}_{\text{Freeze/Cap}}$ | | | -1.00*** |
| | | | (0.29) |
| *Fixed Effects* | | | |
| Year FE | Yes | Yes | Yes |
| University FE | Yes | Yes | Yes |
| Non U.S. Citizen FE | Yes | Yes | Yes |
| Observations | 161,462 | 161,462 | 117,581 |
| $R^2$ | 0.27 | 0.30 | 0.28 |

This table investigates the impact of tuition freezes and caps on academic wages. We estimate OLS regressions with the dependent variable being the log of the annual 9-month base salary. The explanatory variables in Column 1 are the field indicator variable for Finance and the indicator variable for tuition freezes and caps, which equals 1 if there is a tuition freeze or cap on undergraduate tuition at public four-year universities in a state and 0 otherwise, as well as the interaction of two indicator variables. Column 2 also includes field indicator variables for Computer Science, Economics, and Business, as well as their interactions with the indicator variable for tuition caps and freezes. Column 3 additionally includes the share of undergraduate students, as well as its triple interactions with the field indicator variable for Finance. Tuition freezes and caps data is from Deming and Walters (2018) and Miller and Park (2022). 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.