Monopsony in Academia and the Gender Pay Gap: Evidence from California

Zhanhan Yu * Alfonso Flores-Lagunes†

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Abstract

We investigate monopsony power in a highly-skilled labor market given by tenure-ranked faculty in the University of California system, and analyze differential monopsony power exposure by gender. We infer the campus-level labor supply elasticity by estimating the elasticity of separations utilizing individual-level faculty data and two instruments based on campus revenues and salary scales. We find that the "exploitation rate," a common measure of monopsony power, is 7% for tenure-ranked faculty. There is a statistically significant difference in the monopsony power experienced by male and female faculty, but it appears to account for a relatively small percentage of the observed gender pay gap.

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*Economics Department, Adam Smith Business School, University of Glasgow, Glasgow, UK; Email: yuzhanhan@gmail.com.

†Department of Economics and Center for Policy Research, Syracuse University; IZA, and GLO; 426 Eggers Hall, Syracuse NY 13244-1020; Telephone: +1 315-443-9045; Email: afloresl@syr.edu.

1 Introduction

There is a growing consensus among economists that in most labor markets firms have power to set wages.[1] Robinson (1933) first documented that geographical isolation, workers' idiosyncratic preferences, and information frictions can lead to market failures and an upward-sloping labor supply curve to the firm. The upward-sloping labor supply curve is leveraged by the firm to exert influence upon the wage paid to workers. Manning (2003a) further developed this idea and demonstrated that firms can be monopsonists despite the existence of many competitors.[2] In a frictional labor market, firms possess monopsony power to set the wage below workers' marginal revenue product (MRP).[3]

Most of the existing studies investigating monopsony power focus on relatively low-wage occupations.[4] Comparatively little is known about monopsony power in high-skilled occupations. High-skilled workers, who work in jobs requiring specialized knowledge such as university professors, lawyers, and doctors, earn relatively higher salaries. Meanwhile, they are likely to have fewer outside job options and thus face a "thin" labor market in that few employment opportunities are available at any given point of time. Manning (2003b) argues that monopsony is naturally linked to "thin" labor markets where the opportunities to change jobs are hard to find, giving employers some power to set the wage.

The first question we ask is whether monopsony power exists in a high-skill labor market. Specifically, we investigate whether monopsony exists in the labor market of university faculty,

[1] There has been burgeoning interest about monopsony power since at least 2010. See Manning (2021), Ashenfelter et al. (2022), and Card (2022) for reviews.

[2] The model in Manning (2003a), building on Burdett and Mortensen (1998), hinges on search frictions. Other work, such as Manning (2006), Bhaskar and To (1999), Boal and Ransom (1997), Card et al. (2018), and Lamadon, Mogstad, and Setzler (2022), also show that imperfect information, variation in worker preferences, and firm differentiation can all be the sources of monopsony power, even in a market with a large number of firms.

[3] The interest in monopsony power goes beyond the field of labor economics. For instance, there is an emerging interest in monopsony models in industrial organization, where monopsony power comes from the idiosyncratic tastes among workers of non-wage amenities offered by firms (Manning 2021). In this literature, a firm's market power is affected by its market share and size (Azar, Berry, and Marinescu 2022; Azar et al. 2019; Berger, Herkenhoff, and Mongey 2022).

[4] Prominent examples are teachers (Falch 2010; Ransom and Sims 2010), nurses (Staiger, Spetz, and Phibbs 2010; Matsudaira 2014), grocery retailers (Ransom and Oaxaca 2010; Dube, Giuliano, and Leonard 2019), and ride-sharing drivers (Caldwell and Oehlsen 2022). Yeh, Macaluso, and Hershbein (2022) quantify the monopsony power for manufacturing workers in the U.S.

using data from the eight public R1 research campuses in the University of California (UC) system.[5] For this purpose, we collect publicly-available information on faculty salaries in the UC system and merge it with information obtained online on faculty characteristics, career trajectories, and research productivity indicators (measured with publication metrics from Scopus, the Elsevier's citation database). We focus on a public R1 research university for several reasons. First, academic faculty in public universities are government employees and their payroll records are publicly accessible. Second, we can trace the career trajectory for the vast majority of faculty in research universities from either their payroll records or their online academic profiles, along with other relevant individual characteristics that affect their salaries. Lastly, it is feasible to quantitatively measure research productivity for these faculty since research is a central part of their job and most of them have a publication history. This allows us to control for a key dimension of worker productivity and explore its role on salary differentials. Our faculty data contains 8,089 tenure-track faculty members who work in the campuses in our sample during the period 2010-2018.

After documenting the presence of monopsony power among research faculty in the UC system, we analyze how much of the observed gender wage gap can be explained by the difference in exposure to monopsony power by female and male faculty. Monopsonistic employers can reduce wages further for workers whose labor supply is less responsive to changes in wages. Thus, if females have a lower wage elasticity of labor supply, this can be a contributing factor to the observed gender wage gap.[6] The gender wage gap in academia has attracted attention.[7] Existing studies suggest that the unequal pay for women in higher education is likely to be a product of differences in the promotion rate between men and women (Ginther and Hayes 1999, 2003; Kahn 1993; McDowell, Singell, and Ziliak 1999; Ginther and Kahn 2004; Kleemans and Thornton 2023), biases in the evaluation of teaching and research (Mason and Goulden 2002; Chen and

[5]A R1 research university is a four-year university categorized as having very high research activity, following the 2010 Carnegie Classification of Institutions of Higher Education. Two campuses in the UC system (Merced and San Francisco) do not enter into this classification, and are thus excluded from the analysis.

[6]Empirical evidence, primarily from relatively low-wage occupations, generally suggests that female's labor supply is less elastic than males' (Ransom and Oaxaca 2010; Hirsch, Schank, and Schnabel 2010; Barth and Dale-Olsen 2009; Webber 2016; Sharma 2023). Evidence on the gender difference in monopsony power from high-skilled occupations is lacking.

[7]The attention has transcended the academic discourse. During the period from 2018 to 2020, there were more than ten equal pay lawsuits against universities in the U.S. such as Arizona, Illinois, Rutgers, Syracuse, and Texas.

Crown 2019; Boring 2017; Hengel 2022), and work-family issues (Antecol, Bedard, and Stearns 2018). A recent study finds that enforcing pay disclosure laws effectively reduces gender pay gap in Canadian universities (Baker et al. 2023). Our study explores whether monopsony is also a contributing factor to the gender pay gap in our sample of R1 campuses from the UC system. Most existing studies on the gender pay gap in higher education focused on a single field or a single university, whereas this study provides evidence from a larger sample of public university campuses and multiple fields.

To estimate the rate of wage-setting power, several empirical studies leverage the theoretical insight that firms in a monopsonistic labor market face an upward-sloping labor supply curve and estimate the wage elasticity of labor supply to the individual firms. Since labor demand and labor supply are determined simultaneously, identifying the wage elasticity of labor supply requires exogenous changes in wages. Some studies leverage wage variations driven by random or quasi-random experiments.[8] Other studies, recognizing the obstacles of directly estimating the labor supply elasticity, adopt a worker separation-based approach to estimate the labor supply elasticity from the wage elasticity of separations (e.g., Ransom and Oaxaca 2010; Ransom and Sims 2010; Barth and Dale-Olsen 2009; Hirsch, Schank, and Schnabel 2010; Webber 2016; Dube, Giuliano, and Leonard 2019; Bassier, Dube, and Naidu 2021; Sharma 2023). This approach is based on the dynamic monopsony model (Manning 2003a), which shows that the wage elasticity of labor supply equals the wage elasticity of separations subtracting the wage elasticity of recruits. Under the assumption that, on average, one firm's recruits are other firms' separations (in the steady state), the wage elasticity of separations equals minus the wage elasticity of recruits. Therefore, estimating the wage elasticity of separations alone suffices to recover the wage elasticity of labor supply.

We adopt the separation-based approach to infer the wage elasticity of labor supply from the wage elasticity of separations. We measure monopsony power using the so-called "exploitation rate", which is defined as the proportional gap between the MRP and the wage, and it is equal

[8]For example, Staiger, Spetz, and Phibbs (2010) exploits the legislated change in registered nurse wages at VA (Department of Veterans Affairs) hospitals to explore monopsony in the nurse labor market; Falch (2010) examines the labor market of public school teachers utilizing the institutional change in the wage determination process in Norway; and Caldwell and Oehlsen (2022) conducts a series randomized experiments in collaboration with Uber to analyze the labor market of ride-sharing drivers.

to the inverse of the wage elasticity of labor supply (Robinson 1933; Ashenfelter, Farber, and Ransom 2010). Estimating the wage elasticity of separations still faces the challenge of finding exogenous variation in wages, since unobserved factors, such as ability, may simultaneously affect faculty's salaries and separation decisions. To deal with this endogeneity of salaries in the separation equation, we employ two instrumental variables exploiting plausibly exogenous variation in salaries to faculty that are driven by changes in campus revenues and in pre-specified salary scales. These instruments, which are related to faculty compensation, are arguably exogenous to the individual faculty decision to separate from the university.

We find evidence that monopsony exists in the UC labor market for tenure-ranked faculty: the exploitation rate is robustly estimated at 7%. While we do not find statistically significant differences in the exposure to monopsony power across faculty groups, such as tenured/non-tenured and U.S./foreign born, we do find heterogeneity in the monopsony power across campuses, which could be related to their location. Moreover, we find evidence that male and female faculty members experience a statistically different level of monopsony power: on average, female faculty face a 1.3 pp (percentage point) higher exploitation rate relative to male faculty. This difference is driven by those faculty born in the U.S., among whom females experience a 2 pp higher level of monopsony power. Lastly, we find that the differential exposure to monopsony power would represent relatively little (8 to 12%) of the observed gender pay gap in the UC system. We conjecture that this is the result of the institutional setting we examine: campuses with salary transparency and public pay scales.

A recent study that also examines monopsony in academia is Goolsbee and Syverson (2023). They use university-level data from the Integrated Postsecondary Education Data System (IPEDS) and employ lagged college applications as an instrument for labor demand to estimate the inverse elasticity of labor supply. There are fundamental differences between our work and theirs. First, by using aggregate data, they are able to analyze the universe of U.S. higher education institutions, while we concentrate on eight R1 campuses in the UC system. Second, our novel faculty-level data allows us to control for individual-level faculty characteristics such as educational background, field, experience, rank, and research productivity indicators. Third, Goolsbee and Syverson (2023) separately analyze non-tenure-ranked faculty. In contrast, we concentrate on tenure-ranked faculty, since the research productivity information is more relevant for this group. Therefore, our study provides relevant complementary evidence.

The rest of paper is organized as follows. The next section outlines the monopsony model and discusses the separation-based approach to estimate the extent of monopsony power. Section 3 describes the data compiled and used for the analysis. We also provide a brief discussion of the compensation structure in the UC system and its implications for the choice of instrumental variables. The empirical evidence of monopsony power in the tenure-ranked faculty labor market in the UC system is presented in Section 4. In Section 5, we examine gender differences in monopsony power in the present setting, and investigate their contribution to the observed gender pay gap in the UC system. Section 6 concludes.

2 The Monopsony Model

We start by setting up a standard static monopsony model to show the relationship between the firm-level wage elasticity of labor supply and the rate of exploitation. We then motivate the separation-based approach to infer the wage elasticity of labor supply by estimating the wage elasticity of separations. Lastly, we show that the female-to-male salary ratio (the gender wage gap) can be decomposed into 1) the difference in the marginal revenue product (MRP) between males and females, i.e., the gender difference in productivity, and 2) the difference in the labor supply elasticity between genders, an indicator of differential exposure to monopsony power.

2.1 The Static Model of Monopsony

Consider a monopsonist firm that has a revenue function $Y(N)$. The firm faces a labor supply curve that relates the wage paid, w, to the level of employment N, denoted as $N(w)$, with inverse function denoted by $w(N)$. The total labor costs can then be written as $w(N)N$. The firm optimally chooses the level of employment to minimize the total labor costs given the revenue-maximizing level of production.[9] The cost minimization problem can be written as:

$$\min\{w(N)N\}, \; s.t. \; Y(N) = \bar{Y},$$

with first-order condition:

$$w(N) + w'(N)N = Y'(N).$$

The wage elasticity of labor supply can be written as: $\varepsilon_{Nw} = wN'(w)/N(w)$. Rearranging the first-order condition, we arrive at the following key relationship:

$$\frac{\mathrm{MRP} - w}{w} = \frac{1}{\varepsilon_{Nw}} = \mathrm{E} \tag{1}$$

where MRP (marginal revenue product) is given by $Y'(N)$. Equation (1) shows that the proportional gap between the MRP and the wage is equal to the inverse of the wage elasticity of labor supply. This proportional gap is known in the literature as the "rate of exploitation" (Robinson 1933; Ashenfelter, Farber, and Ransom 2010). Note that in a perfectly competitive labor market, $\varepsilon_{Nw} \to \infty$, and thus $\mathrm{E} \to 0$. Thus, under perfect competition in the labor market, the exploitation rate is zero and the familiar equality of the wage to the MRP holds. A non-zero E implies a discrepancy between the wage and the MRP, that is, the power of the firm to set the wage below the MRP. As such, the rate of exploitation is a measure of monopsony power. Equation (1) also reveals the relationship between monopsony power (E) and the wage elasticity of labor supply (ε_{Nw}), pointing out a way to identify monopsony power through the estimation of the firm-level labor supply elasticity. In the following section, we describe an alternative approach to estimate the wage elasticity of labor supply to the individual firm.

2.2 The Dynamic Model of Monopsony

Moving to a dynamic model of monopsony allows us to motivate our empirical approach. Consider a firm with size at time t defined by its labor units, N_t. Assume that workers leave the firm over time at a rate $s(w_t)$, which is a decreasing function of the wage (w_t), and recruits arrive at the firm at a rate $R(w_t)$, which is an increasing function of the wage. The firm size in the next period $(t+1)$

[9] In our empirical setting, firms are public universities. In the context of non-profit-maximizing organizations, this optimization problem may be targeting other outcomes. For example, instead of maximizing revenue, the goal for universities may be to maximize the value of educational services or the research knowledge generated by faculty, subject to a budget constraint. Therefore, public universities face a similar resource allocation problem as private firms.

can then be written as:

$$N_{t+1} = [1 - s(w_t)]N_t + R(w_t). \tag{2}$$

In a steady state, the number of recruits should balance the number of separations, i.e.,

$$s(w)N(w) = R(w) \text{ , or equivalently, } N(w) = R(w)/s(w). \tag{3}$$

Equation (3) can be interpreted as the firm's long-run labor supply function in the steady-state equilibrium. Writing Equation (3) in terms of elasticities, we obtain the wage elasticity of labor supply as a function of the wage elasticities of separations and recruits:

$$\varepsilon_{Nw} = \varepsilon_{Rw} - \varepsilon_{sw}, \tag{4}$$

Equation (4) shows that the wage elasticity of labor supply (ε_{Nw}) can be obtained as the difference between the wage elasticity of recruits (ε_{Rw}) and the wage elasticity of separations (ε_{sw}). In practice, however, the wage elasticity of recruits is difficult to estimate since the typical data does not contain information about the wage offers made by the firm to recruits.

Manning (2003a) offered the insight that, under the assumption that the market is in a steady state equilibrium, one firm's recruits from other firms by offering higher wages should be another firm's quits. Thus, the wage elasticity of recruits equals the negative of the wage elasticity of separations, and the wage elasticity of labor supply to the firm becomes:[10]

$$\varepsilon_{Nw} = \varepsilon_{Rw} - \varepsilon_{sw} = -2\varepsilon_{sw}. \tag{5}$$

This relationship allows bypassing the difficulty of estimating the wage elasticity of recruits (ε_{Rw}), and the only object needed to estimate the wage elasticity of labor supply to the firm is the wage elasticity of separations.

Our estimation strategy relies on the steady-state assumption, as does the literature cited before that uses the separation-based approach. We argue that this assumption is likely to hold for occupations facing a "thin" labor market, such as university professors. Workers who have specialized skills valued by a smaller number of employers usually have fewer outside options (Caldwell and Danieli, forthcoming). The mobility of these workers tends to be largely within the industry. In the university faculty labor market, the probability of a faculty who moves to a university from another

[10] See Manning (2003a) for the formal derivation of this result.

university is very high. Indeed, in our sample, all faculty that joined the eight campuses in the UC system during our sample period moved from other universities, and over 90% of faculty that left the UC system during the same period moved to other universities.

One common concern is that the separation-based approach ignores the potential sensitivity to the wage of the separation and recruitment from non-employment. However, the proportion of separations to and recruitment from non-employment are low in the university faculty labor market. The separation rate to non-employment is about 0.36% in the sample.[11] Moreover, in academia, the recruitment of associate and full professors is almost exclusively from faculty who were already professors at other universities. For assistant professors, the vast majority of them are recruited as newly minted Ph.D. holders or junior researchers (post-doc/acting assistant professors), who can be considered as being employed by universities before moving to a tenure-ranked position. In our sample, none of the recruited assistant professors came from unemployment.

2.3 Monopsony and the Gender Pay Gap

The gender pay gap can be linked to the wage elasticity of labor supply to the firm and to monopsony power. To show this, we write Equation (1) separately for male (M) and female (F) workers, i.e.,

$$E_M = \frac{MRP_M - w_M}{w_M} = \frac{1}{\varepsilon^M_{Nw}};\ E_F = \frac{MRP_F - w_F}{w_F} = \frac{1}{\varepsilon^F_{Nw}}. \tag{6}$$

Rearranging Equation (6), we obtain:

$$w_M = \frac{MRP_M}{1+\frac{1}{\varepsilon^M_{Nw}}};\ w_F = \frac{MRP_F}{1+\frac{1}{\varepsilon^F_{Nw}}} \tag{7}$$

Plugging w_M and w_F of Equation (7) into the gender pay gap ratio $(w_M - w_F)/w_M$, we have:

$$\begin{aligned} \frac{w_F - w_M}{w_M} &= \frac{\eta_{FM}\cdot\psi_{FM} - 1 + \varepsilon^F_{Nw}(\eta_{FM}-1)}{1+\varepsilon^F_{Nw}} \\ &= \frac{\eta_{FM}\cdot(\psi_{FM}+\varepsilon^F_{Nw})}{1+\varepsilon^F_{Nw}} - 1 \\ \text{or,}\quad \frac{w_F}{w_M} &= \frac{\eta_{FM}\cdot(\psi_{FM}+\varepsilon^F_{Nw})}{1+\varepsilon^F_{Nw}} \end{aligned} \tag{8}$$

[11] Among 812 faculty members who quit the UC system, only 4 faculty became self-employed (according to announcements in their personal websites). Another 25 faculty members probably became non-employed, as we found no updates on their websites and no information on job network platforms, such as LinkedIn.

where $\eta_{FM} = MRP_F/MRP_M$ is the female-to-male ratio of the MRP, and $\psi_{FM} = \varepsilon^F_{Nw}/\varepsilon^M_{Nw}$ is the corresponding ratio of the wage elasticity of labor supply.

Note that the gender ratio of the labor supply elasticity can equivalently be expressed as the male-to-female ratio of exploitation rates, $\psi_{FM} = E_M/E_F$, reflecting the gender difference in exposure to monopsony power. In other words, Equation (8) shows that both the difference in the extent of exposure to monopsony power between males and females and the difference in productivity between genders contribute to the gender pay gap. When $\psi_{FM} = 1$, the gender pay gap is solely determined by the gender gap in productivity, η_{FM}. Any difference in the labor supply elasticity by gender (i.e., $\psi_{FM} \neq 1$) could result in the salary ratio diverging from the productivity ratio (η_{FM}).

We can obtain a simplified expression under the assumption that male and female workers have the same MRP (i.e., $\eta_{FM} = 1$), which is a common assumption in the literature (e.g., Ransom and Oaxaca 2010; Barth and Dale-Olsen 2009; Vick 2017):

$$\frac{w_F - w_M}{w_M} = \frac{\psi_{FM} - 1}{1 + \varepsilon^F_{Nw}}; \text{ or } \quad \frac{w_F}{w_M} = \frac{\psi_{FM} + \varepsilon^F_{Nw}}{1 + \varepsilon^F_{Nw}}. \tag{9}$$

In general, it is not feasible to empirically check whether $\eta_{FM} = 1$ since productivity is usually unobserved. In our setting, however, we have access to two indicators of research productivity. Under the assumptions that a central component of productivity of faculty at R1 universities is research productivity, and that the Scopus' publication metrics are a good approximation to faculty's research productivity, we can empirically assess whether $\eta_{FM} = 1$.[12] In Section 5, we employ this information to approximate η_{FM}, along with estimates of ψ_{FM}, to estimate the female-to-male salary ratio using Equation (8). Then, we analyze the extent to which exposure to monopsony power contributes to the observed gender pay gap by comparing the estimated gender salary ratio with the observed ratio.

[12] Using publication metrics as a measure of faculty productivity is far from perfect since it ignores teaching and service activities. Moreover, there is empirical evidence indicating that publication metrics may already reflect gender biases such as differential acknowledgement of contributions (e.g., Ross et al. (2022)). However, we think that our attempt to explicitly measure productivity, even partially, can help reduce biases in the estimation of the labor supply elasticity and generate useful information about the gender wage gap.

3 Data

To employ the separation-based approach and estimate the separation elasticity, we need faculty-level information on separations and wages (salaries) at the university campus level. Since both the separation decision and the wage are correlated with unobservable factors (e.g., ability), we also need exogenous variation in wages to deal with the resulting endogeneity. In this section, we describe the data sources and data construction process. We also discuss the determination and the components of faculty salaries in the UC system. Inspired by the compensation structure, we propose two instrumental variables for faculty salaries, which allow us to estimate the elasticity of separations—and thus the elasticity of labor supply—arguably free of endogeneity bias.

3.1 Data Sources

We link the publicly available faculty salary data with scraped public information on faculty's educational background, career trajectory, work experience, and publication metrics. First, to obtain data on faculty-level wages and separations, we retrieve salaries from 2010 through 2018 from an open-access employee pay dataset published by the University of California. To fulfill the requirement of FOIA and open government transparency, the University of California publishes the employee payroll data annually via an online website.[13] This payroll data set provides information on the annual compensation and the employee's full name, job title, and campus of employment. It allows us to track both the salary trend and the transition history for faculty members working in the UC system. In addition, to create covariates capturing faculty-specific confounding factors that affect both salaries and faculty's separation decisions, we search online for faculty members' department profiles and personal websites using key words including the faculty member's full name, job title, and affiliation. We scrape information on the faculty member's gender, department of employment (used to infer the field of specialization), educational background, and work history from their online profile and curriculum vitae. Moreover, leveraging the advantage that research productivity is a good proxy of faculty's research ability and can be quantitatively measured by

[13] Data Source: https://ucannualwage.ucop.edu/wage/. Data is available from 2010 onwards. We downloaded the payroll data from 2010 through 2018 on June 2nd, 2020.

publication statistics, we include controls for research productivity to reduce omitted variable bias. To do this, we collect data on research productivity by scraping publication metrics of each faculty member from Scopus.[14]

We employ two instruments for the faculty salary to deal with its endogeneity in the separation equation. One is the campus revenue, and the other is the UC salary scales. We retrieved annual school revenue data from fiscal year 2009-2010 to fiscal year 2017-2018 from the UC System Online Infocenter.[15] The information on UC's salary scales from academic year 2009-2010 to academic year 2017-2018 is extracted from the UCOP Human Resource website.[16] We justify our use of these two instruments below.

3.2 Data Construction and Variables

We restrict our sample to tenure-ranked faculty and exclude faculty who passed away, retired, or were fired during the sample period.[17] The final dataset contains 8,089 tenure-ranked faculty affiliated with eight R1 campuses in the UC system during 2010-2018. The coverage rate of our final sample is well above 91% of the corresponding official "employee headcount" available from the UC system. Details about the sample construction is provided in Online Appendix A.

We define a binary indicator, $Separation_i$, which equals one if faculty member i left his/her campus of employment during the sample period. Our faculty salary variable is denoted as $lnSalary_i$, which measures the logarithm of the average annual salary of faculty member i during his/her employment period at the UC-system campus from 2010 to 2018. Because of the discrepancy between the measurement scale of the salary data (which is measured at the calendar year) and the recruitment and compensation schedule in the UC system (which are typically based on the academic year), we observe considerable changes in the amount of annual salaries for the year when

[14]Data Source: https://www.scopus.com/home.uri.

[15]Data Source: https://www.universityofcalifornia.edu/about-us/information-center/revenue-and-expense-data.

[16]Data Source: https://www.ucop.edu/local-human-resources/your-career/compensation/salary-and-pay.html.

[17]Death, retirement, and layoff are regarded as "natural death" and "involuntarily" separations. Since faculty layoffs are usually a result of violations of law or university policy, such as involvement in a sexual harassment lawsuit, we identify them by checking university and local news. Retirements are confirmed by checking the department's website, such as looking for the "Emeritus" status. Deaths are verified by checking memorials, university news, and other online sources.

a faculty member is newly recruited to or separated from the university. In this case, simply taking average over all of the observed salary records in the sample likely introduces measurement errors to the salary variable. Because this measurement error often occurs in observations for faculty members who had been recruited to or separated from a UC-system campus, it is also highly correlated with the faculty member's separation behavior. Thus, the resulting measurement error in the salary variable would likely bias the estimation of the wage elasticity of separations. To handle this feature, we exclude the salary record for the year of separation/recruitment and only consider the salary records from years before the separation and/or after the recruitment when calculating the average annual salary rate for transitioning faculty members.

Faculty separations and salaries are simultaneously affected by various factors, including but not limited to experience, educational background, work history, and ability. To alleviate omitted variable bias, we create and include a rich set of covariates to control for these confounding factors. In particular, we create dummy variables for faculty characteristics, indicating the faculty member's gender, job title, field of specialization, and campus of employment. We also observe faculty's educational background, such as the year of graduation and the degree granting school(s). Based on this information, we create a discrete variable $Experience_i$ measuring the number of years since the faculty member graduated from the last degree. We include four additional indicators: $UGinUC_i$ and $PhDinUC_i$ are dummy variables indicating whether the faculty member is an undergraduate or graduate UC alumni, while $UGinForeign_i$ and $PhDinForeign_i$ indicate whether the faculty member obtained Bachelor's or Ph.D. degree from foreign institutions, respectively. From faculty's online profiles and curriculum vitae, we observe their work history, such as post-doctoral experiences, career trajectories, and service experiences. To control for confounders associated with post-doctoral experiences, we construct two discrete variables: $PostdocNum_i$ counts the number of institutions where the post-doctoral experience was gained and $PostdocYrs_i$ measure the total duration of the post-doctoral experience in years. We also create a binary indicator $EverAdmin_i$ to indicate whether the faculty member has ever taken administrative positions such as dean, provost, director, or chair of a department. Moreover, we measure research productivity by two publication metrics: the total number of citations and the H-index. H-index, proposed by Hirsch (2005), is a publication metric that measures the citation impact of the publications. It has been commonly used in academia as an indicator of the productivity of scholars. Variables $lnHindex_i$ and $lnCitation_i$ denote the logarithm of the H-index and the total number of citations, respectively.

Lastly, we create two instrumental variables (IVs) for faculty salaries. We use $lnRevenue_i$ and $lnScale_i$ to denote the campus revenue and the salary scales, respectively. For each faculty member, we calculate the logarithm of the average revenue received by the campus they work for and the logarithm of the average salary scale based on his/her title, field, and pay schedule over the years they have worked at the university. Similar to the construction of the faculty salary variable, we exclude the year(s) a faculty member moves to and/or leaves the university when calculating the campus revenue and the salary scales IVs. To do so, we first merge the faculty salary records to the university revenue data by year and campus, and merge the faculty salary records to the salary scales data by year, title, field, and pay schedule. Next, we calculate the campus revenue IV and the salary scales IV by taking the average of the campus revenue and salary scales over the years used in the calculation of the salary variable for a given faculty member, and then taking the logarithm. Since the university revenue data is reported by the fiscal year and the salary scales data is measured by the academic year, whereas the salary records are in calendar year, we match the calendar year with the "lagged" fiscal year and academic year. For example, data from fiscal year 2015-2016 and academic year 2015-2016 are matched to calendar year 2016. In essence, the campus revenue and the salary scales IVs capture the past level of campus revenue and salary scales specific to each faculty member during their tenure at the given UC-system campus.[18]

We present in Table 1 some descriptive statistics. The average annual salary of male faculty members is about 18% higher than that of female faculty members. The difference is statistically significant. It implies a female-to-male salary ratio of about 0.84.[19] The unconditional average separation rate is about 0.1 for both male and female faculty, implying a statistically insignificant gender difference.

We find statistically significant differences in indicators for educational background and work

[18] For more details on the data construction procedure, see Online Appendix A.

[19] Since $lnSalary_F - lnSalary_M \approx -0.18 = ln(Salary_F/Salary_M)$, we can recover the female-to-male salary ratio as $Salary_F/Salary_M = \exp(-0.18) = 0.84$.

experience between male and female faculty in our sample. Female professors are more likely to have graduated from a UC campus, with a 3.5 pp higher likelihood at the graduate level and a 2.1 pp higher probability at the undergraduate level. In addition, male professors have a 3.5 pp higher probability of receiving a Ph.D from a foreign institution and an 8.9 pp higher probability of receiving a bachelor's degree from a non-US college. On average, compared to females, male professors have 4.7 more years of experience since graduation and 0.27 more years of postdoctoral experience. They also have worked for 0.064 more institutions during their postdoctoral period. However, we do not see a statistically significant difference in the probability of taking an administrative position by gender. Moreover, we observe a considerable gender difference in faculty's research productivity, based on the publication metrics. Both the logarithm of the total number of citations and the logarithm of the H-index are found to be statistically higher for male relative to female faculty.

3.3 Structure of Compensation in the UC System as a Source of Exogenous Variation

Faculty compensation in the UC system is primarily determined by a range of salary scales that are evaluated annually and updated periodically.[20] The salary scales apply to the entire system; they are used by all UC campuses for the same categories of academic appointees. Salary scales vary across academic ranks and disciplines. For example, faculty members working in the Law schools and the Business schools use different salary scale tables. The salary scales for academic faculty can be classified into four field categories: General, Business/Economics/Engineering, Law, and Veterinary Medicine; and two pay schedule categories: Academic Year (9-months) and Fiscal Year (12-months). In addition to the system-wide salary scales, merit-based adjustment is another major factor determining faculty salaries. The amount of merit adjustment considers various aspects, including the faculty's performance and the availability of funds at the campus level.

The compensation structure in the UC system provides the basis for instrumental variables

[20]The UC system normally adjusts its salary scale annually. One exception occurred during the academic years of 2009-2010 to 2012-2013 when the salary scale adjusted every two years. More information can be found on UCOP Human Resources: https://www.ucop.edu/local-human-resources/your-career/compensation/salary-and-pay.html.

for the individual faculty's salary. First, because the availability of funds plays a role on the merit-based adjustment of salaries, changes in the campuses' revenue can affect faculty salaries.[21] Short-term variations in the campus revenue are unlikely to be correlated with factors that affect the separation decision of individual faculty members. Panel (a) in Figure 1 shows the logarithm of campus revenue for the UC campuses from the fiscal year 2008-2009 through fiscal year 2017-2018. Overall, we observe a gradual increase in the campus revenue of the eight UC campuses from 2008 through 2018, with variations in the rate of change among the campuses. Panel (b) in Figure 1 plots the correlation between the campus average logarithm of faculty salaries against the logarithm of campus revenue for each campus from 2010 to 2018.[22] There is a strong positive relationship between the campus revenue and the campus average faculty salary, suggesting that the campus revenue is a plausible candidate to be used as instrumental variable for individual faculty salaries.

Second, according to the UC system's faculty compensation policy: "The[se] salary scales are published by Academic Personnel (AP) at UCOP, and include minimum salary for 20 "steps" of faculty achievement (Assistant Professor I-VI, Associate Professor I-V, and Professor I-IX).." (UCOP Academic Personnel).[23] This implies that the corresponding salary scales provide a reference salary for individual faculty. Figure 2 shows an example of the salary scales from the academic year 2017-2018 for ladder-ranked faculty who work in Business/Economics/Engineering and whose salaries are paid by academic year (9-months). The salary scales not only vary across job title (i.e., ladder rank), but also vary within the job title. For example, there are six steps within the Assistant Professor title, and in the academic year 2016-2017, the annual salary scales ranged from \$80,300 in Step I to \$100,900 in Step VI.[24] Figure 3 shows the correlation between the salary scales and individual faculty salaries. Panel (a) plots individual faculty salaries against year, from AY2009-2010 through AY2017-2018 for faculty members who work in Business/Economics/Engineering

[21] Sources of campus revenue includes private gifts, state educational appropriations, auxiliary enterprises, and student tuition and fees.

[22] We match the campus revenue in fiscal year 2009-2010 to calendar year 2010, and thus it can be considered the one-year lagged campus revenue. In other words, the campus revenue in fiscal year 2009-2010 is paired with the average salary in calendar year 2010.

[23] See the UC Academic Personnel and Programs https://www.ucop.edu/academic-personnel-programs/compensation/index.html and https://www.ucop.edu/academic-personnel-programs/_files/uc-faculty-comp-summary-jun-2014.pdf

[24] Such wide range in salary scales, across and within the job title provides campuses with flexibility in the salary bargaining process with individual faculty. Note that the specific "step" an individual belongs to is endogenous. For this reason, we employ the mean salary scale over all steps within a rank as the instrument, as explained below.

and are paid by academic year.[25] We plot salaries and salary scales for each ladder rank (job title) separately and mark the salary scale of the highest step, lowest step, and the mean scale by title with square, diamond, and circle symbols, respectively. Panel (a) illustrates that all salaries are tightly bounded from below by the scale of the lowest step within a given title. For assistant and associate professors, their salaries are typically above the mean salary scale. Although about 30% of salaries fall within the range between scales of the lowest step and the highest step, we also observe a share of salaries that exceed the scale of the highest step. Put together, we find that UC's salary scales provide a system-wide baseline salary standard for faculty members in the UC system.

In Panel (b), we present the correlation between the mean salary scales and individual faculty salaries for each title. Similar to Panel (a), we display the correlation using the example of faculty members who work in Business/Economics/Engineering and are paid by academic year. We observe a strong positive relationship between the mean salary scales and individual faculty salaries. The short-term variation in the salary scales are primarily affected by shocks to the overall university faculty labor market and/or changes at comparable universities, and thus can be viewed as exogenous to the individual faculty salary.[26] We thus use the mean salary scale as the second instrumental variable for individual faculty salaries.[27] Note that the campus revenue instrument lacks variation across fields and rank within campus, while the salary scales instrument lacks variation across campuses. Therefore, in our analysis, we employ the two instruments together to span the largest amount of variability.

[25] Similar to campus revenue, the salary scales are also half-year lagged. Specifically, for example, we match the salary scales in the academic year 2017-2018 with the calendar year 2018.

[26] According to UCOP HR, "salary scales are determined according to the comparison of the university's internal evaluation and external salary data gathered and updated through industry-specific surveys of companies and universities with similar pay programs and practices."

[27] The exact amount of compensation received by faculty depends on which step s/he belongs to. Unfortunately, we do not observe the exact step to which a faculty member is assigned in the employee pay data. Moreover, the determination of the step a faculty member belongs to depends on peer-reviewed job evaluations and the number of years the faculty member has been in a given step, which is likely correlated with faculty's unobserved factors. If it is the case, then it gives us another reason to use the mean salary scale, which captures the exogenous variation of the salary scales in general, instead of the specific scale of each step.

4 Analysis of Monopsony Power in the UC System

We begin by presenting estimates from ordinary least squares (OLS) and discuss the problem of omitted variable bias that likely renders these estimates biased. Then, we use the instrumental variables motivated in Section 3.3 in a two-stage least squares (2SLS) framework to handle the likely endogeneity of individual-level faculty salaries. Subsequently, we explore the heterogeneity in the labor supply elasticity and the rate of exploitation across faculty groups and campuses.

4.1 OLS

Consider a linear probability model where the separation indicator ($Separation_i$) is linearly related to the faculty member's salary ($lnSalary_i$):

$$Separation_i = \alpha_0 + \alpha_1 \ln Salary_i + \delta \mathbf{X}_i + u_i \tag{10}$$

where $\mathbf{X}_i$ is a vector of control variables, u_i is the error term, δ is a vector of coefficients, and α_1 is the coefficient of interest. $\mathbf{X}_i$ controls confounding factors that are correlated with both individual faculty salaries and faculty's separation decisions. Specifically, $\mathbf{X}_i$ consists of a gender dummy, polynomials of the $Experience_i$ variable (up to cubic), and covariates capturing faculty's educational background, work history, and research productivity, as detailed in Section 3.2. Following the literature (Ransom and Sims 2010, among others), we calculate the wage elasticity of separations, $\hat{\varepsilon}_{sw}$, by dividing the estimated salary coefficient, $\hat{\alpha}_1$, by the mean separation rate $\bar{s}$. The wage elasticity of labor supply is then estimated by multiplying the estimated wage elasticity of separations $\hat{\varepsilon}_{sw}$ by -2, following Equation (5). We also obtain an estimate of the rate of exploitation, a measure of monopsony power, by calculating the inverse of the estimated wage elasticity of labor supply, following Equation (1). Standard errors of these estimates are obtained by bootstrapping.

We present OLS estimates in Table 2. Column (1) shows estimates from a baseline model controlling for gender, polynomials of experience, educational background, and work history. Columns (2) - (5) subsequently add covariates of job title, the campus of employment, field of specialization, and research productivity. As shown in Column (5), where the model includes the full set of controls, the wage elasticity of separation is estimated at -1.57, implying a wage elasticity of labor supply of 3.14 ($= -1.57 \times (-2)$). The corresponding estimate of the rate of exploitation is 31.9% ($= 1 \div 3.14$). This estimate implies that, on average, faculty are paid about 31.9% less than their MRP.

Since the construction of the faculty salary variable $lnSalary_i$ relies on the number of years the faculty member has worked at the campus, and because the length of employment observed for each faculty member in the sample varies depending on when they entered or exited the payroll dataset, we experiment with weighting the regression based on the number of years that each faculty member has been observed in the sample. Column (6) in Table 2 presents OLS results from this weighted regression. After adding weights, the estimated wage elasticity of separations is reduced to -0.9, implying a higher rate of exploitation of 55.8%.

We expect the OLS estimates of $\hat{\alpha}_1$ and $\hat{\varepsilon}_{sw}$ to be biased due to unobserved factors that are simultaneously correlated with the separation decision and the individual faculty salary. For example, faculty members' unobserved ability is likely to be positively correlated with both salary and the separation decision: more able faculty likely earn higher salaries and are also more likely to move. In the absence of proper controls for those unobserved factors, the OLS estimates would likely overestimate the salary coefficient (α_1). Assuming that the unobserved factors are positively correlated with both the salary and the separation decision, and holding constant the mean separation rate ($\bar{s}$), the overestimation of α_1 results in an underestimated wage elasticity of labor supply and an overestimated rate of exploitation (the degree of monopsonistic power).[28] For this reason, in the next section we bring in instrumental variables to deal with this endogeneity problem.

4.2 2SLS

We now estimate Equation (10) by 2SLS instrumenting for the faculty salary (*lnSalary*). We use the two instrumental variables motivated in Section 3.3: the campus revenue and the salary scale.

[28]The reasoning is as follows. Let $\hat{\alpha}_1 = \alpha_1 + bias$. Because α_1 is negative, a positive bias in $\hat{\alpha}_1$ suggests a larger α_1 in absolute value. To obtain the wage elasticity of labor supply, we multiply the wage elasticity of separations by -2, and thus the sign of the labor supply elasticity becomes positive. Since $\hat{\alpha}_1$ has a smaller absolute value than α_1, $\hat{\varepsilon}_{Nw} = \hat{\alpha}_1 \times (-2) < \alpha_1 \times (-2) = \varepsilon_{Nw}$. Therefore, the OLS estimate tends to underestimate the wage elasticity of labor supply. Because the wage elasticity of labor supply enters into the function of the exploitation rate in the denominator: $\mathrm{E} = 1/\varepsilon_{Nw}$, underestimating the labor supply elasticity would overestimate the exploitation rate.

The 2SLS estimates using the tenure-ranked sample are summarized in Table 3. First-stage results (regressing the faculty salary on the two instruments and corresponding controls) and F statistics are shown in Panel A. Panel B presents the second-stage estimates of the salary coefficient, the wage elasticity of separations, and the rate of exploitation.

Panel A suggests that both the campus revenue and the salary scales are positively correlated with individual faculty salaries. For example, Column (2) implies that a 1% increase in the campus revenue is associated with a 0.66% increase in the faculty salary, while a 1% increase in the salary scales is associated with a 0.98% increase in the faculty salary. The first-stage estimates are statistically different from zero at the 1% significance level and the corresponding first-stage F statistics are sizable, strongly suggesting no evidence of the weak instrumental variable concern.

Column (1) in Panel B reports the second-stage estimates using the baseline model, which imply an estimated wage elasticity of separation of -2.2 and an estimated rate of exploitation of 22.4%. These estimates change considerably after conditioning on title, field, campus, and research productivity, underscoring the importance of controlling for these factors. As shown in Column (2), the estimated wage elasticity of separation increases to -7.6, implying an estimated rate of exploitation of 6.6%. Notably, weighting the regression by the length of years working at the campus does not substantially change the estimates. As shown in Column (3), the estimated rate of exploitation remains close to 7% (7.4%). Overall, the magnitude of the estimated wage elasticity of labor supply from 2SLS is substantially larger than that from OLS, resulting in a substantially smaller estimate of the exploitation rate. The observed direction of the bias is consistent with our prior that the OLS estimates are biased and tend to overestimate the rate of exploitation.

We investigate the heterogeneity in the rate of exploitation across different types of faculty. First, we consider faculty members with different tenure status: non-tenured professors (i.e., assistant professors) and tenured professors (i.e., associate and full professors). In principle, the wage elasticity of separation, and hence the elasticity of labor supply, of tenured faculty members could differ from that of non-tenured faculty members, as those who have already been granted tenure may behave differently when making their separation decisions compared to those who are still pursuing tenure. For example, non-tenured faculty may place a higher weight on attaining tenure when deciding whether to separate from their current employer, while tenured faculty may be more influenced by other factors such as compensation, benefits, and location. As a result, universities' ability to exercise monopsony power could vary across faculty members with different tenure status.

We re-estimate the 2SLS model separately for non-tenured and tenured faculty members. To control for title-specific factors that are correlated with separation, we include a title dummy in the model when pooling associate and full professors. Columns (1) and (2) of Table 4 report the results of this exercise, using the specification that includes all of our control variables but does not weight the regression by the length of years working at the campus. We find that the estimated exploitation rate slightly varies across faculty members with different tenure statuses. Specifically, the estimated rate of exploitation is 8.5% for non-tenured professors and 7.5% for tenured professors. Each of these estimates are statistically different from zero at the 1% significance level. Nonetheless, the difference in estimates between the two faculty groups is not statistically significant. The p-value of the test for the null hypothesis that the estimated exploitation rates are the same for non-tenured and tenured faculty is 0.39. These findings are in contrast to those in Goolsbee and Syverson (2023), which suggest that tenured faculty, especially full professors, are exposed to a higher rate of monopsony power. However, we need to be cautious when comparing our results with Goolsbee and Syverson (2023)'s because both the data and the estimation strategy used in the two studies are different. They employ university-level data, lack many of the control variables we employ, and use college applications as an instrumental variable. At the same time, they focus on a broader sample of U.S. educational institutions.

Next, we explore whether the degree of exposure to monopsony power differs between U.S.-born faculty and foreign-born faculty, as proxied by the country where the faculty member obtained its undergraduate degree.[29] If the wage elasticity of labor supply varies across U.S.-born and foreign-born faculty, they would experience different degrees of monopsony power. On the one hand, the labor supply of foreign-born faculty members may be less responsive to changes in compensation because the cost of separations may be comparably higher for them than for their

[29] Since we do not directly observe the citizenship of faculty members from our data, we use the country where faculty members received their undergraduate degree as a proxy. In other words, faculty members who graduated from a non-US college are classified as foreign-born.

U.S.-born counterparts. For example, foreign-born faculty members who wish to work legally in the United States must obtain a work visa (H1-B), which is tied to their employer. If they switch employers, they must transfer their visa, a process that can be time-consuming and financially costly for the university sponsoring them. This type of barriers increases the cost of separations for foreign-born faculty members, but does not affect U.S.-born faculty. On the other hand, the labor supply of foreign-born faculty members could be more elastic due to migration selection: there may exist unobserved attributes of foreign-born faculty members who choose to work outside of their home countries that also affect their wage elasticity of labor supply. For example, foreign-born faculty may be more ambitious and more willing to switch jobs in exchange for higher compensation relative to U.S.-born faculty.

To investigate this question, we apply our 2SLS model separately to the U.S.-born and foreign-born faculty groups. The model includes a full set of control variables, without weights, and the results are in Columns (3) and (4) of Table 4. The results show a small difference in the estimated exploitation rate between the U.S.-born and foreign-born faculty, on average. The exploitation rate is estimated at 6.4% for U.S.-born faculty and slightly higher at 6.8% for foreign-born faculty. This difference is not statistically different from zero at conventional levels (p-value = 0.49).

Lastly, we explore the heterogeneity in monopsony power across UC campuses. To do this, we re-estimate the 2SLS model separately for each campus in the UC system, using the model that includes the full set of control variables but without weights. We show in Figure 4 the estimated wage elasticity of separations (top panel) and the implied exploitation rate (bottom panel) by campus. We find that, for most campuses, the estimated exploitation rate is about 5%. However, the exploitation rate is found to be higher in UC-Irvine (10%), UC Berkeley (10%), and UCLA (8%), indicating stronger monopsony power in these schools. The difference in monopsony power between these three campuses (Irvine, Berkeley, and Los Angeles) and the rest of the campuses is statistically significant. It is interesting to note that these three UC campuses are located at or near large commuting zones (Los Angeles or San Francisco).[30]

[30]The finding for UC-Irvine is also consistent with the unique housing subsidy offered by this campus, which likely results in less faculty mobility.

4.3 Robustness Exercises

In this section, we address additional considerations related to the estimation of monopsony power in our setting, and show that the previous results are robust over various alternative specifications. The first consideration is that faculty's separation decisions can be affected by factors other than compensation. Leading factors are: (1) non-tenured professors may have to leave the university if they fail to obtain tenure at their place of employment. (2) The departure of foreign faculty to their country of origin: there is a considerable proportion of faculty at UC campuses that are foreign-born, and it is likely that some of them move to foreign universities for personal reasons, such as returning to their country or to be closer to family. Lastly, (3) retirement can also lead faculty to separate from universities. These separations do not necessarily respond to variations in salary, and thus including them may introduce bias into the estimation of the wage elasticity of separations. Unfortunately, the causes of faculty separations are unobserved in our data. However, we do observe where faculty relocated to and the year they obtained their degree, and thus we use that information to flag separations that are potentially associated with non-monetary factors. Our assessment then consists of estimating monopsony power in sub-samples in which we exclude separations that could be motivated by considerations other than salary.

Table 5 shows descriptive statistics of the separation destinations in our data, by gender and across different faculty groups. The first column in the table shows the number of separations observed. We classify the destination into two major categories: academia and industry. Column (2) shows the proportion of separations to academia, defined by separations to universities and their affiliated research institutions.[31] The vast majority of transitions occur to other academic institutions. Columns (3) to (6) further break up the academia category into domestic and foreign institutions, while the domestic institutions are categorized into R1, R2, and Non-R1/R2 universities following the Carnegie Classification of Institutions of Higher Education.[32] Columns (4) and (5) in Table 5 show that, on average, 12% of male faculty who quit and stay in academia moved out of

[31] Research institutions that are not affiliated with universities, or funded by government or private organizations, are counted as industry.

[32] More specifically, the classification of research universities is based on the 2010 Carnegie Classification of Institutions of Higher Education (https://carnegieclassifications.iu.edu/classification_descriptions/basic.php). Universities which are not R1 or R2 research University are classified as Non-R1/R2 universities.

R1 (domestic) universities (i.e., moved to R2 research — 6% and Non-R1/R2 universities — 6%). This number is 14% (5% to R2 research and 9% to Non-R1/R2 others) for female faculty, who are more likely than males to transition to Non-R1/R2 universities. The share of separations out of R1 universities is significantly higher for non-tenured professors, in line with potential tenure-denials: 19% for males and 22% for females. Moreover, we observe a substantial share of separations to foreign universities, particularly among foreign-born faculty members. Among male faculty who quit and remain in academia, 26% of them transition to foreign universities. For U.S.-born males, 18% of transitions are to foreign universities. In contrast, the corresponding figure for foreign-born males is over twice as high, at 42%. This type of transition is much lower among female faculty, with 10% of them moving to foreign universities. Similar to their male counterparts, the percentage is much higher for foreign-born females (23%) compared to U.S.-born females (5%).

Based on the previous information on separation destinations, we construct three sub-samples to gauge the robustness of our previous results. The first sub-sample excludes assistant professors who move out of R1 universities. We presume that moving out of R1 universities (to R2 or Non-R1/R2 universities) can be viewed as a rough indicator of tenure denial. In addition to excluding assistant professors who move out of R1 universities, sub-sample 2 further excludes foreign-born faculty members at all ranks (assistant, associate, and full professors) who transition to foreign universities. Such transitions may be due to personal or family issues that are unrelated to compensation. Sub-sample 3 further excludes potential separations due to retirement reasons from sub-sample 2. To this end, since the age of faculty is not observed in our data, we use years since doctoral graduation and remove faculty who obtained their doctoral degree more than 35 years ago. Columns (1) to (3) in Table 6 re-estimate the 2SLS models using these sub-samples. The upshot is that we obtain very similar estimates as those presented in Table 3 for the entire tenure-ranked sample: the estimate of the exploitation rate hovers around 6-7% and is not statistically different from those estimated by the model with the full set of controls (Columns (2) and (3) of Table 3). Thus, to the extent that these sub-samples capture factors for separation other than salary compensation, we conclude that those factors do not have a large impact on our baseline estimates of monopsony power.

Another potential concern is that we may introduce measurement error into the faculty salary variable in the way we constructed it. As discussed in Section 3.2, this variable is an average of the faculty member's salary over the years s/he is observed employed with a campus during our sample period. To assess whether the main results are sensitive to this construction of the mean salary variable, we first consider a sub-sample (sub-sample 4) which excludes faculty that are observed employed in the campus for less than three years. The reason is that a potential measurement error problem is most likely to occur in the mean salary variable for faculty members who are observed for less than three years at the campus in our data (see also the more detailed discussion about the construction of this variable provided in Appendix A). The estimates using this sub-sample, presented in Column (4) of Table 6, show that the rate of exploitation is again estimated around 7% (7.1%), essentially the same as that estimated using the entire tenure-ranked faculty sample.

Finally, Columns (5) and (6) of Table 6 consider alternative ways of constructing the mean salary variable. In Column (5), the mean salary for each faculty member is calculated using the gross pay records in the latest three years, as opposed to all the years available for that faculty member. In Column (6), the mean salary variable is calculated using the gross pay records in the latest five years, instead of using all available years for that faculty member.[33] The estimates reported in Columns (5) and (6) of Table 6 show that the rate of exploitation in these two alternative ways of constructing the mean salary measure is about 6%, which is very close to and not statistically different from the 6.6% using the original mean salary variable. Thus, we conclude that our estimates of the exploitation rate are robust to different construction measures of the faculty member's salary.

5 Monopsony Power and the Gender Pay Gap

5.1 Gender Differences in Exposure to Monopsony Power

Given the evidence of monopsony power in the eight UC-system campuses documented in the previous section, we explore whether the degree of exposure to this monopsony power differs by gender. To do this, we estimate Equation (10) separately for male and female faculty, employing

[33] If the faculty member left the school during the sample period, we use the gross pay records in three/five years before the separation.

the same instrumental variables. The estimated wage elasticity of separations for male and female faculty, ε_{sw}^{M} and ε_{sw}^{F}, are then computed by dividing the estimated salary coefficients, $\hat{\alpha}_1^M$ and $\hat{\alpha}_1^F$, by the mean separation rate of the corresponding sample, $\bar{s}^M$ and $\bar{s}^F$. Next, we separately estimate the wage elasticity of labor supply and the exploitation rate for each gender group, adopting the same procedures as in Section 4.2. The estimates employing the model specification with the full set of controls (and no weights) are reported in Table 7.

The first column in Table 7 presents the results for the entire tenure-ranked faculty, by gender. As shown in Panel A, the statistically significant first-stage estimates and the large first-stage F statistics indicate that the instrumental variables remain strong. The second-stage estimation in Panel B shows that the wage elasticity of separations is estimated at -8.26 for males and -6.75 for females, implying a rate of exploitation of 6.1% for male and 7.4% for female faculty members—a 1.3 pp difference. Even though the magnitude of the estimated exploitation rates for male and female faculty members is similar to that in the pooled sample, their difference is statistically significant (p-value $= 0.038$).

Next, we examine gender differences in exposure to monopsony power across different types of faculty. First, we re-estimate the models separately for male and female faculty by different tenure status groups. Columns (2) and (3) in Table 7 summarize the results for non-tenured and tenured faculty, respectively. Similar to the first-stage result from the entire sample of tenure-ranked faculty, results in Panel A show strong correlation between our instrumental variables and the faculty salary variable. We do not find evidence of weak instrumental variables, although the F statistics are not as large as before, probably due to the smaller sample sizes.

The second-stage results, reported in Panel B of Column (2), suggest that the wage elasticity of separations is estimated at -5.99 for male faculty and -5.93 for female faculty, with the corresponding exploitation rate estimated at around 8.4% for both female and male assistant professors. We do not find a statistically significant difference between the exploitation rate estimates for male and female non-tenured professors (p-value $= 0.95$), implying a lack of gender difference in exposure to monopsony power. Results in Panel B of Column (3) show that, for tenured professors, the estimates of the rate of exploitation are 6.8% for males and 8.3% for females. However, while the estimates suggest that female tenured professors bear a higher degree of monopsony power than their male counterparts, this difference is not statistically different from zero at conventional significance levels (p-value of 0.26).

The largest difference in the estimated exploitation rate between males and females is found among U.S.-born faculty members. As shown in Column (4), we find that for U.S.-born faculty the estimated exploitation rate of females is 7.5%, almost 2 pp higher than that of males (5.6%). This difference is statistically significant at the 1% level. Comparing to the corresponding results for foreign-born faculty members, as shown in Column (5), there is no statistically significant difference in the monopsony power experienced by foreign-born male and female faculty members. Their estimated rate of exploitation is 6.8% for both groups.

In sum, our results suggest that female faculty members in the UC system experience a higher level of monopsony power of almost 20% (1.3 pp ÷ 6.8%) relative to males. This difference is driven by U.S.-born faculty members, among whom females experience about a 34% (1.9 pp ÷ 5.6%) higher level of monopsony power. Based on this evidence, we next investigate the extent to which differential monopsony power explains the gender pay gap in the UC system.

5.2 Linking Monopsony Power and Observed Research Productivity to the Observed Gender Pay Gap

As shown in Section 2.3, the female-to-male salary ratio can be written as a function of the gender ratios of the MRP (productivity) and the labor supply elasticity (exposure to monopsony power). To examine the contribution of those two factors to the gender pay gap, we estimate the female-to-male salary ratio (the gender pay gap) in Equation (9) using the estimated labor supply elasticities for the faculty samples shown in Table 7. These estimates are summarized in Table 8.

Panel A reports, for reference, the observed gender pay gap. Overall, female faculty earn 16.3% less than males. The corresponding observed gender pay gap is 9.1% for non-tenured faculty, 16% for tenured faculty and U.S.-born faculty, and 17% for foreign-born faculty. Panel B summarizes the labor supply elasticities for males and females and the corresponding estimated gender ratios ($\hat{\psi}_{FM} = \hat{\varepsilon}_F / \hat{\varepsilon}_M$). The female to male ratio of the elasticity of labor supply is estimated at 0.817 for the entire tenure-ranked faculty sample. For non-tenured professors and foreign-born, the estimates are very close to 1 (0.989 and 1.000, respectively), while it is estimated at 0.823 for tenured professors and at 0.745 for U.S.-born faculty.

We next estimate the gender pay gap ratio under the assumption that male and female professors share the same MRP, that is, we fix $\eta_{FM} = 1$ as in Equation (9) and plug in the estimated labor supply elasticities. This is a common assumption in the empirical literature on monopsony power (e.g., Ransom and Sims 2010; Ransom and Oaxaca 2010; Barth and Dale-Olsen 2009; Vick 2017). As shown in Panel C of Table 8, the gender pay gap ratio is estimated at -0.013 for the entire tenure-ranked faculty sample and is statistically different from zero at the 5% level. This implies that, under the equal-productivity assumption, if the UC system took full advantage in its monopsony power across gender, this will lead to 1.3% lower salaries paid to female faculty. Similarly, given the statistically significant corresponding estimate of the gender pay gap ratio for U.S.-born faculty in Column (4) of -0.018, it would lead to a lower salary of about 1.8% for females. For non-tenured and foreign-born faculty, the gender pay gap ratio is estimated to be essentially zero, while it is estimated at -0.014 for tenured faculty and it is not statistically different from zero. The last row in Panel C compares the estimated gender pay gap ratio with the observed gender pay gap in Panel A, thereby inferring the extent to which monopsony power contributes to the gender pay gap in this case. Overall, the differential exposure to monopsony power can explain about 8% $(-0.013/-0.163)$ of the observed gender pay gap. This rate is 12% for U.S.-born faculty.

It is interesting to briefly compare the previous estimates of the contribution of differential exposure to monopsony power to the observed gender gap under the equal-productivity assumption with prior studies. Both Ransom and Oaxaca (2010) and Ransom and Sims (2010) relate their findings to the gender wage gap in the context of grocery store workers and school teachers, respectively, finding that their predicted gender wage gaps can almost fully explain the observed gender pay gap. In contrast, we find that in the UC system, despite the existence of a statistically significant gender differential exposure to monopsony power, it accounts only for about 8-12% of the observed gender wage gap. We conjecture that the disparate conclusion is accounted for by a combination of the level of skill in the different occupations examined and the institutional setting such as the salience of pay transparency laws and the public salary scales.

Next, we relax the equal-productivity assumption between female and male faculty—something not commonly done in the literature—by bringing to bear our information on the observed research productivity. We use that information to estimate the gender ratio of the MRP (η_{FM}) to integrate it into the estimation of the salary gender gap in Equation (8). Thus, we replace the equal-productivity assumption by replacing it with the assumption that research productivity captures the relevant productivity dimension for compensation of faculty at R1 campuses in the UC system. To incorporate our two publication metrics (the H-index and the total number of citations) simultaneously, we begin by calculating the first principal component of these metrics, which we denote by PC. This first principal component explains 98% of the variation in the two publication metrics. Then, to obtain an estimate of the observed research productivity difference ($\hat{\eta}_{FM}$), we use the estimated first principal component of publication metrics (PC) as the dependent variable in a linear regression with a gender indicator and a full set of controls for educational background, work history, job title, field of specialization, and campus of employment as independent variables:

$$\mathrm{PC}_i = \beta_0 + \beta_1 female_i + \gamma \mathbf{X}_i + \varepsilon_i.$$

Since $\beta_1 = PC_F - PC_M = ln(PC_F/PC_M)$, we can calculate the observed research productivity difference ($\hat{\eta}_{FM}$) by $\exp(\hat{\beta}_1)$.

Table 9 presents the estimates from the previous linear model for the different samples. The estimated coefficient of the gender indicator is -0.168 using the entire faculty sample (Column 1), suggesting that, on average, the research productivity (as measured by PC) of female faculty is about 16.8% lower than that of male faculty. The corresponding observed research productivity difference ($\hat{\eta}_{FM}$) is estimated at 0.845. Similarly, we estimate $\hat{\eta}_{FM} = 0.881$ for non-tenured faculty (Column 2), 0.84 for tenured faculty (Column 3), 0.83 for U.S.-born faculty (Column 4), and 0.89 for foreign-born faculty (Column 5). The estimates of observed research productivity difference across samples are statistically equal to each other.

We plug in the observed research productivity difference into Equation (8) to estimate the gender pay gap ratio in two separate exercises. Our first exercise blocks the contribution of the differential exposure to monopsony power by setting $\psi_{FM} = 1$, thereby isolating the impact of the observed research productivity. This assumption could be considered appropriate for the sub-samples in which we do not find a statistically significant gender difference in monopsony exposure. The corresponding results are presented in Panel D of Table 8. All the estimates of the gender pay gap ratio are statistically different from zero. Column (1) shows that, under the equal exposure to monopsony power assumption, the estimated gender pay gap ratio is 15.5% for the entire tenure-ranked faculty sample, suggesting that the difference in the observed research productivity explains about 95% ($-0.155/-0.163$) of the observed gender pay gap. Results in Columns (2)-(5) show a similar pattern: the gender difference in the observed research productivity is estimated to explain about 130% of the observed pay gap for non-tenured faculty, 100% for tenured faculty, 108% for U.S.-born faculty, and 67% for foreign-born faculty. Estimates that explain over 100% of the observed gender pay gap imply that the estimated gender pay gap is greater than the observed gender pay gap. We discuss this aspect at the end of this section. Importantly, we hesitate to interpret the results as suggesting that females are paid less because they are less productive than their male counterparts, given the emerging evidence that the research productivity indicators we employ may be gender-biased. For instance, Ross et al. (2022) find that female researchers in science receive fewer authorship credits and recognition relative to males, while Hengel (2022) finds that females are held to higher standards in top academic journals in economics.

Our second exercise considers the impact of the gender difference in both the observed research productivity and exposure to monopsony power by plugging in estimates of both $\hat{\eta}_{FM}$ and $\hat{\psi}_{FM}$ into Equation (8). We report the corresponding estimates of the gender pay gap ratio in Panel E of Table 8. All estimates across the samples are statistically significant. Column (1) shows that for the entire tenure-ranked faculty sample, the estimated gender pay gap ratio changes from 15.5% in Panel D to 16.5% in Panel E, becoming closer to the observed pay gap of 16.3% in Panel A. As expected given the results in Panel C for non-tenured (Column 2) and foreign-born (Column 5) faculty, the estimates in Panels D and E for these samples are virtually identical. The gender pay gap is estimated at 17% for tenured faculty (Column 3 in Panel E) which is slightly above the observed gap (16%); and it is estimated at 18% for U.S.-born faculty (Column 4) which is almost 3 pp higher than the observed gap.

As noted before, some of the estimated-to-observed gender pay gap ratios in Panels D and E are greater than 100%, implying that the estimated gender pay gap is larger than the observed one. This is not an uncommon finding in the literature (e.g., Ransom and Sims (2010), Ransom and Oaxaca (2010), and Vick (2017)). We conjecture that there are several possible factors contributing to this pattern in our study. First, our estimate of η_{FM} solely reflects the gender difference in faculty's observed research productivity. It could be that our measures do not capture unobserved research productivity aspects that differ by gender. Second, ideally, η_{FM} should also capture faculty's productivity in teaching and service, as they are relevant components of the role of university faculty at R1 universities. However, we do not observe faculty's teaching and service productivity, which can bias our estimation of the gender pay gap ratio in Panels D and E. For example, if female faculty are more productive in teaching, then our MRP measure would tend to underestimate $\hat{\eta}_{FM}$, and thus overestimate the pay gap.

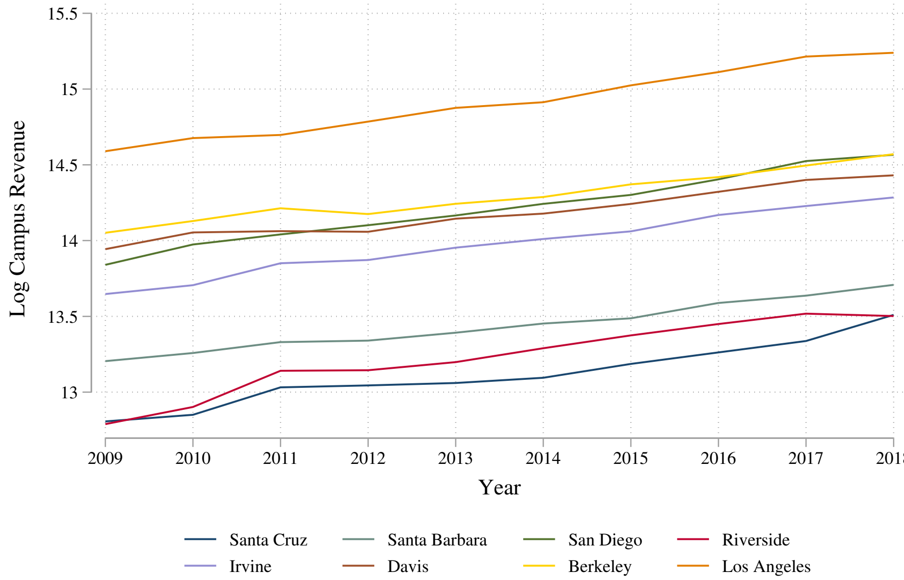
Other factors related to the institutions and environment in which employers operate can prevent employers from fully leveraging their potential monopsony power, thereby resulting in an estimated gender pay gap that is larger than the observed pay gap (e.g., Ransom and Sims (2010), Ransom and Oaxaca (2010), and Vick (2017)). For example, employees' efforts to enhance their bargaining power in salary negotiation by, e.g., forming pay equity committees, could restrict employers' ability to fully capitalize on their potential monopsony power. Indeed, the existence of salary scales in the UC system is an institutional feature that could hamper the exercising of monopsony power. Another possibility is the existence of salary transparency in the UC system, which has been found to reduce the gender pay gap (e.g., Baker et al. 2023).

6 Conclusion

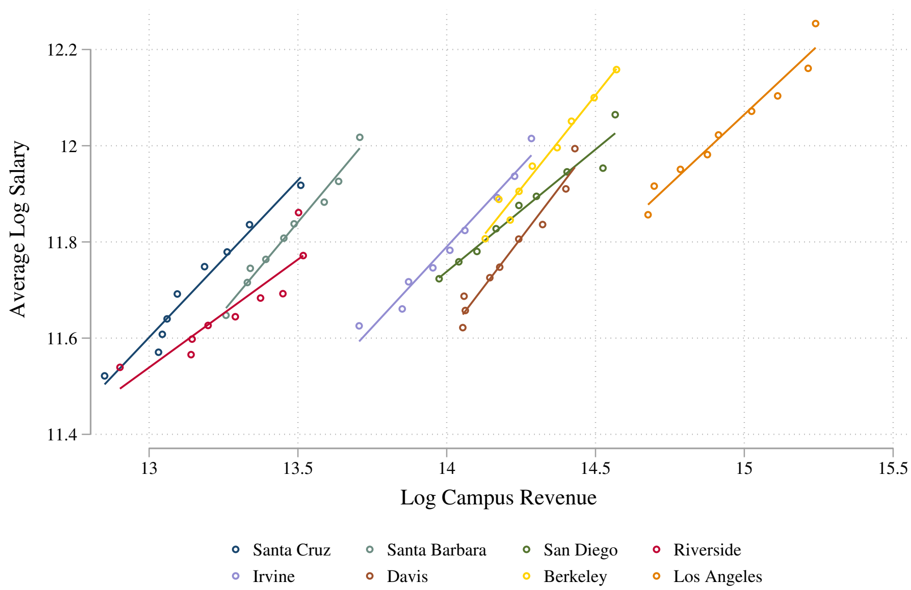
We provide evidence of monopsony in academia using faculty salary data from eight R1 research campuses in the University of California (UC) system, merged with faculty characteristics obtained online. Employing the dynamic monopsony model of Manning (2003a) and estimates of the wage elasticity of separations, we find the exploitation rate is robustly estimated at about 7%. That is, on average, faculty earn 7% below their marginal revenue product due to monopsony power. In addition, while there is no statistically significant difference in the exposure to monopsony power across faculty groups, we find heterogeneity in the monopsony power across campuses. Our results suggest that females experience a statistically higher degree of monopsony power relative to males of about 20%. However, under a commonly employed equal-productivity assumption, we find that this difference in monopsony power exposure would only contribute about 8% to the observed gender pay gap. Furthermore, we document that, gender differences in the observed research productivity—as measured by citation counts and the H-index—would account for the majority of the observed gender pay gap. This finding, however, does not imply the absence of gender bias in compensation in the university system we study, given the emerging evidence that the research productivity indicators we employ may be gender-biased (e.g., Ross et al. 2022 and Hengel 2022), and that we cannot account for other aspects of productivity (e.g., teaching and service).

Our study is one of the first to document estimates of the labor supply elasticity to the employer in a high-skill labor market. Our estimate of the labor supply elasticity to the campus of employment is about 15.1 for the entire tenure-ranked faculty sample, which is considerably larger than the estimates for relatively low-skilled occupations. For example, the wage elasticity of labor supply is estimated to be between 1.0 to 1.9 for Norway public school teachers (Falch 2010), 3.7 for Missouri school teachers (Ransom and Sims 2010), 3.2 for U.S. male grocery retailers employees (Ransom and Oaxaca 2010), and around 0.1 for nurses (Staiger, Spetz, and Phibbs 2010). According to a recent meta-study (Sokolova and Sorensen 2021), the sample mean of the labor supply elasticity estimates using the separation-based approach is 5.9, with a much smaller median at about 1.7. Although our estimates may seem high, available evidence on the labor supply elasticity for relatively high-skill workers has found it to be considerably larger than that of low-skill workers. For example, Bassier, Dube, and Naidu (2021) finds that the labor supply elasticity is three times larger in professional, business, and financial services than in low-wage labor markets.Thus, we consider that our results from the university faculty labor market, a high-skill market, are in line with the existing literature.

It is important to keep in mind that our findings are specific to the UC system R1 campuses that we examine, where an explicit set of salary scales (and frequent reviews) is used to guide the determination of faculty members' compensation. Moreover, the fact that we are able to gather individual faculty salary information online entails a high degree of salary transparency. These features potentially prevent the exertion of monopsony power by enhancing the bargaining position of individual faculty. Also, the UC system holds a prominent global reputation, with seven of the eight campuses in our study being recognized as "Public Ivies" (Greene and Greene 2001). Hence, the implications derived from our study may not generalize to other institutions or countries. It is of natural interest to further explore the presence of monopsony power and its contribution to the pay gap in other universities facing different institutional contexts. One factor of particular interest is the interaction of faculty unions with the monopsony power exerted by universities, and the existence of other types of salary determination rules (or their absence thereof).



(a) Revenue by Campus, 2009-2018.



(b) Correlation Between Campus Revenue and Faculty Salary.

Figure 1: Instrumental Variable: Campus Revenue (IV1).

Notes: Data from the UC System Online Infocenter. The campus revenue is measured in thousands of dollars and from the following sources: Private gifts, State educational appropriations, Auxiliary enterprises, Educational activities, and Student tuition and fees. Campus revenue from the Medical Center is excluded.

TABLE 3
FACULTY--LADDER RANKS--BUSINESS/ECONOMICS/ENGINEERING*
ACADEMIC YEAR

			Salary Scale 7/1/16		Salary Scale 7/1/17	
Rank	Step	Years at Step	Annual	Monthly	Annual	Monthly
Assistant Professor	I	2	79,100	6,591.67	80,300	6,691.67
	II	2	83,100	6,925.00	84,400	7,033.33
	III	2	87,200	7,266.67	88,600	7,383.33
	IV	2	91,900	7,658.33	93,300	7,775.00
	V	2	95,900	7,991.67	97,400	8,116.67
	VI	2	99,200	8,266.67	100,900	8,408.33
Associate Professor	I	2	96,000	8,000.00	97,500	8,125.00
	II	2	99,300	8,275.00	101,000	8,416.67
	III	2	103,400	8,616.67	105,000	8,750.00
	IV	3	106,600	8,883.33	108,700	9,058.33
	V	3	109,600	9,133.33	112,700	9,391.67
Professor	I	3	106,700	8,891.67	108,800	9,066.67
	II	3	109,800	9,150.00	112,800	9,400.00
	III	3	116,000	9,666.67	118,600	9,883.33
	IV	3	122,900	10,241.67	125,300	10,441.67
	V	--	130,100	10,841.67	132,500	11,041.67
	VI	--	139,900	11,658.33	142,000	11,833.33
	VII	--	150,000	12,500.00	152,300	12,691.67
	VIII	--	160,500	13,375.00	163,000	13,583.33
	IX	--	173,500	14,458.33	176,200	14,683.33

Comp Group A06

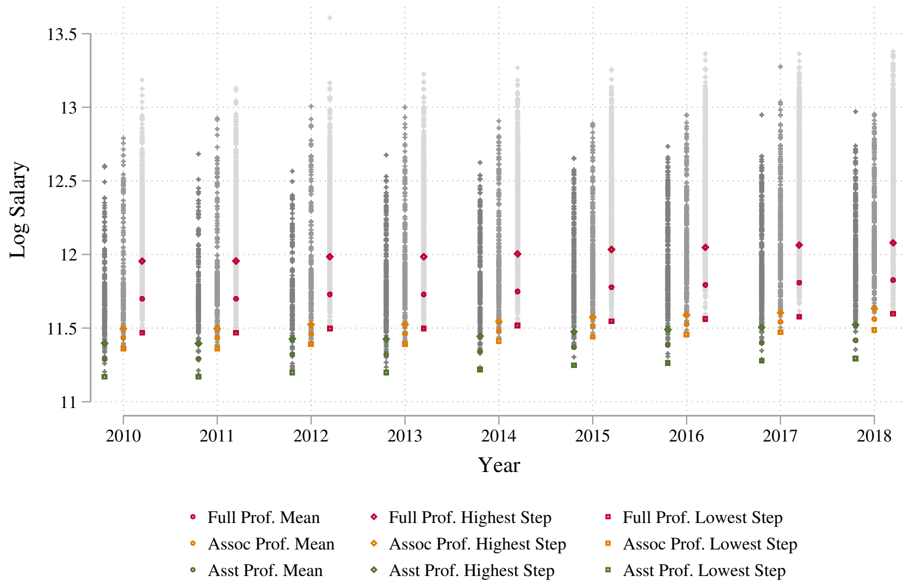
*The Acting Professorial titles, Adjunct Professor Series, Professor in Residence Series, Agronomist in the Agricultural Experiment Station Series, and the Professional Research Series (limited to faculty on research status) in the appropriate disciplines are also paid on the Academic-Year Faculty Ladder Ranks Business/Economics/Engineering salary scale.

For faculty that are on the minimum scale, please see Table 3M

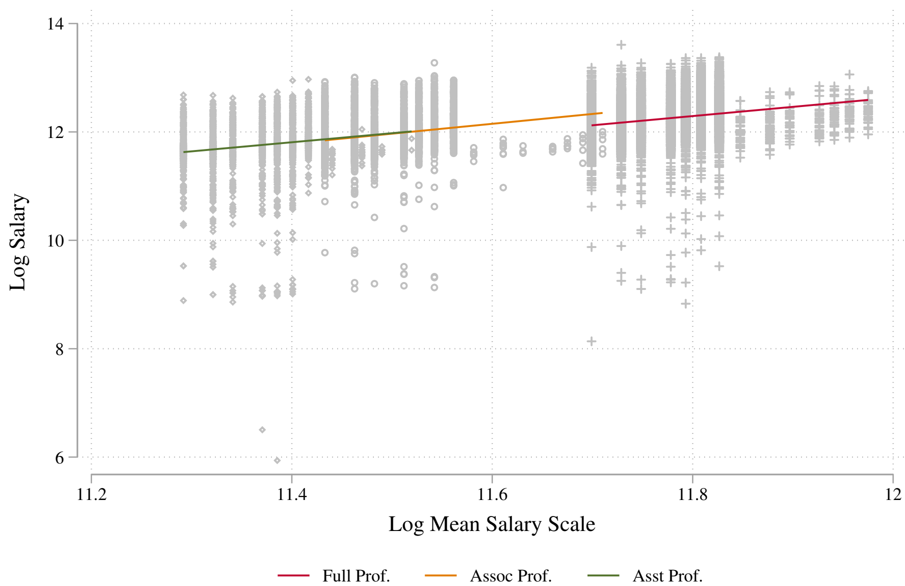
UCOP: Office of Academic Personnel and Programs

Figure 2: Salary Scales in AY2017-18: Faculty-Ladder Ranks-B/E/E, AY.

Notes: Table is downloaded from UCOP HR Table 3. It shows the salary scales for ladder-ranked faculties working in Business/Economics/Engineering and related disciplines whose salaries are paid by academic year.



(a) Faculty Salary and Scales by Title and Year



(b) Correlation Between Mean Salary Scale and Faculty Salary

Figure 3: Instrumental Variable: Salary Scale (IV2).

Notes: Data from the UCOP Human Resources. Log Mean Salary Scale measures the logarithm of the mean salary scale over steps within ladder ranks. We plot data on compensation in the Business/Economics/Engineering category with pay schedule by academic year as an example. Panel (a) plots individual faculty salaries against year, with markers flagging salary scales for each title. Square, diamond, and circle denote the lowest step, highest step, and mean scale by title, respectively. Panel (b) presents the correlation between the individual faculty salaries and the mean salary scale for each title.

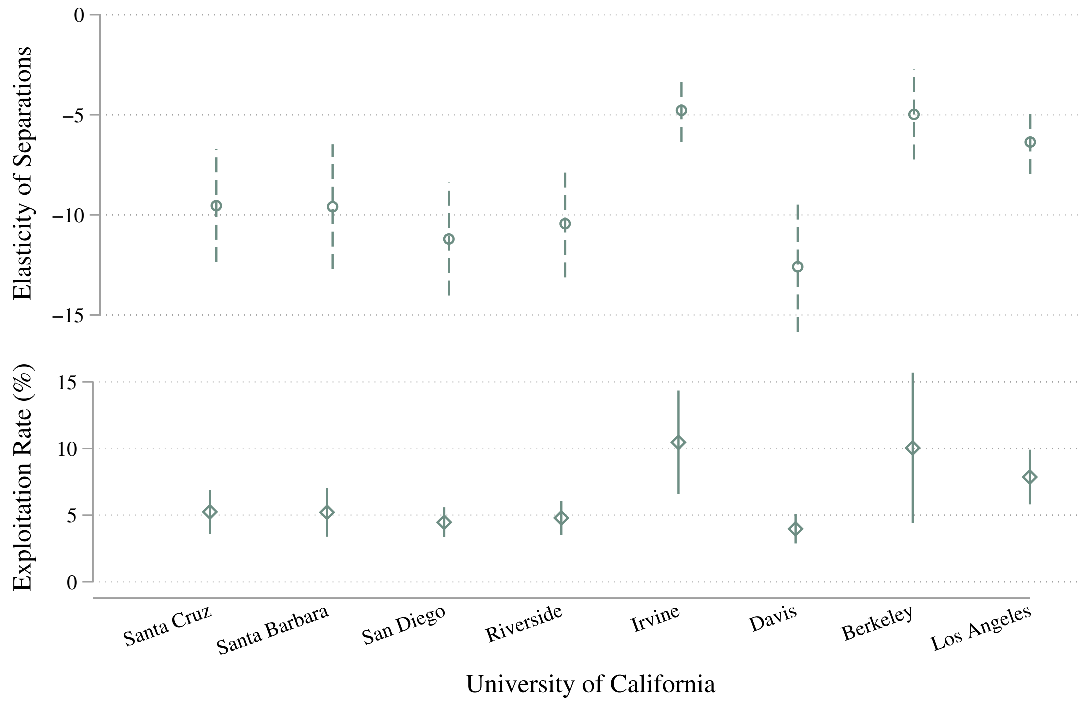


Figure 4: Heterogeneous Monopsony Power Across Campuses.

Notes: This figure reports the 2SLS estimates of the elasticity of separation by campus. We use our preferred model that includes a full set of controls for title, field, and research productivity as well as gender, polynomials of experience, educational background, and work history. We present the point estimate and its 95% confidence intervals. The rate of exploitation (%) is calculated by the formula: $E = 100/[\varepsilon_{sw} \times (-2)]$.

Table 1: Descriptive Statistics, Tenure-Track Sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total		Male		Female		Male − Female	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Difference	t-Stat
lnSalary	11.87	0.41	11.93	0.40	11.76	0.38	0.180***	(19.10)
lnScale	11.48	0.24	11.51	0.23	11.42	0.24	0.095***	(17.21)
lnRevenue	14.15	0.55	14.15	0.55	14.15	0.56	0.000	(0.00)
Separation	0.10	0.30	0.10	0.30	0.11	0.31	-0.007	(-1.00)
Educational Background:								
PhDinUC	0.24	0.43	0.23	0.42	0.26	0.44	-0.035***	(-3.52)
UGinUC	0.10	0.30	0.09	0.29	0.11	0.32	-0.021***	(-3.03)
PhDinForeign	0.13	0.33	0.14	0.34	0.10	0.30	0.035***	(4.53)
UGinForeign	0.27	0.44	0.30	0.46	0.21	0.41	0.089***	(8.55)
Work Experience:								
Experience	19.45	12.92	21.02	13.22	16.33	11.69	4.69***	(15.64)
PostdocNum	0.54	0.77	0.56	0.79	0.50	0.72	0.064***	(3.52)
PostdocYrs	1.62	2.91	1.71	3.05	1.44	2.60	0.270***	(3.87)
EverAdmin	0.04	0.19	0.04	0.18	0.04	0.19	-0.002	(-0.48)
Publication Statistics:								
lnHindex	2.44	1.25	2.62	1.22	2.08	1.21	0.530***	(18.60)
lnCitation	6.32	2.64	6.69	2.58	5.60	2.60	1.080***	(17.72)
N	8089		5377		2712			

Notes: Columns (1) and (2) present the mean and standard deviation of variables for the tenure-track faculty sample. Columns (3)-(4) and (5)-(6) report the mean and standard deviation for male and female faculty separately. Column (7) shows the Male − Female difference in the sample mean (= Column (3) − Column (5)) and Column (8) reports the t statistics of the group difference t-test. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. A detailed description on variables can be found in Appendix A.2.

Table 2: Ordinary Least Squares (OLS) Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Separation					
α_1	-0.106***	-0.078***	-0.094***	-0.146***	-0.157***	-0.059***
	(0.023)	(0.021)	(0.020)	(0.021)	(0.023)	(0.012)
N	8089	8089	8089	8089	8089	8089
Elasticity of Separation	-1.060***	-0.777***	-0.935***	-1.455***	-1.567***	-0.895***
	(0.221)	(0.215)	(0.190)	(0.205)	(0.230)	(0.208)
Exploitation Rate (%)	47.163***	64.388***	53.495***	34.366***	31.910***	55.843***
	(10.590)	(19.670)	(12.878)	(5.208)	(4.988)	(14.759)
Exp^2 & Exp^3	✓	✓	✓	✓	✓	✓
Edu & Work	✓	✓	✓	✓	✓	✓
Title		✓	✓	✓	✓	✓
Campus			✓	✓	✓	✓
Field				✓	✓	✓
Research Productivity					✓	✓
Weighted						✓

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the campus level. Baseline model includes controls for gender and polynomials of the working experience variable. Exp^2 & Exp^3 indicates whether the model includes the quadratic and cubic terms of the experience variable. Edu & Work denotes controls for faculty characteristics of educational background and work history. Title, Campus, and Field indicate whether the model includes the title of the position, the campus of employment, and the field of specialization, respectively. Research Productivity flags whether the model controls for research productivity. Lastly, the row Weighted suggests whether the estimation is weighted by the years of employment in the campus.

Table 3: Two-stage Least Squares (2SLS) Estimates

	(1)	(2)	(3)
Panel A. First Stage:		lnSalary	
lnRevenue	0.153***	0.662***	0.584***
	(0.024)	(0.052)	(0.062)
lnScale	1.030***	0.977***	0.971***
	(0.092)	(0.073)	(0.077)
F Statistics	66.865	315.670	258.044
Panel B. Second Stage:		Separation	
α_1	-0.224***	-0.760***	-0.444***
	(0.031)	(0.081)	(0.064)
N	8089	8089	8089
Elasticity of Separation	-2.231***	-7.572***	-6.732***
	(0.349)	(1.135)	(1.542)
Exploitation Rate (%)	22.412***	6.603***	7.428***
	(3.291)	(0.918)	(1.528)
Title		✓	✓
Field		✓	✓
Campus		✓	✓
Research Productivity		✓	✓
Weighted			✓

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the campus level. All models include faculty characteristics controls for gender, polynomials of the experience variable, educational background, and work history. In Panel A, we report the Sanderson-Windmeijer (SW) First-Stage F statistics.

Table 4: Two-stage Least Squares (2SLS) Estimates, Heterogeneity

	By Tenure Status		By Citizenship	
	Non-Tenured	Tenured	U.S. Born	Foreign Born
	(1)	(2)	(3)	(4)
Panel A. First Stage:	lnSalary			
lnRevenue	0.728***	0.748***	0.654***	0.690***
	(0.062)	(0.062)	(0.060)	(0.057)
lnScale	1.200***	0.949***	0.951***	1.013***
	(0.085)	(0.070)	(0.082)	(0.078)
F Statistics	122.036	295.588	187.344	1477.367
Panel B. Second Stage:	Separation			
α_1	-1.192***	-0.516***	-0.726***	-0.894***
	(0.128)	(0.059)	(0.079)	(0.086)
N	1505	6584	5933	2156
Elasticity of Separation	-5.882***	-6.702***	-7.848***	-7.329***
	(0.521)	(1.230)	(1.212)	(1.061)
Exploitation Rate (%)	8.501***	7.461***	6.371***	6.822***
	(0.735)	(1.249)	(0.906)	(0.977)
Title	✓	✓	✓	✓
Field	✓	✓	✓	✓
Campus	✓	✓	✓	✓
Research Productivity	✓	✓	✓	✓

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the campus level. All models include faculty characteristics controls for gender, polynomials of the experience variable, educational background, and work history. The regressions are not weighted. In Panel A, we report the Sanderson-Windmeijer (SW) First-Stage F statistics. The "Non-Tenured" sub-sample includes tenure-track assistant professors, while the "Tenured" sub-sample includes associate and full professors.

Table 5: Summary of Separation Destinations.

	# of Separations	Academia	·|Academia			
			R1 Research	R2 Research	Non-R1/R2 Others	Foreign Universities
	(1)	(2)	(3)	(4)	(5)	(6)
Male:						
Total	512	85%	62%	6%	6%	26%
Non-Tenured	171	82%	55%	9%	10%	26%
Tenured	341	87%	65%	4%	4%	27%
U.S.-born	327	86%	69%	6%	7%	18%
Foreign-born	185	84%	50%	6%	3%	42%
Female:						
Total	271	91%	76%	5%	9%	10%
Non-Tenured	116	87%	71%	5%	17%	7%
Tenured	155	94%	79%	6%	4%	12%
U.S.-born	204	91%	81%	5%	9%	5%
Foreign-born	67	91%	61%	5%	11%	23%

Notes: The separation to academia is defined by separations to universities and their affiliated research institutions. Research institutions that are not affiliated with universities or are funded by government or private establishments are not accounted academia. The classification of R1 and R2 research universities is based on 2010 Carnegie Classification of Institutions of Higher Education https://carnegieclassifications.iu.edu/classification_descriptions/basic.php. We use the country where faculty members received their undergraduate degree as a proxy of citizenship, i.e., faculty members who graduated from a non-US college are classified as foreign-born.

Table 6: Two-stage Least Squares (2SLS) Estimates: Robustness Checks

Sub-Sample	(1) Sub 1	(2) Sub 2	(3) Sub 3	(4) Sub 4	(5) TT	(6) TT
Panel A. First Stage:			lnSalary			
lnRevenue	0.670***	0.661***	0.656***	0.570***	0.638***	0.679***
	(0.052)	(0.054)	(0.059)	(0.074)	(0.039)	(0.043)
lnScale	0.980***	0.977***	1.010***	0.972***	0.902***	0.941***
	(0.073)	(0.074)	(0.074)	(0.080)	(0.062)	(0.068)
F Statistics	295.483	267.229	274.145	269.256	328.113	370.181
Panel B. Second Stage:			Separation			
α_1	-0.719***	-0.669***	-0.642***	-0.620***	-0.832***	-0.801***
	(0.073)	(0.075)	(0.073)	(0.087)	(0.086)	(0.082)
N	8040	7961	6940	7584	8089	8089
Elasticity of Separation	-7.581***	-7.788***	-6.923***	-7.042***	-8.291***	-7.983***
	(1.150)	(1.148)	(1.002)	(1.435)	(1.131)	(1.110)
Exploitation Rate (%)	6.595***	6.420***	7.222***	7.100***	6.031***	6.263***
	(0.925)	(0.879)	(0.976)	(1.349)	(0.770)	(0.809)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the campus level. All models contain a full set of control variables, including the job title, field of specialization, and campus dummies, research productivity indicators, and the baseline faculty characteristics controls. "TT" denotes the whole sample with 8089 tenure-track faculty. "Sub 1 - Sub 4" denotes the four sub-samples 1-4; please refer to section 4.3 for their definitions. In the Panel A, we report the Sanderson-Windmeijer (SW) First-Stage F statistics.

Table 7: Estimation of the Rate of Exploitation by Gender: 2SLS.

	Overall	By Tenure Status		By Citizenship	
		Non-Tenured	Tenured	U.S. Born	Foreign Born
	(1)	(2)	(3)	(4)	(5)
Panel A. First Stage:	lnSalary				
Male: lnRevenue	0.703***	0.781***	0.751***	0.718***	0.671***
	(0.0478)	(0.0898)	(0.0777)	(0.0521)	(0.0839)
Male: lnScale	0.975***	1.082***	0.980***	0.940***	1.031***
	(0.0794)	(0.0630)	(0.0839)	(0.0880)	(0.0985)
F Statistics	323.0	151.8	151.0	183.4	484.4
N	5377	877	4500	3784	1593
Female: lnRevenue	0.599***	0.656***	0.753***	0.566***	0.730***
	(0.0672)	(0.0851)	(0.140)	(0.0856)	(0.132)
Female: lnScale	0.957***	1.357***	0.877***	0.943***	0.969***
	(0.0727)	(0.196)	(0.0908)	(0.0797)	(0.0794)
F Statistics	202.9	53.05	75.50	158.9	82.67
N	2712	628	2084	2149	563
Panel B. Second Stage:					
Elasticity of Separation:					
Male	-8.262***	-5.990***	-7.288***	-8.910***	-7.371***
	(1.421)	(0.690)	(1.535)	(1.428)	(1.606)
Female	-6.753***	-5.925***	-5.997***	-6.636***	-7.368***
	(0.707)	(0.866)	(0.901)	(0.847)	(0.902)
Exploitation Rate (%)					
Male	6.052***	8.347***	6.860***	5.612***	6.783***
	(0.952)	(1.042)	(1.305)	(0.828)	(1.355)
Female	7.404***	8.439***	8.337***	7.535***	6.786***
	(0.774)	(1.243)	(1.260)	(0.945)	(0.877)
Difference (Female − Male)	1.352	0.092	1.477	1.923	0.003
p-value	0.038	0.949	0.258	0.001	0.998

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the campus level. All models contain a full set of control variables, including the job title, field of specialization, campus dummies, research productivity indicators, and the baseline faculty characteristics controls. We report the Sanderson-Windmeijer (SW) First-Stage F statistics.

Table 8: Estimated Female to Male Salary and Salary Gap Ratios.

	Overall	By Tenure Status		By Citizenship	
		Non-Tenured	Tenured	U.S. Born	Foreign Born
	(1)	(2)	(3)	(4)	(5)
Panel A. Observed Gender Salary Ratio:					
$(W_F - W_M)/W_M$	-0.163***	-0.091***	-0.160***	-0.156***	-0.167***
	(0.010)	(0.026)	(0.009)	(0.012)	(0.014)
Panel B. Elasticity of Labor Supply ($\hat{\varepsilon}_{Nw}$):					
Male	16.524***	11.981***	14.577***	17.820***	14.743***
	(2.842)	(1.379)	(3.070)	(2.856)	(3.212)
Female	13.507***	11.850***	11.995***	13.272***	14.736***
	(1.414)	(1.731)	(1.801)	(1.693)	(1.805)
Elasticity of Labor-	0.817***	0.989***	0.823***	0.745***	1.000***
Supply Ratio, $\hat{\psi}_{FM}$	(0.088)	(0.167)	(0.148)	(0.069)	(0.247)
Panel C. Assume No Difference in Productivity: $\eta_{FM} = 1$					
$(\hat{W}_F - \hat{W}_M)/\hat{W}_M$	-0.013**	-0.001	-0.014	-0.018***	-0.000
	(0.006)	(0.013)	(0.012)	(0.005)	(0.016)
Estimated/Observed (in %)	8%	0.9%	9%	12%	0%
Panel D. Assume No Difference in Exposure to Monopsony Power: $\psi_{FM} = 1$					
$(\hat{W}_F - \hat{W}_M)/\hat{W}_M$	-0.155***	-0.119**	-0.160***	-0.169***	-0.112***
	(0.034)	(0.052)	(0.037)	(0.042)	(0.025)
Estimated/Observed (in %)	95%	130%	100%	108%	67%
Panel E. Consider Differences in Productivity and Exposure to Monopsony Power					
$(\hat{W}_F - \hat{W}_M)/\hat{W}_M$	-0.165***	-0.119**	-0.171***	-0.184***	-0.112***
	(0.036)	(0.061)	(0.038)	(0.042)	(0.025)
Estimated/Observed (in %)	101%	131%	107%	118%	67%

Note: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the campus level. $\hat{\varepsilon}_{Nw}$ is calculated by multiplying the estimated elasticity of separation of Table 7 by (-2). Following Equation (8), $(\hat{W}_F - \hat{W}_M)/\hat{W}_M = ([\hat{\eta}_{FM} \cdot (\hat{\psi}_{FM} + \hat{\varepsilon}^F_{Nw})]/[1 + \hat{\varepsilon}^F_{Nw}]) - 1$. The ratio of estimated pay gap to the observed gap (Estimated/Observed in %) is calculated by dividing the estimated gender pay gap ratio $(\hat{W}_F - \hat{W}_M)/\hat{W}_M$ by the observed gender pay gap ratio $(W_F - W_M)/W_M$ and multiplying by 100.

Table 9: Estimation of the Observed Research Productivity Difference.

	Overall	Non-Tenured	Tenured	U.S. Born	Foreign Born
	(1)	(2)	(3)	(4)	(5)
	1^{st} Principal Component of Publication Metrics				
Female	-0.168***	-0.126**	-0.174***	-0.185***	-0.119**
	(0.0264)	(0.0503)	(0.0304)	(0.0300)	(0.0551)
R^2	0.433	0.460	0.409	0.454	0.379
N	8089	1505	6584	5933	2156
Title	✓	✓	✓	✓	✓
Field	✓	✓	✓	✓	✓
Campus	✓	✓	✓	✓	✓
Observed Research-	0.845***	0.881***	0.840***	0.831***	0.888***
Productivity Difference ($\hat{\eta}_{FM}$)	(0.0223)	(0.0443)	(0.0256)	(0.0250)	(0.0489)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include faculty characteristics controls for gender, educational background, and work history. Denote the first principal component of publication metrics (H-index and total number of citations) as PC. We estimate the OLS model: $\text{PC}_i = \beta_0 + \beta_1 female_i + \gamma \mathbf{X}_i + \varepsilon_i$. Since $\beta_1 = PC_F - PC_M = ln(PC_F/PC_M)$, we can estimate the observed research productivity Ratio ($\hat{\eta}_{FM}$) by taking the exponential of β ($\exp(\beta_1)$). The "Non-Tenured" sample includes tenure-track assistant professors, while the "Tenured" sample includes associate and full professors.

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Online Appendix

A More on the Data and Variables

A.1 Data Construction

In this Appendix, we provide additional details on the data construction process. The data is constructed by combining three datasets: faculty salaries, scraped faculty characteristics, and research productivity metrics. We retrieve tenure-ranked faculty salaries from the University of California's employee pay dataset. The information about faculty characteristics is collected via online searching. We collect research productivity metrics from the Scopus database.

To fulfill the requirement of FOIA and open government transparency, the University of California publishes the employee pay data annually via an online website (https://ucannualwage.ucop.edu/wage/). The available data starts from 2010. We downloaded the salary data from 2010 through 2018 on June, 2020. The employee pay dataset contains the full name, title, campus of employment, and the compensation (including the gross pay, regular pay, overtime pay, and other pay) of the employee. Using the full name and campus of employment to identify the employee, we are able to construct up to 9-years panel data of salary for employees who worked in the UC system during 2010-2018.

The salary panel data allows us to observe the duration of the employment with the UC system. In other words, we know from the salary panel whether the employee has ever left the UC system, either temporarily or permanently, and the year of departure. For example, if we observe payroll records for a given employee were terminated since 2015, we could infer that this faculty member left the campus in 2015. A more realistic case is that the gross pay to this faculty member in 2014 was shrunk, likely by about 50%, and eventually reduced to zero in 2015, since the employment of a university faculty member is usually by the academic year, i.e., the recruitment generally occurs in the Fall or Summer semester. We can also distinguish a permanent from a temporary departure. If the faculty member is on-leave or had a short-term visiting to other university, then we would observe the pay to the faculty member sharply reduced or ceased in some years, resuming after the temporary leave.

The employee pay data of the UC system contains the salary data of both faculty and nonacademic employees. We confine the sample to the academic faculty and filter out non-academic employees by imposing restrictions on the title. In other words, only employees whose titles contain "professor" would be included in the sample. Based on the titles in the payroll record, we generate three title dummies to indicate whether faculty are titled "Assistant", "Associate", or "Full" professors in the last year when the faculty member was observed to have the payroll record.[34]

[34] According to the University of California Academic Personnel Manual, the prefix "Acting" will be accorded only to a person on a temporary appointment. For assistant professors, this prefix is often used under the circumstance when faculty are appointed before their Ph.D. thesis is completed or accepted by the degree-granting university (i.e., Acting Assistant Professor). We keep "Acting Assistant Professor" and code it as "Assistant Professor", but exclude "Acting Associate Professor" or "Acting Professor".

Utilizing the information about the full name, campus of employment, and title, we conducted online searches of faculty's personal website, department profile, and CV/resume to collect information about the faculty's gender, department of employment, educational background, and work history. Specifically, we observe the gender and department of employment of each faculty member, which helps us to construct the gender and field dummies. Since we are interested in the gender pay gap, it is important to have a precise gender indicator. We rely on three ways to determine faculty's gender. The primary approach is to use the photos on their department profiles, personal websites, or Linkedin profiles, etc. We also consult the gendered pronouns used by faculty (e.g., in his/her biography, self-introduction, and research introduction, etc.) as a complementary resource. For example, if a faculty member uses "she/her" in her biography to refer to herself, then we assign "female" to that faculty member. Occasionally, neither the photo nor the self-use gendered pronouns are available. In this case we turn to the gendered pronouns used by a third-party. For instance, we assign gender based on the gendered pronouns used by students to refer to the faculty member in reviews on *RateMyProfessors.com* (https://www.ratemyprofessors.com) or the gendered pronouns for the faculty member in news on the institutional websites.[35] Based on the assigned gender, we then generate a dummy variable *Female* that equals one if the faculty member is recognized as female and zero if the faculty member is male. We infer and assign the field to faculty based on the name of department of employment. We generate a set of dummy variables indicating the field to which the faculty belongs. We provide a crosswalk between the name of department and the Major Field Categories classified by the National Survey of Student Engagement (NSSE) in Appendix B . For the educational background, we collect information on the faculty's degree-granting institutions, including doctorate, masters, and bachelors degrees, along with the year of graduation from each institution. For the work history, we collect information on faculty members' post-doctoral and work experience, including the name of previous employer(s) and the work duration with each employer. Later in this Appendix, we will discuss in more detail about the construction of covariates according to the information on educational background and work history.

We measure faculty's research productivity using two publication metrics — the total number of citations and the H-index, a commonly-used citation impact statistic from Scopus, an abstract and citation database of Elsevier. We scrape the total number of citations and H-index from Scopus' website (https://www.scopus.com/home.uri). We identify each faculty member by the full name. To avoid mismatching scholars with the same name, we also use affiliation and field as key words to facilitate the matching. We identify 8,367 faculty members in the final dataset, which covers 92.7% of the tenure-track sample.[36] We create two variables: *lnHindex* and *lnCitation*, as measures of faculty's observed research productivity. They are defined as the logarithm of the H-index and total number of citations, respectively.

As previously noted, the salary panel data helps us detect whether a faculty member permanently

[35] In some rare cases (< 5) that a faculty member use gender-neutral pronouns such as "they", we rely on the third-party-used gendered pronouns to assign gender.

[36] An alternative source is Google Scholar (GS), which has been argued to have the best coverage of conferences and most journals (Meho and Yang 2007). However, a large proportion of our faculty does not have a GS author profile. In our sample, we can only identify 4,556 faculty members who have the GS profile. Therefore, we rely primarily on Scopus records as it provides a much better coverage of the sample.

left the campus of employment during 2010-2018. We verify the employment status of each faculty member in our online searching process. Specifically, we check whether the faculty member left the campus of employment during 2010-2018 for those whose compensation had been terminated during the sample period.[37] Moreover, we record the name of the employer to which the faculty member move and the year of the separation. We create a dummy variable *Separation* that equals to one if a faculty member is found to no longer work at the UC system campus of employment.

We identify 15,192 faculty members with at least one payroll record from 2010 to 2018. For only 506 of them (3.3%), we found no personal information on the internet. Among the rest of the 14,686 faculty members, 2048 (13%) are Emeritus faculty or passed away. They are defined to be in retirement status. While 10 faculty members (0.07%) were fired due to sexual harassment cases or felony crimes. We exclude retired and fired faculty members from the sample of study since their separations are considered as "natural death" and "involuntarily" leave. To further refine the sample to tenure-ranked (or ladder-rank) faculty, we then exclude 3,022 (19.9%) non-ladder-rank faculty members whose title contains "Adjunct", "Visiting", "Clinical", or "In Residence". We further dropped 580 (3.8%) faculty members that only have a single payroll record. Those faculty members either newly joined the UC campus of employment in 2018 or left the campus of employment in 2010. In the following discussion, we illustrate that it is difficult to obtain a precise measure of the annual salary solely based on the payroll record in the year when the job starts or terminate. To avoid introducing measurement errors to the salary, we exclude those faculty members from the sample. We further exclude 664 faculty members who have no Scopus record and 273 faculty members without doctorate-granting university information. The final data set then contains 8,089 faculty members.

It is worth noting that the employee pay data includes salaries for both academic and non-academic employees. We distinguish faculty from a non-academic employee solely by the title. It may raise concerns regarding the representatives of the sample. There may be a small chance that our sample fails to include some tenure-ranked faculty whose titles do not contain "professor". To check the coverage rate of our sample, we first collect the employee headcount from the UC system's Online Infocenter (https://www.universityofcalifornia.edu/infocenter/uc-employee-headcount). It provides a system-wide count of all unique employees with any earnings regardless of full-time or part-time status. Employees with more than one type of appointment are counted in their principal position. The headcount data is posted by year and campus. Comparing the headcount data with the number of faculty members identified in the sample in each campus and each year, we calculate the coverage rate by simply dividing the number of observations by the headcount. Table C.1 summarizes the average coverage rate by campus. The average coverage rates are over 90% for all of the eight campuses, suggesting that the sample has acceptable coverage.

A.2 Variables

Our salary measure is based on the gross pay. Because the payroll data is measured according to the calendar year while the compensation and recruitment in the UC system are based on the

[37] Any separations in the year 2010 will cause a faculty member to have only one payroll record. Because we exclude faculty that only have a single payroll record from our sample, we only consider quits between 2011 and 2018.

academic or fiscal year, the payroll record in the year when the job starts or terminates contains only a share of the annual compensation. For example, faculty members who left their campus of employment in Fall 2016 would still see their compensation for Spring 2016 appear in their 2016 payroll record. Therefore, for faculty members who left their original UC campus of employment and move to a new university, their compensation usually dropped significantly in the year when the separation occurred (i.e., the termination year), or put it differently, in their last compensation record. A similar pattern applies to faculty members who joined the UC system in the sample during 2010-2018. That is, there would be a jump in salaries in the year after the starting year. To precisely measure transitioning faculty members' compensation, we constructed a mean salary variable, *MeanSalary*, by taking the average of gross pay excluding the first and/or the last salary records.[38] Formally, for a transitioning faculty member i who worked in campus s during time period $t, t+1, ..., T$, the mean salary $MeanSalary_i$ is calculated according to the following formula:

$$MeanSalary_i = \begin{cases} \frac{1}{T-t-1} \sum_{j=t+1}^{T-1} GrossPay_{ij} & \text{if } T-t-1 > 3 \\ \frac{1}{T-t} \sum_{j=t+1}^{T} GrossPay_{ij} & \text{if } T-t-1 \leq 3 \text{ and } T == 2018 \\ \frac{1}{T-t} \sum_{j=t}^{T-1} GrossPay_{ij} & \text{if } T-t-1 \leq 3 \text{ and } T < 2018 \end{cases}$$

where $GrossPay_{ij}$ denotes the gross pay for faculty member i in calendar year j. The mean salary variable for non-transitioning faculty members corresponds to the average gross pay from 2010 to 2018. Using the mean salary variable, we define the *lnSalary* variable as the logarithm of the mean salary, i.e. $lnSalary_i = \log(MeanSalary_i)$.

Next, we construct the two instrumental variables for the individual faculty salaries. The first one is the campus revenue (IV1). We retrieved annual revenue data from Fiscal Year 2009-2010 (matched to payroll record in year 2010) to Fiscal Year 2017-2018 (matched to payroll record in year 2018) from the UC System Online Infocenter. We only consider revenue from the following sources: private gifts, state educational appropriations, auxiliary enterprises, educational activities, and student tuition and fees. Revenue from the Medical Center is excluded. Since our sample only covers general campus faculty (excludes UC Health), the funds from the medical center have little relevance to the salary determination of faculty in the sample. We then calculate the mean campus revenue for each faculty member by taking the average of the revenue of the campus of employment over the years used in the calculation of the mean salary for the faculty member. For example, the mean campus revenue for a non-transitioning faculty who worked in UC Irvine during 2010-2018 would be calculated by taking the average of the campus revenue of UC Irvine from FY 2009-2010 to FY 2017-2018. For transitioning faculty i who worked in campus s during time period $t, t+1, ..., T$, the mean campus revenue $MeanRevenue_i$ is calculated according to the following formula:

$$MeanRevenue_i = \begin{cases} \frac{1}{T-t-1} \sum_{j=t+1}^{T-1} CampusRevenue_{s,j-1} & \text{if } T-t-1 > 3 \\ \frac{1}{T-t} \sum_{j=t+1}^{T} CampusRevenue_{s,j-1} & \text{if } T-t-1 \leq 3 \text{ and } T == 2018 \\ \frac{1}{T-t} \sum_{j=t}^{T-1} CampusRevenue_{s,j-1} & \text{if } T-t-1 \leq 3 \text{ and } T < 2018 \end{cases}$$

[38] If the transitioning faculty member has more than three payroll records, the mean salary is calculated by excluding both the first and the last records. If the faculty only has two or three payroll records, the construction of the mean salary depends on whether s/he left the campus of employment: if the faculty left, then we exclude the last record; if not, then we drop the first record. Faculty that only have a single payroll record are excluded from the sample.

where *lnRevenue* denotes the campus revenue IV (IV1) and is calculated by the logarithm of the mean campus revenue variable, i.e., $lnRevenue_i = \log(MeanRevenue_i)$. The second instrumental variable is the salary scale (IV2). We extract the system-wide salary scale of the UC system from the UCOP Human Resources website (https://www.ucop.edu/local-human-resources/your-career/compensation/salary-and-pay.html). The scales were updated every two academic years from Academic Year 2009-2010 until Academic Year 2013-2014 and then switched to yearly updates. Since Academic Year 2011-2012, the effective date changed from October 1st to July 1st. Scales can be classified into several categories by field such as General, Business/Economics/Engineering, Law, and Veterinary Medicine, and by pay schedule, e.g., paid by Fiscal Year (12 months) or Academic Year (9 months). We collect salary scale data from the 2009-2010 to the 2017-2018 Academic Years and merge them into the sample by title, field, and pay schedule. We calculate the mean salary scale for each faculty member by averaging his/her corresponding salary scales over the same period used in calculating the mean salary. Thus, for non-transitioning faculty members who worked in the campus of employment during 2010-2018, the mean salary scale variable, *MeanScale*, is calculated by taking the average of their corresponding salary scales from AY 2009-2010 to AY 2017-2018. For transitioning faculty i who worked in school s during time period $t, t+1, ..., T$, the mean salary scale variable is calculated using the following formula:

$$MeanScale_i = \begin{cases} \frac{1}{T-t-1}\sum_{j=t+1}^{T-1} SalaryScale_{i,j-1} & \text{if } T-t-1 > 3 \\ \frac{1}{T-t}\sum_{j=t+1}^{T} SalaryScale_{i,j-1} & \text{if } T-t-1 \leq 3 \text{ and } T == 2018 \\ \frac{1}{T-t}\sum_{j=t}^{T-1} SalaryScale_{i,j-1} & \text{if } T-t-1 \leq 3 \text{ and } T < 2018 \end{cases}$$

where *SalaryScale* represents the corresponding salary scales for faculty member i, given his/her title, field, and pay schedule. *lnScale* denotes the salary scale IV (IV2) and is calculated by the logarithm of the mean salary scale variable, i.e., $lnScale_i = \log(MeanScale_i)$.

Note that, by design, the two instrumental variables — campus revenue and salary scale — are lagged measures because of the discrepancy in the measurement time of the compensation, the campus revenue, and the salary scale variables. Specifically, the compensation data is measured in calendar years, while the campus revenue data is measured in fiscal years and the salary scales are measured in academic years. We pair the calendar year with the "lagged" fiscal and the academic year. For example the fiscal year 2009-2010 and academic year 2009-2010 are matched to the calendar year 2010.

As noted before, we create a set of control variables based on faculty members' educational background and work history. *UGinUC* and *PhDinUC* are variables indicating whether faculty received bachelor's or post-graduate degrees from institutions in the UC system, respectively. *UGinForeign* and *PhDinForeign* are dummy variables indicating whether the degree-granting institutions are foreign universities. *Experience* is a discrete variable measuring the number of years since graduation. It is constructed by calculating the number of years between 2018 and the year when the faculty member obtained his/her highest degree. *Postdoc Num* is a discrete variable that measures the number of postdoctoral spells.[39] *Postdoc Yrs* is a discrete variable that measures the total years of postdoctoral experience. Lastly, to distinguish faculty who ever took an

[39]Any research position post-graduation in any research institution such as universities, research centers, and laboratories is coded as a postdoctoral spell. Different positions in the same institution are combined to one spell. Positions in two different institutions are coded as two spells.

administrative job, we use a dummy variable *EverAdmin* as an indicator for taking administrative positions such as dean, provost, director, or chair of a department.

B Fields Based on NSSE Major Field Categories

The field that a specific faculty belongs to is inferred by the department s/he works at. We classified the fields in the sample into 14 main groups based on the National Survey of Student Engagement (NSSE)'s major field categories: a). ARTS & HUMANITIES, b). BIOLOGICAL SCIENCES, AGRICULTURE, & NATURAL RESOURCES, c). PHYSICAL SCIENCES, MATHEMATICS, & COMPUTER SCIENCE, d). SOCIAL SCIENCES, e). BUSINESS, f). COMMUNICATIONS, MEDIA, & PUBLIC RELATIONS, g). EDUCATION, h). ENGINEERING, i). HEALTH PROFESSIONS, j). SOCIAL SERVICE PROFESSIONS, and k). OTHER MAJORS (NOT CATEGORIZED). Three interdisciplinary fields are separately listed instead of putting them in the OTHERS category: l). CHEMISTRY & BIOCHEMISTRY, m). COGNITIVE SCIENCE, n). COMPUTER SCIENCE & ELECTRICAL ENGINEERING. Information of what majors and fields are included in each category is listed below:

- ARTS & HUMANITIES:
  Arts, fine and applied; Architecture; Art history; English (language and literature); French (language and literature); Spanish (language and literature); Other language and literature; History; Humanities (general); Music; Philosophy; Religion; Theater or drama; Other fine and performing arts; Other humanities;

- BIOLOGICAL SCIENCES, AGRICULTURE, & NATURAL RESOURCES:
  Biology (general); Agriculture; Biochemistry or biophysics; Biomedical science; Botany; Cell and molecular biology; Environmental science/studies; Marine science; Microbiology or bacteriology; Natural resources and conservation; Natural science; Neuroscience; Physiology and developmental biology; Zoology; Other agriculture and natural resources; Other biological sciences;

- PHYSICAL SCIENCES, MATHEMATICS, & COMPUTER SCIENCE:
  Physical sciences (general); Astronomy; Atmospheric science (including meteorology); Chemistry; Computer science; Earth science (including geology); Mathematics; Physics; Statistics; Other physical sciences;

- SOCIAL SCIENCES:
  Social sciences (general); Anthropology; Economics; Ethnic studies; Gender studies; Geography; International relations; Political science; Psychology; Sociology; Other social sciences;

- BUSINESS:
  Accounting; Business administration; Entrepreneurial studies; Finance; Hospitality and tourism; International business; Management; Management information systems; Marketing; Organizational leadership or behavior; Supply chain and operations management; Other business;

- COMMUNICATIONS, MEDIA, & PUBLIC RELATIONS:
  Communications (general); Broadcast communications; Journalism; Mass communications and media studies; Public relations and advertising; Speech; Telecommunications; Other communications;

- EDUCATION:
  Education (general); Business education; Early childhood education; Elementary, middle school education; Mathematics education; Music or art education; Physical education; Secondary education; Social studies education; Special education; Other education;

- ENGINEERING:
  Engineering (general); Aero-, astronautical engineering; Bioengineering; Biomedical engineering; Chemical engineering; Civil engineering; Computer engineering and technology; Electrical or electronic engineering; Industrial engineering; Materials engineering; Mechanical engineering; Petroleum engineering; Software engineering; Other engineering;

- HEALTH PROFESSIONS:
  Allied health; Dentistry; Health science; Health technology (medical, dental, laboratory); Healthcare administration and policy; Kinesiology; Medicine; Nursing; Nutrition and dietetics; Occupational safety and health; Occupational therapy; Pharmacy; Physical therapy; Rehabilitation sciences; Speech therapy; Veterinary science; Other health professions;

- SOCIAL SERVICE PROFESSIONS:
  Criminal justice; Criminology; Forensics; Justice administration; Law; Military science; Public administration, policy; Public safety and emergency management; Social work; Urban planning;

- OTHER MAJORS (NOT CATEGORIZED):
  Classics; Comparative Border Studies; Counseling, Clinical, and School Psychology; Earth & Marine Science; Global Governance; History of Consciousness; Human Ecology; Information Systems and Technology Management; Literary Journalism; Population Health and Reproduction; Science and Technology Studies; Statistics, CS, Math & EE;

C Tables

C.1: Average Coverage Rate by Campus.

Campus	Coverage rate (%)	In sample − Headcount
Berkeley	97%	-34
Davis	95%	-56
Irvine	91%	-86
Los Angeles	99%	-12
Riverside	92%	-53
San Diego	91%	-88
Santa Barbara	91%	-71
Santa Cruz	91%	-48