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

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Abstract

We investigate the existence of monopsony power in a highly-skilled labor market given by tenure-ranked faculty in public research universities in California, analyze differences in monopsony power by gender, and relate them to the observed gender pay gap. We collect and use publicly-available information of faculty salaries in the University of California system and merge it with information obtained online on faculty characteristics, career trajectories, and research productivity indicators. We infer the university-level labor supply elasticity by estimating the elasticity of separation. To deal with the endogeneity of the salary in the separation equation, we employ instrumental variables exploiting exogenous variation in salaries driven by changes in school revenues and salary scales. We find evidence of monopsony power: the "exploitation rate," a common measure of monopsony power, is conservatively estimated at about 7% for tenure-track faculty. Full professors experience a higher rate of monopsony power than associate and assistant professors. Lastly, while the estimated monopsony power is not found to differ by gender for assistant and associate professors, it does so for full professors, with women facing a higher exploitation rate relative to males.

Keywords: Monopsony; Higher Education; Gender Wage Gap
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1 Introduction

There is a growing consensus among economists that in most labor markets firms have power to set the wage.[1] Robinson (1969) 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

[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]Other theoretical work, such as Burdett and Mortensen (1998), Manning (2006), Bhaskar and To (1999), and Boal and Ransom (1997), 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 of non-wage amenities offered by firms among workers (Manning 2021). In this literature, a firm's market power is affected by its market share and size. Card et al. (2018), Azar, Berry, and Marinescu (2019), and Azar et al. (2019) are some examples of monopsony studies in the so-called "New Classical Monopsony" literature (Manning 2021).

[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 2018)

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, using data from eight public R1 research universities in the University of California (hereafter 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). We focus on public R1 research universities 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 an important part of their job and most of them have publication history. The faculty data contains 8,089 tenure-track faculty members who work in the universities in our sample during the period 2010-2018.

After documenting the presence of monopsony power among research faculty in the UC system, we then analyze how much of their 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

[5]A R1 research university is a four-year university categorized as having very high research activity.

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), biases in the evaluation of teaching and research (Mason and Goulden 2002; Chen and Crown 2019; Boring 2017; Hengel 2017), and work-family issues (Antecol, Bedard, and Stearns 2018). Our study suggests that monopsony is also a contributing factor to the gender pay gap in higher education. Moreover, 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 universities and multiple fields.

To estimate the rate of wage-setting power, 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 for 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

[6]Empirical evidence, primarily from 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). 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.

[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 (2018) conducts a series randomized experiments in collaboration with Uber to analyze the labor market of ride-sharing drivers.

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). 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 follow the latter literature and 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 to the inverse of the wage elasticity of labor supply (Robinson 1969; 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 university revenues and in pre-specified salary scales. These instruments, which are related to faculty compensation, are argued to be exogenous to the individual faculty decision to separate from their university.

We find evidence that monopsony exists in the UC labor market for tenure-ranked faculty: the exploitation rate is conservatively estimated at about 7%. Moreover, we find that the rate of monopsony power is heterogeneous across faculty groups and universities. Full professors are found to bear a higher rate of monopsony power than associate and assistant professors. Also, universities located in the largest cities possess stronger monopsony power. Importantly, we find that female full professors are exposed to a higher rate of monopsony on average, compared to male full professors. Conversely, the extent of monopsony power is not found to differ by gender for assistant and associate professors. We relate the estimated monopsony power to the observed gender pay gap. Our back-of-the-envelop calculation suggests that monopsony can explain 8% of the overall gender pay gap for tenure-track faculty overall, and up to 40% of the gender pay gap for full professors.

A recent study that also examines monopsony in academia is Goolsbee and Syverson (2019). 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 several differences between our work and theirs. First, by using aggregated data, they are able to analyze the universe of U.S. higher education institutions, while we concentrate on eight R1 universities in a state system. Second, in contrast to aggregate information, our novel faculty-level data allows us to control for individual-level faculty characteristics such as educational background, field, experience, rank, and research productivity information. This allows us to better control for omitted variable bias in the estimation of the labor supply elasticity and the exploitation rate. Third, Goolsbee and Syverson (2019) 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. For the above reasons, we consider our study as shedding important complementary evidence to Goolsbee and Syverson (2019).

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 at 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 association between the firm level wage elasticity of labor supply and the rate of exploitation. The exploitation rate is defined as the proportional gap between the wage and the marginal revenue product, and it is a standard measure of monopsony power in the labor market. We then motivate the separation-based approach to infer the wage elasticity of labor supply by estimating the wage elasticity of separations. This approach derives from the dynamic monopsony model (Manning 2003a; Burdett and Mortensen 1998), which implies that, at the firm level, the wage elasticity of labor supply equals the wage elasticity of recruits minus the wage elasticity of separations. Manning (2003a) further demonstrated that, under certain assumptions outlined below, the wage elasticity of separations is equal to the negative of the wage elasticity of recruits. Therefore, estimating the wage elasticity of separations is enough to recover the wage elasticity of labor supply. This method is widely used in the monopsony literature (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). Lastly, we discuss how to link the female to male salary ratio (the gender wage gap) with the gender ratio of marginal revenue product and the gender ratio of the labor supply elasticity, an indicator of the gender difference of exposure to monopsony power.

2.1 The Static Model of Monopsony

Assume 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:

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

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:

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

[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.

where MRP denotes the marginal revenue product, $Y'(N)$. Equation (1) shows that the proportional gap between the marginal revenue product 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, 1969; Ashenfelter et al., 2010). Note that in a perfectly competitive labor market, $\varepsilon_{Nw} \to \infty$, and thus $E \to 0$. 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 can be used to measure monopsony power. Equation (1) also reveals the relationship between monopsony power (E) and the wage elasticity of labor supply (ε_{Nw}), which points out to a straightforward way to identify monopsony power through the estimation of the firm-level labor supply elasticity.

Since the monopsonist firm faces an upward-sloping labor supply curve ($\varepsilon_{Nw} < \infty$), estimation of its wage elasticity of labor supply requires exogenous variations in the labor demand. The most widely-used source of exogenous variation is with instrumental variables in the form of firm-level labor demand shocks. In the following section, we introduce an approach to estimate the wage elasticity of labor supply for the individual firm based on the dynamic monopsony model.

2.2 The Dynamic Model of Monopsony

Moving to a dynamic model of monopsony allows us to motivate our empirical approach. Consider a firm whose size at time t is defined by labor units of the firm, 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 $(t+1)$ 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. Equation (3) can be written in terms of elasticities:

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

which suggests that the wage elasticity of labor supply (ε_{Nw}) can be estimated by 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 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.

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

Our estimation strategy relies heavily on this assumption (as so does the literature cited before that uses the separations 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 2018). 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 university is very high. Indeed, in our sample, all faculty that joined the eight universities 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 particular concern is that this 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, who can be considered as being employed by universities before moving to a tenure-ranked position.[12]

[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.

[12]Only 7 out of 1,844 ($\approx 0.38\%$) assistant professors joined the UC system during 2010-2018 who worked as junior researchers (post-doc/acting assistant professors) at other universities, while the rest were Ph.D. candidates.

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. First, we write Equation (1) separately for male (M) and female (F) workers, i.e.,

$$E_M = \frac{MRP_M - w_M}{w_M} = \frac{1}{\varepsilon_{Nw}^M};\ E_F = \frac{MRP_F - w_F}{w_F} = \frac{1}{\varepsilon_{Nw}^F} \tag{6}$$

Rearrange Equation (6), we obtain:

$$w_M = \frac{MRP_M}{1+\frac{1}{\varepsilon_{Nw}^M}};\ w_F = \frac{MRP_F}{1+\frac{1}{\varepsilon_{Nw}^F}} \tag{7}$$

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

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

where $\eta_{FM} = MRP_F/MRP_M$ is the female to male ratio of the MRP, and $\psi_{FM} = \varepsilon_{Nw}^F/\varepsilon_{Nw}^M$ is the female to male ratio of the wage elasticity of labor supply. We know from Equation (8) that the female to male salary ratio is a function of η_{FM} and ψ_{FM}. Specifically, $\psi_{FM} = E_M/E_F$, i.e., the gender ratio of the labor supply elasticity can be expressed as the male to female ratio of exploitation rates, reflecting the gender difference in exposure to monopsony power. Thus, gender differences in both the exposure to monopsony power and in productivity 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 can result in the salary ratio diverging from the productivity ratio (η_{FM}). For example, a significant gender gap in labor supply elasticity implies a considerable gender difference of exposure to monopsony power, which can amplify any productivity gap and result in a sizable gender pay gap, even though the gender difference in productivity may be trivial. Alternatively, the female to male salary ratio can be less than one, i.e., women earn lower wages than men, even though there may exist monopsony power against men ($\psi_{FM} > 1$), as long as the observed gender gap in productivity is sizable, i.e., $\eta_{FM} << 1$.

We can obtain a simplified expression if the assumption that male and female workers have the same MRP is imposed (i.e., $\eta_{FM} = 1$):

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

In general, it is not feasible to empirically check whether $\eta_{FM} = 1$ since productivity is usually unobserved. In our setting, we can assess whether $\eta_{FM} \approx 1$ by assuming that (1) the main component of productivity in R1 universities is the faculty's research productivity, and (2) that the Scopus' publication metrics is a good approximation to the faculty's research productivity.[13] In section 5, we employ that information to approximate η_{FM} along with estimates of ψ_{FM} to estimate the female to male salary ratio using Equation (8). We then can compare the estimated gender salary ratio with the observed ratio to analyze the extent that monopsony contributes to the observed gender pay gap.

3 Data

To employ the separation-based approach introduced in section 2.2 and estimate the separation elasticity, we need faculty-level information on separations and wages (salaries) at the university

[13]We acknowledge that using publication statistics as a simple measure of faculty's productivity is far from perfect, however, we believe that our attempt to explicitly measure, even partially, the (research) productivity of faculty can help reduce biases in the estimation of labor supply elasticity and the rate of exploitation.

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 in the UC system, we suggest two instrumental variables for faculty salaries, which allows us to estimate the elasticity of separations—and thus the elasticity of labor supply to the universities—free of endogeneity bias.

3.1 Faculty Data

The data used in this study comes from multiple sources. We link the publicly available faculty salary data with scraped public information on faculty's educational background, career trajectory, work experience, and citation metrics. We retrieve salaries from 2010 through 2018 from an open-access employee pay dataset published by the University of California.[14] We restrict our sample to tenure-ranked faculty and exclude faculty who passed away, retired, or were fired during the sample period.[15] We then search online for the faculty's department profile and personal website using key words including the full name, title, and the university of employment. We scrape information on the faculty's educational background, working history, and career trajectory from their online profile and curriculum vitae. Lastly, we scrape the faculty's publication statistics from the Elsevier's citation database Scopus.

The final dataset contains 8,089 tenure-ranked faculty. We observe faculty characteristics such

[14]The salary data is downloaded from https://ucannualwage.ucop.edu/wage/.

[15]Death, retirement, and layoff are consider as "natural death" and "involuntarily" separations.

as gender, title, university and department of employment; educational background such as the year of graduation and the degree granting school(s); working history such as post-doctoral experience and whether the faculty member has ever taken any administrative jobs; and publication metrics such as the total number of citations and the H-index.[16] Moreover, we observe the annual salary and separation status of each faculty. Specifically, we observe whether the faculty member left the university and, if so, when and where the faculty member moved. Detailed information on the data construction procedure can be found in Appendix C.

Table 1 presents 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.[17] The average and unconditional separation rate is about 0.1 for both male and female faculty. There is not a statistically significant gender difference in the average separation rate in our sample. We also 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 greater—and statistically so—for male faculty than female faculty in our sample.

[16]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.

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

3.2 Compensation in the UC System as a Source of Exogenous Variation

Faculty compensation at the UC system is primarily determined by a range of salary scales which are evaluated annually and updated periodically.[18] The salary scales apply to the entire system; they are used by all UC universities for the same categories of academic appointees. Salary scales vary across academic ranks and disciplines. For example, faculty members working in the Law school or the Business school use different salary scale tables. The salary scales for academic faculty can be classified into four categories by field: General, Business/Economics/Engineering, Law, and Veterinary Medicine; and two categories by pay schedule: Academic Year (9-months) and Fiscal Year (12-months). In addition to the system-wide salary scales, the merit-based adjustment is another major factor determining faculty salaries. The amount of merit adjustment is determined by various aspects, including the faculty's performance and the availability of funds.

The compensation structure in the UC system provides the basis for instrumental variables 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 universities' revenues can affect faculty salaries.[19] Short-term variation in the universities' revenues are unlikely to be correlated with factors that affect the separation decision of individual faculty members. Panel (a) in Figure 1 shows the revenues by university from the fiscal year 2008-2009 through fiscal year 2017-2018. Overall, we observe gradual increases in the university revenues of the eight UC schools from 2008 through 2018. The rate of change varies across schools. Panel (b) in Figure 1 plots the correlation between the average

[18] The UC system normally adjusts annually its salary scale. One exception was during the academic years of 2009-2010 to 2012-2013 when the salary scale adjusted every two years. More information can be found from UCOP Human Resources (UCOP HR)website.

[19] Sources of school revenues includes private gifts, state educational appropriations, auxiliary enterprises, and student tuition and fees.

of the salary variable ($lnsalary$) and the average of the university revenue variable ($lnRevenue$) from 2010 to 2018 by school.[20] There is a strong linear relationship between the university revenue and the university average faculty salary, suggesting that the university revenue is a plausible candidate to be used as instrumental variable for individual faculty salaries.

Second, according to the UC system's compensation policy: "An employee's salary must be within the salary range that is assigned to the job title".[21] 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 title (i.e., ladder rank), but also vary within the title. For example, there are six steps within the Assistant Professor title, and in the academic year 2016-2017, the annual salary scales range from \$80,300 in Step I to \$100,900 in Step VI.[22] Figure 3 shows the correlation between the salary scales and faculty salaries. Panel (a) shows the correlation between the average of the salary variable and the average of the salary scale variable, from AY2009-2010 through AY2017-2018 for faculty members who work in Business/Economics/Engineering and are paid by academic year.[23] We plot salaries and salary scales by ladder rank (title) and indicate the maximum, minimum, and mean scales within the title. Clearly, salaries are tightly bounded above

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

[21]See the UCOP Human Resources (UCOP HR) website https://www.ucop.edu/local-human-resources/your-career/compensation/salary-and-pay.html.

[22]Such wide range in salary scales, across and within the job title provides universities with the flexibility in the salary bargaining with individual faculty.

[23]As in the case of the university revenue variable, we match the salary scales in the academic year 2017-2018 with the calendar year 2018. Hence, the salary scale variable is also one-year lagged.

the minimum scale. In Panel (b), we show the correlation between the mean salary scales and individual faculty salaries by title. Similar to Panel (a), we display the correlation using faculty who work in Business/Economics/Engineering and are paid by academic year as an example. We observe a strong positive linear 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.[24] We thus use the mean salary scale as the second instrumental variable for individual faculty salaries.[25]

4 Analysis of Monopsony Power in the UC System

To estimate the degree of monopsony power, we estimate the wage elasticity of separations, using individual-level faculty data from eight R1 universities in the UC system. We then estimate the wage elasticity of labor supply—and thus the rate of exploitation—from the estimated wage elasticity of separations, leveraging the separation-based approach outlined in section 2.2.

We begin 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 3.2 in a two-stage least squares (2SLS) framework to handle the

[24]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."

[25]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 to faculty's unobserved factors. If it is the case, then it gives us another reason to use the mean salary scale. For these reasons, we use the mean salary scale within each title as our instrumental variable.

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 universities.

4.1 OLS

Consider a linear probability model where $Separation_i$ is the separation indicator that equals one if faculty member i is observed quitting from the UC-system university of employment during the sample period, and is linearly related to the faculty member's logarithm of the mean salary over the years the faculty was employed at the university ($lnSalary$):[26]

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

where $\mathbf{X}_i$ is a vector of control variables, u_i is the error term, and α_0 and α_1 are parameters to be estimated. We include in $\mathbf{X}_i$ factors that are correlated with both individual faculty salaries and the separations, which include gender, years of experience (up to a cubic term), indicators of educational background, and working history. We calculate the wage elasticity of separations, $\hat{\varepsilon}_{sw}$, by dividing the estimated salary coefficient, $\hat{\alpha}_1$, by the baseline mean separation rate $\bar{s}$.

We present OLS estimates in Table 2. Column (1) shows estimates from a baseline model controlling for gender, educational background, working experience, and years of experience (up to cubic). Columns (2) - (5) subsequently add the title of the position, the university of employment, field of specialization indicators, and research productivity controls. Looking at Column (5), which includes the full set of controls, the wage elasticity of separations 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

[26]The mean salary captures the faculty's historical salary rate. If the faculty left the school, e.g., in 2015, the mean salary rate is calculated using the faculty's gross pay records before 2015. More details on the construction of the salary variable can be found in Appendix C.2.

of exploitation is 32% ($= 1 \div 3.14$).[27] This estimate implies that, on average, faculty are paid about 32% less than their MRP.

The construction of $lnSalary_i$ for a faculty member depends on how many years the faculty has been employed at the university. Since we have different number of years of salary data for different faculty members (based on when they began employment in the UC system), we experiment with weighting the regression by the number of years the faculty member has been in the UC system. Column (6) in Table 2 presents the result 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 56%.

As mentioned before, we expect the OLS estimates ($\hat{\alpha}_1$ and $\hat{\varepsilon}_{sw}$) to be biased due to unobserved factors that are related simultaneously to separations and the individual faculty salary. For example, a faculty's unobserved ability (or discipline) could be positively correlated with both salary and the separation decision: more able faculty earn higher salaries and they are also more likely to move to a better job. 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 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.

[27]Recall that as discussed in Section 2, the wage elasticity of labor supply can be written as $\varepsilon_{Nw} = -2\hat{\varepsilon}_{sw}$, where $\hat{\varepsilon}_{sw}$ is the estimated elasticity of separations. We compute the exploitation rate using $E = (MRP - w)/w = 1/\varepsilon_{Nw}$.

[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, $\hat{\alpha}_1 \times (-2) < \alpha_1 \times (-2)$. Therefore, the OLS estimate tends to underestimate the wage elasticity of labor supply.

4.2 2SLS

We now estimate Equation (10) by 2SLS instrumenting for the likely endogenous faculty salary (*lnSalary*). We use the two instrumental variables the university revenue and the salary scale, motivated in Section 3.2. The reason we employ both variables is because they have different levels of variation. The university revenue does not have variation within universities (i.e., it is the same for all fields of specialization), while the salary scale does not vary across universities (i.e., it is the same for all universities). Employing the instruments together allows us to exploit a higher level of variation.

The 2SLS estimates are summarized in Table 3. We present results using the tenure-ranked sample in Columns (1)-(3), and results separately for assistant, associate, and full professors in Columns (4)-(6), respectively. 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.

Column (1) shows the estimates using the baseline model, which imply an estimated wage elasticity of separation of -2.2 and an estimated rate of exploitation of 22%. These estimates change significantly after conditioning on title, field, university indicators, and research productivity. As shown in Column (2), the estimated wage elasticity of separation increases to -7.6, implying an estimated rate of exploitation of 7%. Notably, weighting the regression by the length of years working at the school does not substantially change the estimates. As shown in Column (3), the estimated rate of exploitation remains at 7%. Overall, the magnitude of the estimated wage elasticity of labor supply from 2SLS is substantially larger than that from OLS, resulting in a significantly smaller estimate of the exploitation rate. The observed direction of the bias is consistent with our previous discussion that the OLS estimates are positively biased and tend to overestimate the rate of exploitation.

We further investigate the heterogeneity in the rate of exploitation across faculty with different job titles. To do this, we re-estimate the 2SLS model separately for assistant, associate, and full professors.[29] Columns (4)-(6) of Table 3 report the results of this exercise, using the specification that includes all of our control variables. We find that full professors are subject to the highest rate of exploitation (11%), by associate (6%) and assistant (4%) professors.[30] This finding is consistent with existing studies (Goolsbee and Syverson 2019; Monks and Robinson 2001; Ransom 1993) which also find that full professors are exposed to a higher rate of monopsony power.[31]

Lastly, we explore the heterogeneity in monopsony power across universities. To do this, we re-estimate the 2SLS model separately for each university in the UC system, using the model includes the full set of control variables. We show in Figure 4 the estimated wage elasticity of separations (top panel) and the implied exploitation rate (bottom panel) by university. We find that, for most universities, the exploitation rate is about 5%. However, the exploitation rate is found to be higher

[29] We classify the faculty member's title according to the latest title held during the period of employment at the university.

[30] Note that the estimates in Columns (4)-(6) are unweighted. However, as shown in Table B 2 Columns (1)-(3), using weights does not significantly change the estimated exploitation rate.

[31] Goolsbee and Syverson (2019) find that the labor supply elasticity in US universities are 7.8, 3.1, and 1.9 for assistant, associate, and full professors, respectively. Our results may not be directly comparable with Goolsbee and Syverson (2019)'s because both the data and the estimation strategy used in our study are different from theirs. On the one hand, we use faculty data covering only eight R1 research universities in the UC system from 2010-2018, while Goolsbee and Syverson (2019) uses data at the university-level covering not only four-year universities but also two-year universities/colleges across the U.S. mainland. On the other hand, although both studies use the instrumental variable method, the empirical approach used in our study is based on labor turnovers, i.e., we infer the labor supply elasticity by estimating the elasticity of separation, while Goolsbee and Syverson (2019) uses a more stock-based approach that estimates the inverse elasticity of labor supply.

in UC-Irvine (10%), UC Berkeley (10%), and UCLA (8%), indicating stronger monopsony power in these schools. This difference in monopsony power between these three universities (Irvine, Berkeley, and UCLA) and the rest is statistically significant.

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 previously discussed results are robust. The first relevant consideration is that faculty's separation decision can be affected by factors other than compensation. Leading factors are (1) tenure denial, (2) departure of foreign faculty to country of origin, and (3) retirement decisions. Non-tenured assistant and associated professors may have to leave the school if they fail to obtain tenure at their university of employment. There is a considerable proportion of faculty at research universities that are foreign-born. It is not uncommon for these foreign-born faculty to move to foreign universities for personal reasons such as returning to their country or being close to family. Lastly, health and retirement concerns can also lead faculty to separate from universities. All of these separations just described do not necessarily respond to variations in salary, and thus including them in the estimation 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 thus we use that information to flag separations that are likely to be associated with non-monetary factors. Our assessment then consists of estimating monopsony power in sub-samples in which we exclude separations that appear to be motivated by considerations other than salary compensation.

Table 4 shows descriptive statistics of the separation destinations in our data, by gender and job title. 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.[32] 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.[33] Columns (4) and (5) in Table 4 shows that, on average, 12% of male faculty who quit and stay in academia moved out of 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 assistant professors, in line with potential tenure-denials: 19% for males and 22% for females. Moreover, we observe a substantially share of separations to foreign universities. For male faculty who quit and remain in academia, 26 percent of them transit to foreign universities. This type of transition is much lower among female faculty, with only 10 percent of them moving to foreign universities. As expected, most of these transitions are from faculty who are not U.S. citizens (not shown in the table).

Based on the information on separation destinations, we construct three sub-samples to gauge the robustness of our main results. The first sub-sample excludes assistant and associate professors

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

[33]More specifically, the classification of research universities is based on the 2010 Carnegie Classification of Institutions of Higher Education. Universities which are not R1 or R2 research University are classified as Non-R1/R2 universities. For example, teaching colleges are in the Non-R1/R2 category.

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 suggestive indicator of tenure denial.[34] Sub-sample 2 takes sub-sample 1 and further excludes assistant and associate professors who transit to foreign universities. Such transitions may be due by personal or family issues that are unrelated to compensation. Sub-sample 3 is aimed at further excluding potential separations due to health or retirement reasons. To this end, since the age of faculty is not observed in the faculty 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 5 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%. Thus, to the extent that our sub-samples do capture factors for separation other than salary compensation, we conclude that those factors do not have a large impact on our estimates of monopsony power.

A different potential concern is that we may introduce measurement error into the faculty salary variable in the way we construct the (logarithm of the) mean salary variable. In short, this variable is constructed as an average of the faculty member's salary over the years s/he is observed employed with a university during our sample period [35] To assess whether the main results are sensitive to the way of constructing the mean salary variable, we first consider a sub-sample (sub-sample 4) which excludes faculty that are observed employed in the university 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 university in our data (see

[34]Of course, this presumption is an inexact approximation.

[35]See Appendix C for more details on the construction of this and other variables.

also the more detailed discussion provided in Appendix C). The estimates using this sub-sample with presumably less measurement error, presented in Column (4) of Table 5, show that the rate of exploitation is estimated at 7%, essentially the same as that estimated using the entire tenure-ranked faculty sample.

Moreover, Columns (5) and (6) of Table 5 considers 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 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 member.[36] The estimates reported in Columns (5) and (6) of Table 5 show that the rate of exploitation in these two alternative ways of constructing the mean salary measure is about 6%, very close to the 7% 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 mean salary.

5 Monopsony Power and the Gender Pay Gap

5.1 Gender Differences in Monopsony Power Faced

Given the evidence of monopsony power in the eight UC system universities 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

[36]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 in a 2SLS framework. 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 baseline mean separation rate of the corresponding sample, $\bar{s}^M$ and $\bar{s}^F$. The estimates employing the model specification with the full set of controls are reported in Table 6. Panel A presents the first-stage results by gender while Panel B presents the second-stage results along with the estimated wage elasticity of separations and the implied rate of exploitation, both by gender.

The first column in Table 6 presents the results for the entire tenure-ranked faculty. The estimated salary coefficient is -0.81 for male faculty and -0.71 for female faculty, with the difference being statistically significant at the 90% confidence level. The estimated elasticity of separation is -8.26 for males and -6.75 for females. Lastly, the estimated rate of exploitation is 6% for male faculty and a slightly larger 7% for female faculty. Thus, using the entire sample of tenure-track faculty in the UC system, there is only weak evidence that females face a higher rate of monopsony power relative to males.

Next, we consider gender differences in exposure to monopsony power for faculty with different tenure-ranked titles. To do this, we split the sample by tenure-ranks and re-estimate the models separately for male and female faculty. Columns (2)-(4) in Table 6 summarize the results for assistant, associate, and full professors, respectively. For assistant professors, the difference in the estimated salary coefficients between females and males is small (0.05) and not statistically significant. The wage elasticity of separations is estimated at -5.99 for male faculty and -5.93 for female faculty. The estimated rate of exploitation is 8% for both female and male assistant professors, implying a lack of gender difference in exposure to monopsony power for them. For associate professors, the estimated salary coefficient is larger in magnitude for female faculty (-1.044) than male faculty (-0.805), but the difference is not statistically significant at conventional levels. The corresponding estimate of the rate of exploitation is 8% for males and 5% for females. Lastly, for full professors, the estimated salary coefficient is -0.29 for females but almost twice of that (-0.52) for males. Hence, female full professors bear a rate of exploitation of 11%, while male full professors only of 6%.[37]

In summary, we find that, on average, female and male faculty are exposed to a slightly different rate of monopsony power in the eight UC universities. The difference is statistically significant at the 95% confidence level. Moreover, while the estimated monopsony power is not found to statistically significantly differ by gender for assistant professors, it does significantly differ for full professors, with female full professors facing almost twice as high exploitation rate relative to male full professors. Based on this evidence, we now move to investigate the extent to which differential monopsony power explains the gender pay gap in the UC system, particularly for full professors.

5.2 Linking Monopsony Power 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 and the labor supply elasticity, implying that the gender pay gap is affected by the gender differences in both productivity and the exposure to monopsony power. To examine the contribution of the differential exposure to monopsony power to the gender pay gap, we estimate

[37]In Table 6, we do not weight the estimates by the length of years faculty worked at the university. Table B.2, Columns (4)-(7), shows that weighting does not significantly change the estimates.

the female to male salary ratio in equation (9) using the estimated labor supply elasticities from Table 6. These estimates are summarized in Table 7. Column (1) presents the estimated parameters for the entire tenure-ranked faculty sample. Columns (2)-(4) show the estimated parameters for assistant, associate, and full professors, respectively.

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%, 10.5%, and 11.5% for assistant, associate, and full professors. Next, we estimate the gender ratio of the wage elasticity of labor supply, $\hat{\psi}_{FM}$. Panel B in the table summarizes the labor supply elasticities for males and females, while Panel C reports the corresponding estimated gender ratios. The estimated female to male ratio of the elasticity of labor supply ($\hat{\psi}_{FM}$) for the entire tenure-ranked faculty sample is 0.817. For assistant professors, the estimate is very close to 1 (0.989). Female associate professors are found to have more elastic labor supply, rendering the gender ratio above 1 (1.68), while for full professors, the estimated ratio is 0.539.

Next, we assume that male and female faculty share the same marginal revenue product (MRP), that is, we fix $\eta_{FM} = 1$. This is a common assumption in the empirical literature on monopsony power (Ransom and Sims 2010; Ransom and Oaxaca 2010; Webber 2016, among others) . Under this assumption, we estimate the salary ratio ($\hat{W}_F/\hat{W}_M$) by plugging in the estimated gender ratio of the labor supply elasticity ($\hat{\psi}_{FM}$) and the estimated labor supply elasticity for female faculty ($\hat{\varepsilon}^F_{Nw}$) into the Equation (9). As shown in Panel D, we estimate the female to male salary ratio at 0.987 for the entire tenure-ranked faculty sample, suggesting that, under the equal-productivity assumption, the small differential exposure to monopsony power does not lead to differential salaries between females and males. Similarly, we find estimated female to male salary ratios close to 1 for assistant (0.99) and associate (1.03) professors. For full professors in Column (4), the estimated female to male salary ratio is 0.95, implying a proportional gender pay gap of almost 5%. This result suggests that under the equal-productivity assumption, differential exposure to monopsony power leads to lower salaries paid to female full professors.

We can compare the estimated gender pay gap in Panel D with the observed gender pay gap in Panel A by dividing the estimated gender pay gap by the observed gender pay gap, and infer the extent to which monopsony power contributes to the gender pay gap. This is reported at the bottom of Panel D. Differential exposure to monopsony power can explain about 8% ($-0.013/-0.163$) of the observed gender pay gap in the entire tenure-ranked faculty sample. For full professors, we estimate the gender pay gap at -0.046 and the observed gender pay gap is -0.115. Thus, under the equal-MRP assumption, monopsony power can explain about 40% ($-0.046/-0.115$) of the gender pay gap among full professors. Because there is no gender difference in the estimated labor supply elasticity among assistant professors, the impact of monopsony power on their gender pay gap is trivial (1%). Conversely, for female associate professors, their estimated labor supply elasticity is slightly larger than for males. Thus, the female to male salary ratio is estimated at 1.032 for associate professors, implying that females earn 3.2% higher salaries relative to male associate professors.

Next, we relax the equal-productivity assumption between female and male faculty by bringing to bear our proxy information on research productivity. In other words, we estimate the gender ratio of the marginal revenue product ($\hat{\eta}_{FM}$) in Equation (8), and integrate it into the estimation of the salary gender gap in Equation (8). To estimate the productivity gap, we employ an OLS model of the logarithm of the H-index statistics as a function of a gender indicator and a full set of controls for educational background, working experience, title, field, and university indicators:

$$lnHindex_i = \beta_0 + \beta_1 Female_i + \mathbf{X}_i + \varepsilon_i.$$

Thus, $\beta_1 = lnHindex_F - lnHindex_M = ln(Hindex_F/Hindex_M)$ and the ratio of the MRP ($\hat{\eta}_{FM}$) can be obtained as $\exp(\beta_1)$.

Table 8 presents the estimates form the OLS model. Column (1) shows the estimates for the entire tenure-ranked faculty sample, while Columns (2) to (4) show the estimates for assistant, associate, and full professors, respectively. The estimated coefficient of the gender indicator is -0.154 in the entire faculty sample, suggesting that, on average, the H-index of female faculty is about 15.4% lower than that of male faculty. The corresponding estimated gender ratio of the MRP ($\hat{\eta}_{FM}$) is 0.86, obtained by taking the exponent of the gender coefficient. Similarly, we estimate $\hat{\eta}_{FM} = 0.89$ for assistant professors, $\hat{\eta}_{FM} = 0.85$ for associate professors, and $\hat{\eta}_{FM} = 0.86$ for full professors.

Next, to estimate the gender pay gap ratio, we plug in the estimated gender ratio of the MRP and the estimated labor supply elasticity into Equation (8). The estimates are shown in Panel E of Table 7. Once we consider the gender difference in both productivity and the labor supply elasticity, the estimated gender pay gap ratio is -0.15 for the entire sample of faculty, -0.11 for assistant professors, -0.12 for associate professors, and -0.18 for full professors. For the assistant professors, due to the absence of the gender difference in the labor supply elasticity, the female to male salary ratio is estimated merely by $\hat{\eta}_{FM}$. Column (3) in Panel D illustrates the scenario where women earn less than men even if male faculty bear a higher rate of exploitation, as discussed in Section 2.3. The estimated gender pay gap in Panel D becomes closer to the observed gender pay gap after considering the gender gap in productivity. For example, overall the gender difference of productivity and exposure to monopsony power explain 94% of the observed gender pay gap. A great portion of the gender pay gap can be attributed to the gender difference in productivity.

η_{FM} solely reflects the gender difference in faculty's research productivity. Ideally, η_{FM} should also capture faculty's productivity in teaching and/or services, as teaching and/or services are essential components of the job for university faculty. Unfortunately, we do not observe faculty's teaching evaluation, and productivity in professional/administrative services is generally hard to measure quantitatively. Lacking information on faculty's teaching productivity and a good measure of the service productivity, we are unable to take account of other aspects, except for research productivity, in the MRP measure. we narrow our analysis to the R1 research university where research and publication contribute heavily to the faculty's salary function. But the problem of measurement error in the MRP measure is unavoidable, and may bias the estimation of the salary ratio in Panel D. For example, if female faculty are more productive in teaching, then our MRP measure tends to underestimate $\hat{\eta}_{FM}$, and thus overestimate the salary gap. This may explain why the estimated gender pay gap in Panel D is even greater than the observed one.

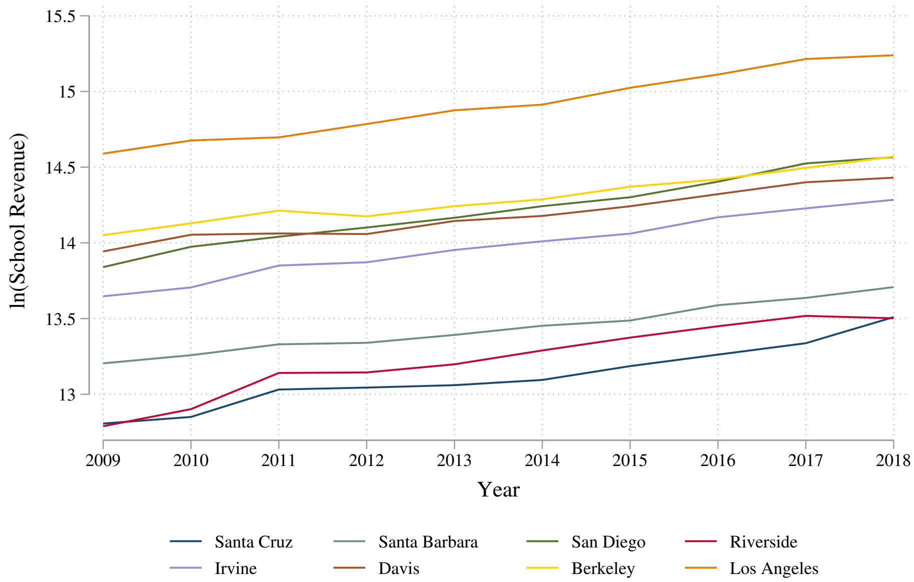
6 Conclusion

We provide evidence of monopsony in academia using faculty data from eight R1 research universities in the University of California system. We find the rate of exploitation is about 7%, which means on average, faculty earn 7% less than their marginal revenue product.

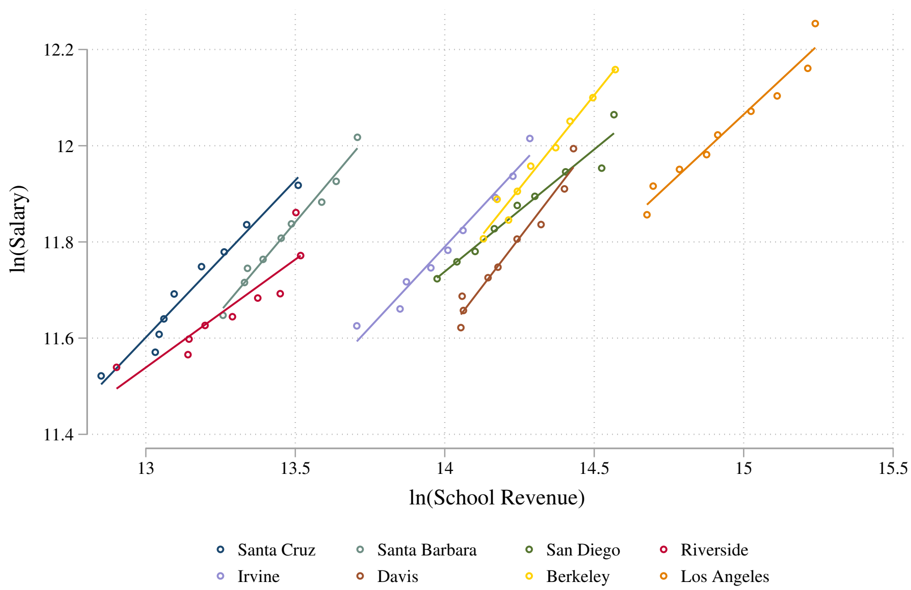
Our estimates of the labor supply elasticity to the individual university are considerably larger than the estimates for low-skilled and low-wage occupations. For example, the wage elasticity of labor supply is estimated to be between 1.0 to 1.9 for Norway public school teachers (Falch 2010), 3.7 for Missouri school teachers (Ransom and Sims 2010), 3.2 for U.S. male grocery retailers (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. We argue that the large estimates of the labor supply elasticity obtained from the sample of UC universities is reasonable. Although, empirical evidence on the labor supply elasticity for high-skill workers is limited in general, the wage elasticity of labor supply is found to be much larger in high-wage jobs. For example, Bassier, Dube, and Naidu (2021) finds that the labor supply elasticity is three times greater in professional, business, and financial services than in low-wage labor markets. Since the wage elasticity of labor supply and the rate of exploitation are inversely related, we provide a conservative estimation of the monopsony power in the university labor market.

Moreover, we find heterogeneity in the monopsony power across universities and faculty groups. Full professors are found to face stronger monopsony power compared to associate and assistant professors. Among the eight universities, Some universities are found to possess greater monopsony power than others. The extent of monopsony power could be affected by other factors. For example, faculty union may play a role on preventing faculty members from being exploited by the university, and thus the rate of monopsony power in universities with a strong faculty union may be smaller. The relationship between union and monopsony power in academia can be an interesting topic for future studies.

Lastly, we provide evidence that monopsony can help understand the gender pay gap in academia. While no statistically significant gender difference in the monopsony power is found among associate and assistant professors, we find evidence that female full professors are likely to experience a higher rate of exploitation than male full professors. Our back-of-the-envelop calculation indicates that monopsony power explains about 8% of the overall gender pay gap for tenure-track faculty, and about 40% of the gender pay gap for full professors, but contribute little to the gender pay gap among assistant and associate professors.



(a) Revenue by School, 2009-2018.



(b) Correlation Between School Revenue and Faculty Salary.

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

Notes: Data from the UC System Online Infocenter. The school revenue is measured in thousands of dollars. Variable $ln(SchoolRevenue)$ is the logarithm of school revenue from the following sources: Private gifts, State educational appropriations, Auxiliary enterprises, Educational activities, and Student tuition and fees. School 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

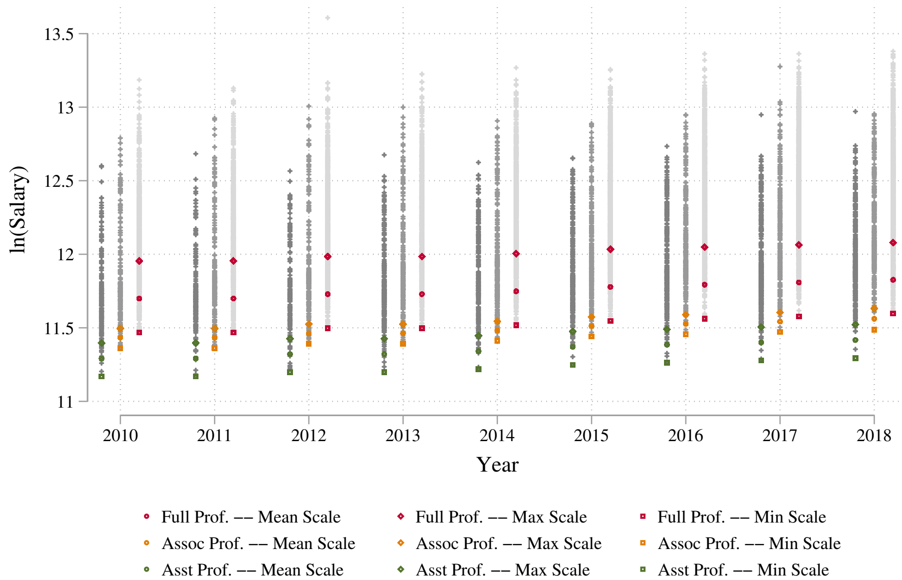
*The Acting Professorial titles, Adjunct Professor Series, Professor in Residence Series, Agronomist in the Agricultural Experiment Station Series, and the Professional Research Series (limited to faculty on research status) in the appropriate disciplines are also paid on the Academic-Year Faculty Ladder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

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

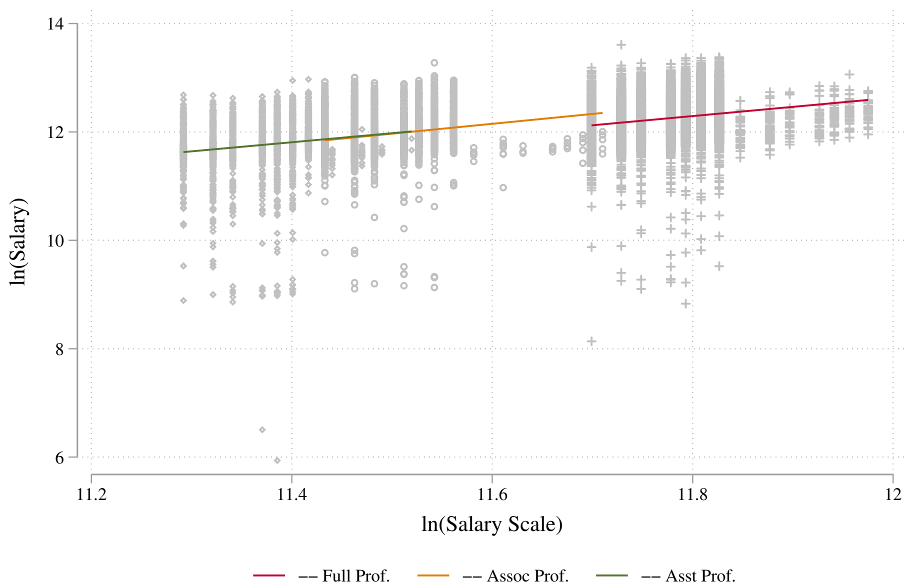
UCOP: Office of Academic Personnel and Programs

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 deciplines whose salaries are paid by academic year.



(a) Relationship Between Salary Scale and Faculty Salary Within Title.



(b) Correlation Between Salary Scale and Faculty Salary Across Title.

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

Notes: Data from the UCOP Human Resources. Variable $ln(SalaryScale)$ is the logarithm of the mean salary scale over steps within ladder ranks. We use compensation in the Business/Economics/Engineering category with pay schedule by academic year as an example. Panel (a) shows the relationship of individual faculty salaries with the salary scales. Square, diamond, and circle markers denote the minimum, maximum, and mean scale within the title, respectively. Panel (b) presents the correlation between the individual faculty salaries and the average salary scale (averaged over schools) by title.

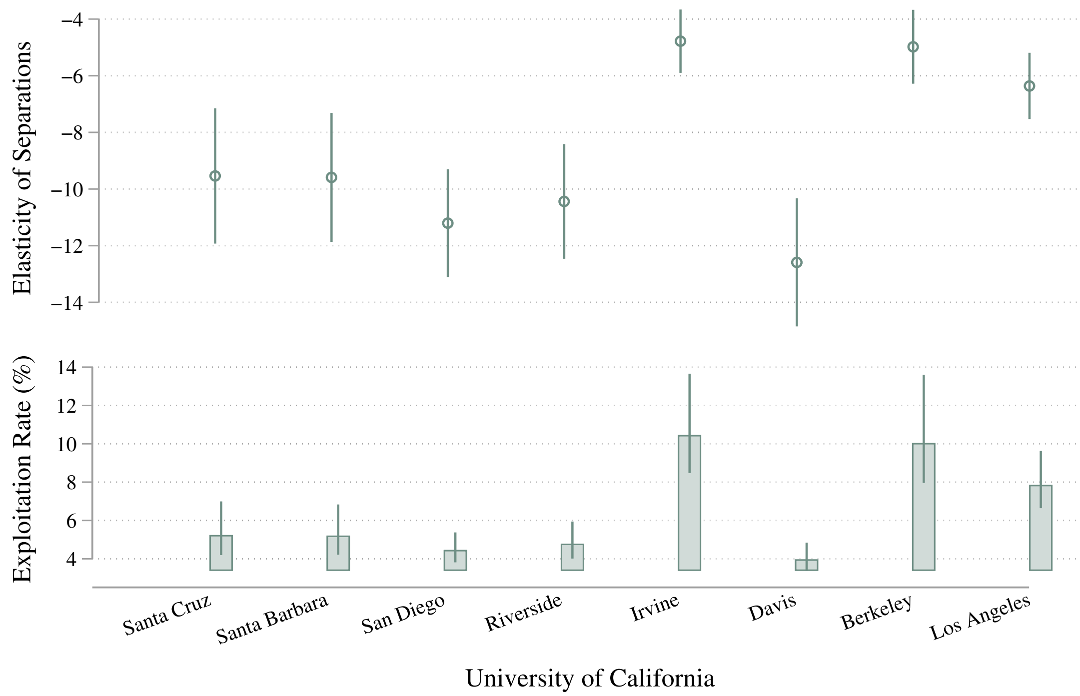


Figure 4: Heterogeneous Monopsony Power Across Universities.

Notes: This figure reports the 2SLS estimates of the elasticity of separation by university. Model includes title, field, and research productivity controls as well as faculty characteristics controls for gender, the cubic polynomials of years of experience, educational background, and working experience. Confidence Intervals are at 95% significance level. 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.	Diff	t-Stat
lnSalary	11.87	0.41	11.93	0.40	11.76	0.38	0.18***	(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	0.000057	(0.00)
Separation Rate	0.10	0.30	0.10	0.30	0.11	0.31	-0.0071	(-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)
Working Experience:								
Experience	19.45	12.92	21.02	13.22	16.33	11.69	4.69***	(15.64)
Postdoc Num	0.54	0.77	0.56	0.79	0.50	0.72	0.064***	(3.52)
Postdoc Yrs	1.62	2.91	1.71	3.05	1.44	2.60	0.27***	(3.87)
EverAdmin	0.04	0.19	0.04	0.18	0.04	0.19	-0.0021	(-0.48)
Publication Statistics:								
lnHindex	2.44	1.25	2.62	1.22	2.08	1.21	0.53***	(18.60)
lnCitation	6.32	2.64	6.69	2.58	5.60	2.60	1.08***	(17.72)
N	8089		5377		2712			

Notes: * $p < 0.05$, **$p < 0.01$, *** $p < 0.001$. A detailed description on variables can be found in Appendix C.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***
	(0.009)	(0.010)	(0.010)	(0.012)	(0.012)	(0.011)
N	8089	8089	8089	8089	8089	8089
Elasticity of Separation	-1.060	-0.777	-0.935	-1.455	-1.567	-0.895
Exploitation Rate	47%	64%	53%	34%	32%	56%
Exp^2 & Exp^3	✓	✓	✓	✓	✓	✓
Edu & Work	✓	✓	✓	✓	✓	✓
Title		✓	✓	✓	✓	✓
University			✓	✓	✓	✓
Field				✓	✓	✓
Research Productivity					✓	✓
Weighted						✓

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. Baseline model includes controls for gender and the years of experience. Exp^2 & Exp^3 indicates whether the model includes the quadratic and cubic terms of the years of experience variable. Edu & Work denotes faculty characteristics controls for educational background and working experience.

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

	Overall			By Job Title		
				Assistant	Associate	Full
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. First Stage:	lnSalary					
lnRevenue	0.153***	0.662***	0.584***	0.728***	0.658***	0.749***
	(0.006)	(0.030)	(0.042)	(0.056)	(0.055)	(0.058)
lnScale	1.030***	0.977***	0.971***	1.200***	1.095***	0.909***
	(0.018)	(0.026)	(0.025)	(0.073)	(0.060)	(0.034)
F Statistics	2154.121	1211.835	959.123	292.094	345.461	555.520
Panel B. Second Stage:	Separation					
α_1	-0.224***	-0.760***	-0.444***	-1.192***	-0.856***	-0.437***
	(0.016)	(0.028)	(0.026)	(0.070)	(0.069)	(0.031)
N	8089	8089	8089	1505	1723	4861
Elasticity of Separation	-2.231	-7.572	-6.732	-11.874	-8.531	-4.354
Exploitation Rate	22%	7%	7%	4%	6%	11%
Title		✓	✓	✓	✓	✓
Field		✓	✓	✓	✓	✓
University		✓	✓	✓	✓	✓
Research Productivity		✓	✓	✓	✓	✓
Weighted			✓			

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include faculty characteristics controls for gender, the cubic polynomials of the years of experience, educational background, and working experience. We report the Sanderson-Windmeijer (SW) First-Stage F statistics .

Table 4: Summary of Separation Destinations.

	# of Separations	Academia	·|Academia			
			R1 Research	R2 Research	Non-R1/R2 Others	Foreign Schools
	(1)	(2)	(3)	(4)	(5)	(6)
Male:						
Assistant	171	82%	55%	9%	10%	26%
Associate	126	83%	62%	5%	3%	30%
Full	215	89%	67%	4%	4%	25%
	512	85%	62%	6%	6%	26%
Female:						
Assistant	116	87%	71%	5%	17%	7%
Associate	72	93%	76%	9%	4%	10%
Full	83	94%	81%	3%	4%	13%
	271	91%	76%	5%	9%	10%

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.

Table 5: Two-stage Least Squares (2SLS) Estimates: Robustness Check

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. First Stage:	lnSalary					
lnRevenue	0.674***	0.667***	0.666***	0.570***	0.638***	0.679***
	(0.031)	(0.032)	(0.032)	(0.036)	(0.032)	(0.031)
lnScale	0.981***	0.977***	1.011***	0.972***	0.902***	0.941***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.028)	(0.027)
F Statistics	1199.318	1191.583	1249.136	1001.782	926.801	1109.546
Panel B. Second Stage:	Separation					
α_1	-0.715***	-0.660***	-0.632***	-0.620***	-0.832***	-0.801***
	(0.027)	(0.027)	(0.027)	(0.030)	(0.030)	(0.028)
N	8023	7941	6917	7584	8089	8089
Elasticity of Separation	-7.685	-7.893	-7.044	-7.042	-8.291	-7.983
Exploitation Rate	7%	7%	6%	7%	6%	6%
Sample	Sub 1	Sub 2	Sub 3	Sub 4	TT	TT

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. All models contains the full set of control variables including job title, field, and university 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. We report the Sanderson-Windmeijer (SW) First-Stage F statistics.

Table 6: Estimation of the Rate of Exploitation by Gender: 2SLS.

	Overall	By Job Title		
		Assistant	Associate	Full
	(1)	(2)	(3)	(4)
Panel A. First Stage:	lnSalary			
Male: lnRevenue	0.703***	0.781***	0.609***	0.754***
	(0.0395)	(0.0724)	(0.0726)	(0.0722)
Male: lnScale	0.975***	1.082***	1.149***	0.932***
	(0.0337)	(0.0895)	(0.0767)	(0.0438)
F Statistics	735.7	171.4	209.4	346.7
N	5377	877	985	3515
Female: lnRevenue	0.599***	0.656***	0.797***	0.723***
	(0.0460)	(0.0911)	(0.0845)	(0.0968)
Female: lnScale	0.957***	1.357***	0.907***	0.863***
	(0.0402)	(0.127)	(0.103)	(0.0512)
F Statistics	478.4	116.6	130.5	216.3
N	2712	628	738	1346
Panel B. Second Stage:	Separation			
Male: α_1^M	-0.810***	-1.230***	-0.805***	-0.522***
	(0.035)	(0.091)	(0.087)	(0.039)
Female: α_1^F	-0.710***	-1.179***	-1.044***	-0.288***
	(0.049)	(0.109)	(0.116)	(0.056)
Difference (Female − Male)	0.100	0.050	-0.238	0.234
p-value	0.097	0.724	0.100	0.001
Elasticity of Separation:				
Male	-8.262	-5.990	-6.100	-8.451
Female	-6.753	-5.925	-10.268	-4.556
Exploitation Rate:				
Male	6%	8%	8%	6%
Female	7%	8%	5%	10%

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Instrumental variables used: the school revenue (IV1) and the salary scale (IV2). All models contains the full set of control variables including job title, field, university dummies, research productivity indicators, and the baseline faculty characteristics controls. We report the Sanderson-Windmeijer (SW) First-Stage F statistics.

Table 7: Estimated Female to Male Salary and Salary Gap Ratios.

	Overall	By Job Title		
		Assistant	Associate	Full
	(1)	(2)	(3)	(4)
Panel A. Observed Gender Salary Ratio:				
W_F/W_M	0.837	0.909	0.895	0.885
$(W_F - W_M)/W_M$	-0.163	-0.091	-0.105	-0.115
Panel B. Elasticity of Labor Supply ($\hat{\varepsilon}_{Nw}$):				
Male	16.524	11.98	12.2	16.902
Female	13.506	11.85	20.536	9.112
Panel C. Gender Ratios (Female/Male):				
Elasticity of Labor Supply Ratio, $\hat{\psi}_{FM}$	0.817	0.989	1.683	0.539
MRP Ratio, $\hat{\eta}_{FM}$	0.857	0.890	0.849	0.861
Panel D. Assume $MRP_M = MRP_F$:				
$\hat{W}_F/\hat{W}_M$	0.987	0.999	1.032	0.954
$(\hat{W}_F - \hat{W}_M)/\hat{W}_M$	-0.013	-0.001	0.032	-0.046
Predicted/Observed (in %)	8%	1%	-30%	40%
Panel E. Add MRP Ratio η_{FM}:				
$\hat{W}_F/\hat{W}_M$	0.846	0.889	0.876	0.822
$(\hat{W}_F - \hat{W}_M)/\hat{W}_M$	-0.154	-0.111	-0.124	-0.178
Predicted/Observed (in %)	94%	122%	118%	155%

Notes: $\hat{\varepsilon}_{Nw}$ is calculated based on 2SLS results using instrumental variables the school revenue (IV1) and the salary scale (IV2) in Table 6. Assuming $MRP_M = MRP_F$ is equivalent to assume $\eta_{FM} = 1$. Following Equation (8), $\hat{W}_F/\hat{W}_M = [\hat{\eta}_{FM} \cdot (\hat{\psi}_{FM} + \hat{\varepsilon}^F_{Nw})]/[1 + \hat{\varepsilon}^F_{Nw}]$. Row 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 $(W_F - W_M)/W_M$.

Table 8: Estimation of the Marginal Revenue Product Ratio η.

	Overall	By Job Title		
		Assistant	Associate	Full
	(1)	(2)	(3)	(4)
	lnHindex			
Female	-0.154***	-0.117***	-0.164***	-0.150***
	(0.0233)	(0.0432)	(0.0417)	(0.0337)
N	8089	1505	1723	4861
Title	✓			
Field	✓	✓	✓	✓
University	✓	✓	✓	✓
R^2	0.438	0.463	0.499	0.332
MRP Ratio ($\hat{\eta}_{FM}$)	0.857	0.890	0.849	0.861

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 working experience. We estimate the OLS model: $lnHindex = \beta_0 + \beta_1 Female + \mathbf{X} + \varepsilon$. Since $\beta_1 = lnHindex_F - lnHindex_M = ln(Hindex_F/Hindex_M)$, we can calculate the MRP Ratio ($\hat{\eta}_{FM}$) by taking the exponential of β ($\exp(\beta_1)$).

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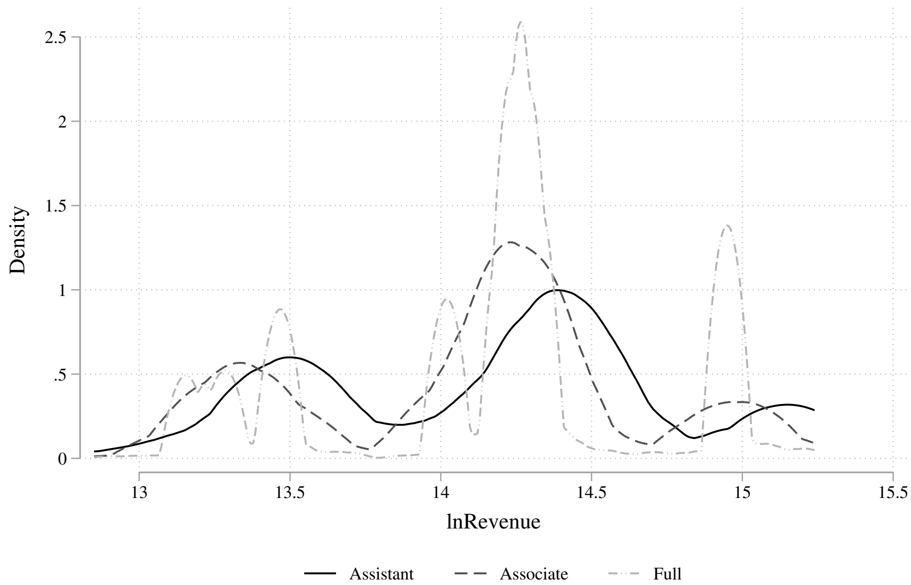
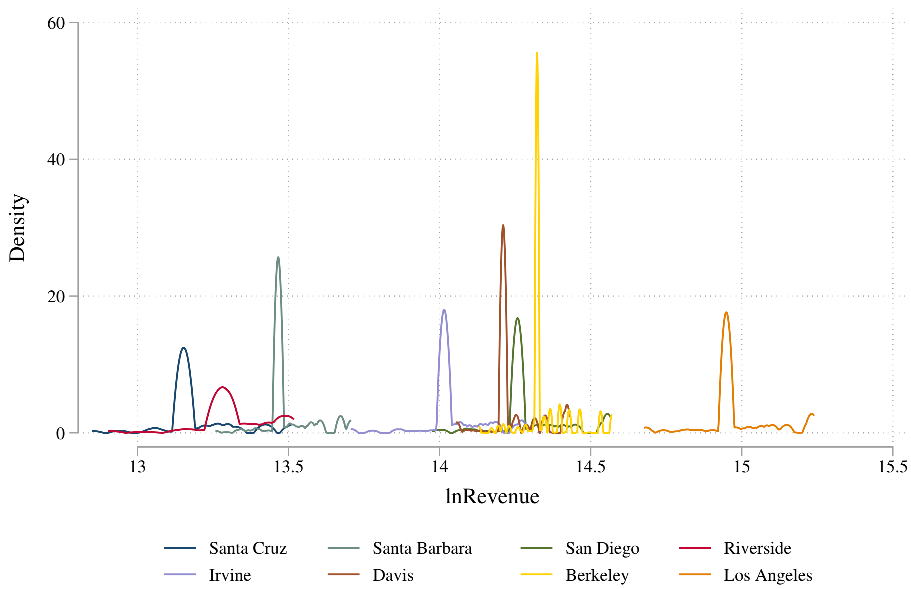
A Figures

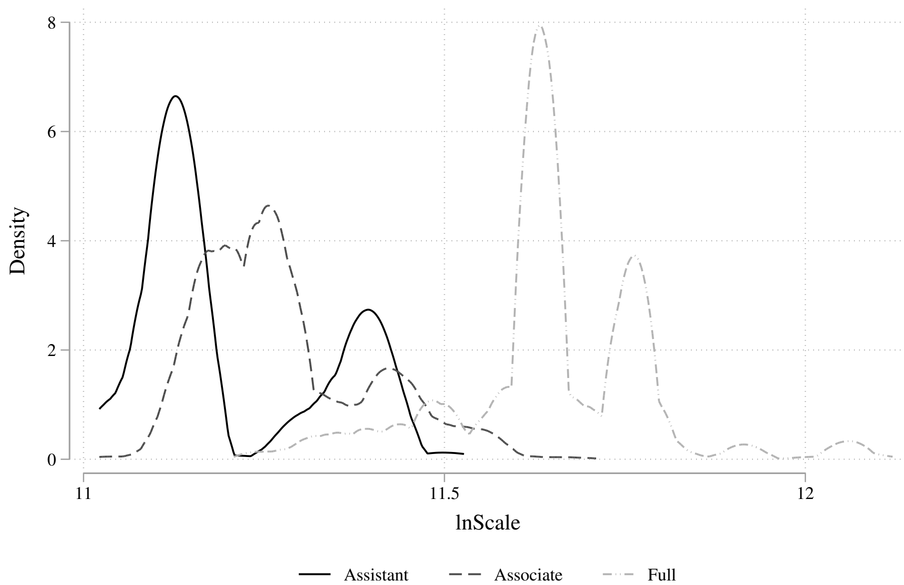


(a) Variation Across Titles.

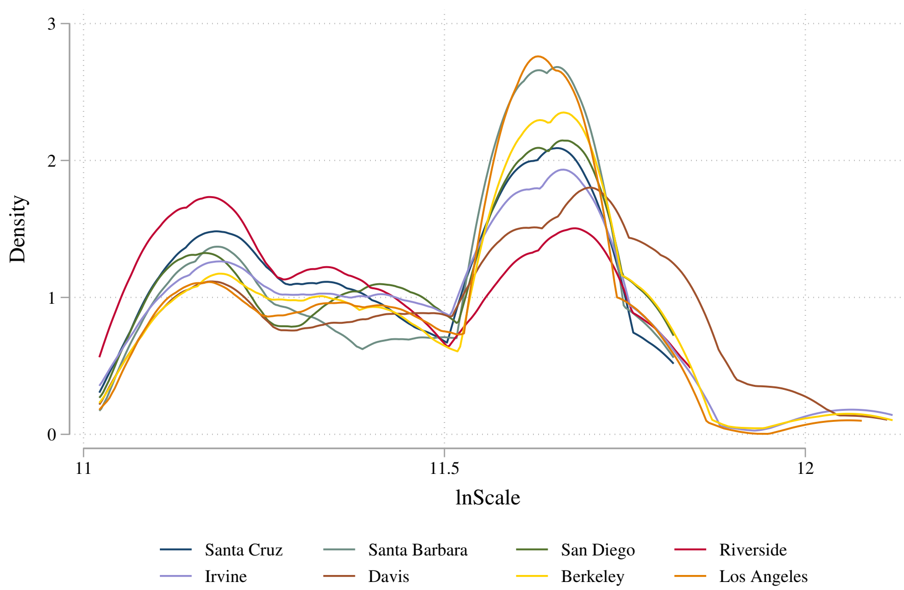


(b) Variation Across Universities.

A.1: Variations in the School Revenue IV.



(a) Variation Across Titles.



(b) Variation Across Universities.

A.2: Variations in the Salary Scale IV.

B Tables

B.1: Average Coverage Rate by School.

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

B.2: Robustness Check: 2SLS, Add Weights.

	By Job Title			Overall	By Job Title		
	Assistant	Associate	Full		Assistant	Associate	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Second Stage:				Separation			
Overall: α_1	-1.151***	-0.684***	-0.206***				
	(0.079)	(0.076)	(0.027)				
Male: α_1^M				-0.492***	-1.177***	-0.644***	-0.270***
				(0.033)	(0.106)	(0.096)	(0.034)
Female: α_1^F				-0.385***	-1.208***	-0.839***	-0.085*
				(0.045)	(0.125)	(0.127)	(0.047)
Difference (Female − Male)				0.106	-0.031	-0.195	0.185
p-value				0.055	0.850	0.220	0.001
F Statistics							
Overall	295.420	256.965	467.205				
Male				563.9	162.5	159.9	288.9
Female				408.6	122.1	92.05	186.0
N	1505	1723	4861	8089	1505	1723	4861
Elasticity of Separation $\hat{\varepsilon}_{sw}$							
Overall	-17.446	-10.369	-3.118				
Male				-7.797	-5.469	-6.780	-7.156
Female				-5.360	-5.687	-12.484	-1.991
Exploitation Rate E							
Overall	3%	5%	16%				
Male				6%	9%	7%	7%
Female				9%	9%	4%	25%
Weighted	✓	✓	✓	✓	✓	✓	✓

[1] Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[2] All models contains the full set of control variables including job title, field, university dummies, research productivity indicators, and the baseline faculty characteristics controls.
[3] We report the Sanderson-Windmeijer (SW) First-Stage F statistics. Elasticity of Separation $\hat{\varepsilon}_{sw}$ is estimated by dividing the salary coefficient by the baseline separation mean $\bar{s}$. The implied Exploitation Rate $E = 1/[-2\hat{\varepsilon}_{sw}]$.

B.3: Robustness Check: 2SLS, Single IV.

	IV1: School Revenue		IV2: Salary Scale		IV1 + IV2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. First Stage:	lnSalary						
lnRevenue	0.157***	0.933***			0.149***	0.674***	0.662***
	(0.006)	(0.032)			(0.005)	(0.028)	(0.030)
lnScale			0.929***	1.113***	1.000***	0.925***	0.977***
			(0.017)	(0.026)	(0.026)	(0.017)	(0.026)
F Statistics	754.662	859.230	2861.827	1835.157	1165.824	1824.004	1211.835
Panel B. Second Stage:	Separation						
α_1	-0.340***	-2.156***	-0.310***	-0.174***	-0.251***	-0.655***	-0.760***
	(0.039)	(0.081)	(0.022)	(0.028)	(0.024)	(0.022)	(0.028)
N	8089	8089	8089	8089	8089	8089	8089
Elasticity of Separation $\hat{\varepsilon}_{sw}$	-3.389	-21.479	-3.087	-1.735	-2.496	-6.523	-7.572
Exploitation Rate E	15%	2%	16%	29%	20%	8%	7%
Title	✓	✓		✓	✓		✓
Field	✓	✓	✓	✓	✓	✓	✓
University		✓	✓	✓		✓	✓
Research Productivity	✓	✓	✓	✓	✓	✓	✓

[1] Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$.
[2] All models include faculty characteristics controls for gender, cubic polynomials of years of experience, educational background, and working experience.
[3] We report the Sanderson-Windmeijer (SW) First-Stage F statistics. Elasticity of Separation $\hat{\varepsilon}_{sw}$ is estimated by dividing the salary coefficient by the baseline separation mean $\bar{s}$. The implied Exploitation Rate $E = 1/[-2\hat{\varepsilon}_{sw}]$.

C More on the Data and Variables

C.1 Compiling Use Data

In this section, we provide more details on the data construction process. The use data is constructed by combining three sets of data: the faculty salary data, the scraped faculty characteristics, and research productivity measures. The faculty salary data is retrieved from the University of California (UC)'s employee pay data. The faculty characteristics are collected via online searching. Measures of the research productivity are scraped from the Scopus database.

Faculty Salary Data

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

The salary panel data not only provides information about the amount of salary received by employees but also allows researchers to observe the duration of an employee working in the institution. In other words, from the salary panel, we know whether the employee left the institution, either shortly or permanently, and the year of leave. For example, if we observe the employee pay to a faculty member was stopped since 2015, then we may infer this faculty member left the school in 2015. A more likely case is that the employee pay to this faculty member in 2014 was shrunk, say by more than 50% and there was no payment 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/Summer semester. We can also distinguish the permanent leave from the temporary leave. If the faculty member is on-leave or had a short-term visiting to other schools, then, we would observe the pay to the faculty member was sharply reduced or ceased in some years, and was back to normal or resumed 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, that only employees whose titles contain "professor" would be included in the sample.

Based on the title appeared in the payroll record, we generate three dummy variables to indicate whether faculty are titled "Assistant", "Associate", or "Professor" in the last year when the faculty member was observed to have the payroll record.[38]

[38] 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".

Faculty Characteristics Data

Based on the full name, school, and title, we conduct online searching of faculty's personal website, department profile, and CV/resume to collect information about faculty's gender, working department, educational background, and work history.

Specifically, we observe the gender and working department of each faculty member, which helps us to construct the gender and field indicators. Since we are interested in the gender pay gap in the university, 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 is available, then we turn to the gendered pronouns used by a third-party. In this case, we assign gender based on the gendered pronouns used by students to refer to the faculty member in reviews on RateMyProfessors.com or the gendered pronouns for the faculty member in news on the institutional websites[39]. 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 working field to faculty based on the name of department they worked at. 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 10 Major Field Categories classified by NSSE in Appendix D .

For the educational background, we collect information on faculty's doctoral-granting institutions, master granting institutions, and bachelor granting institutions as well as the year of graduation from each institution. For the work history, we collect information on both the post-doctoral experience and work experience, including the name of previous employer(s) and the work duration in each employer. Later in this section, we discuss the control variables generated according to the information on educational background and work history.

As discussed above, the salary panel data helps us to observe whether a faculty member permanently left the school during 2010-2018. We verify the employment status of each faculty member in the online searching process. Specifically, we check whether faculty indeed left the university during 2010-2018 for faculty whose compensation had been terminated during the sample period.[40] Moreover, if a faculty member left the school, 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 one if a faculty member is found to no longer work at a school in the UC system.

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

[40]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.

Research Productivity Data

We use the publication statistics to measure faculty's research productivity. We scrape the number of total citations and H-index, a commonly-used citation impact statistics from the Scopus, an abstract and citation database of Elsevier. We identify each faculty member by full name. To avoid mismatching scholars with the same name, we also add 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.[41]

We create two variables to measure faculty's research productivity: *lnHindex* and *lnCitation*, which are the logarithm of h-index and total citation number, respectively.

The Final Use Data

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 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-track (or ladder-rank) faculty, we then exclude 3,022 (19.9%) non-tenure-track 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 school in 2018 or left the school 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 start 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 Ph.D. granting school information. The final data set then contains 8,089 faculty members.

Coverage

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. 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

[41] 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 better coverage of the sample.

the number of faculty members identified in the sample in each school and each year, we calculate the coverage rate by simply dividing the number of observations by the headcount. Table B.1 summarizes the average coverage rate by school. The average coverage rates are over 90% for all of the eight schools, suggesting that the sample has acceptable coverage.

C.2 Descriptions on Variables

The Salary Measure

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 academic year or fiscal year, the payroll record in the year when the job started or terminated covers only a part of the annual compensation.[42] For example, faculty who left the school in Fall 2016 would still see his compensation for Spring 2016 appear in his/her 2016 payroll record. Therefore, for faculty who left his/her original working institution and move to a new school, the compensation usually dropped significantly in the year when the separation occurred (i.e., the termination year). Put it differently, in the last compensation record.[43] To precisely measure the compensation level of both faculty who once worked and who continue working in the UC system, we constructed the *MeanSalary* variable by taking the average of gross pay excluding the first and/or the last salary records.[44] The *MeanSalary* variable reduces the measurement errors and helps to capture the salary history before the movement for faculty members who left the school. Formally, for a faculty member i worked in school s during time period $t, t+1, ..., T$, the mean salary $MeanSalary_{si}$ can be calculated according to the following formula:[45]

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

$$lnSalary_i = \log\left(MeanSalary_i\right)$$

lnSalary is the logarithm of mean salary.

Instrumental Variables

We are using two instrumental variables of the salary.

[42] Salary schedule in Academic Year (Fiscal Year) is paid by nine-month (twelve-month) periods.

[43] A similar pattern applies to faculty who joined the universities in the sample during 2010-2018: there would be a jump of salary in the year after the start year.

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

[45] Using this formula, we may underestimate the mean outcomes for faculty members who left and stayed less than 3 years in the school. However, including these faculty members does not change the results significantly. In the robustness check, I will show that the results from a sample excluding these faculty members are similar to the results reported.

IV1: School Revenue. We retrieved the annual school revenue data during Fiscal Year 2009-2010 (matched to payroll record in year 2010) and Fiscal Year 2017-2018 (matched to payroll record in year 2018) from the UC System Online Infocenter. We only consider school revenue from the following sources: Private gifts, State educational appropriations, Auxiliary enterprises, Educational activities, and Student tuition and fees. School 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 school revenue for each faculty member by first summing the revenue of the university where faculty worked over the years used in the calculation of the mean salary for that faculty, and then taking the average. For example, the mean school revenue for faculty worked in UC Irvine during 2010-2018 would be calculated by taking the average of the school revenue in UC Irvine during FY 2010-2011 and FY 2016-2017. Thus, FY 2009-2010 and FY 2017-2018 are excluded. Formally, for faculty i worked in school s during time period $t, t+1, ..., T$, the mean school revenue for faculty i, $MeanRevenue_{si}$ can be calculated according to the following formula:

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

$$lnRevenue_i = \log\left(MeanRevenue_i\right)$$

The first instrumental variable *lnRevenue* is the logarithm of mean school revenue.

IV2: Salary Scale. The system-wide salary scale used in the UC system is extracted from the UCOP Human Resources website. 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 fields such as General, Business/Economics/Engineering, Law, and Veterinary Medicine and by compensation schedule, e.g., paid by Fiscal Year (12 months) or Academic Year (9 months). We collect scale data from 2009-2010 to 2017-2018 Academic Years and merge them into the sample by title, field, and compensation schedule. We calculate the mean salary scale for each faculty member over the years s/he spent on a given campus, excluding the first and/or the last year (i.e., the same period used in the calculation of the mean salary). Similarly, for faculty i worked in school s during time period $t, t+1, ..., T$, the mean salary scale for faculty i, $MeanScale_{si}$ can be calculated according to the following formula:

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

$$lnScale_i = \log\left(MeanScale_i\right)$$

The second instrumental variable *lnScale* is the logarithm of the mean salary scale.

Note that by design, the two instrumental variables — school revenue and salary scale are lagged measures. It is caused by two factors. Firstly, the measurement periods of the employee pay data, the school revenue data, and the salary scale data are mismatched. The employee pay data is in calendar years, while the school revenue data is measure at fiscal years and the salary scales are according to the academic years (e.g 2016-2017 Academic Year). We pair the calendar year with the “lagged” fiscal year and the academic year. For example the fiscal year 2009-2010 and academic year 2010-2011 are matched to the calendar year 2010. Secondly, the mean school revenue and mean salary scales are calculated over years when faculty stayed in the school removing the first year and the last year of the stay. Thus, these two mean variables capture the historical records of school revenue or salary scales.

Control Variables

Now, we describe control variables on educational background and work experience.

Several variables are constructed to measure faculty’s educational background. First, whether faculty received bachelor’s or doctoral degrees from schools that belong to the UC system. Two variables are constructed to control for being UC alumni: *UGinUC*: A dummy variable which equals one if faculty obtained a Bachelor’s degree in the UC system; *PhDinUC*: A dummy variable which equals one if faculty obtained a PhD in the UC system. Second, we consider whether the degree granting institutions are foreign or domestic. *UGinForeign* and *PhDinForeign* are two dummy variables which equal to one if faculty obtained any Bachelor’s degree or Ph.D from foreign institutions (institutions outside the United States), respectively.

As for the work experience post-graduation, first, we consider the number of years since graduation. *Experience* is a discrete variable measuring the number of years since the faculty member joined the job market. It is estimated by calculating the number of years between 2018 and the year when the faculty member obtained his/her highest degree. We also construct two variables controlling for faculty’s postdoctoral experience. One is *Postdoc Num*: A discrete variable that measures the number of postdoctoral experience. Any research position post-graduation in any research institution such as universities, research centers, and laboratories is coded as postdoctoral experience. Different positions in the same institution are combined to one experience. Positions in two different institutions are coded as two experiences. Another is *Postdoc Yrs*: A discrete variable that measures the total years of postdoctoral experience. Lastly, to distinguish faculty who have ever took an administrative job, we use a dummy variable *EverAdmin* as an indicator of whether the faculty member has ever taken administrative positions such as the Dean, Provost, or Director. *EverAdmin* equals to one if the faculty member had worked as both faculty and academic administrator in the current institution and 0 otherwise.

D Fields Based on NSSE 10 Major Field Categories

The field that a specific faculty belongs to is inferred by the department s/he works at. I classified the fields in the sample into 10 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, e). SOCIAL SCIENCES, f). BUSINESS, g). COMMUNICATIONS, MEDIA, & PUBLIC RELATIONS, h). EDUCATION, i). ENGINEERING, j). HEALTH PROFESSIONS, k). SOCIAL SERVICE PROFESSIONS, and l). OTHER MAJORS (NOT CATEGORIZED). Three interdisciplinary fields are separately listed instead of putting them in the OTHERS category: m). CHEMISTRY & BIOCHEMISTRY, n). COGNITIVE SCIENCE, o). 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;

E Results From Single IV

In the following discussion, we first show 2SLS results using either the school revenue IV or the salary scale IV. Then, we discuss the limitations of employing the single IV and the benefits of using both IVs.

Table B. 3 summurizes results from single IV. We report 2SLS results using the school revenue IV in Columns (1)-(2) and results using the salary scale IV in Columns (3)-(4). All models include faculty characteristics controls for gender, cubic polynomials of years of experience, educational background, and working experience. Panel A shows the first-stage results. Both the school revenue IV and the salary scale IV are positively correlated with salaries. We observe large first stage F statistics and the weak IV problem seems unlikely. We report in Panel B the second-stage results, the estimated wage elasticity of separation, and the implied rate of exploitation.

Column (1) shows that the 2SLS regression using the school revenue IV provides a rate of exploitation of about 15%. We omit university dummies in the model of Column (1). Adding university dummies substantially changes the 2SLS estimates. As shown in Column (2), the estimated rate of exploitation is reduced to 2% after adding university dummies. Such change is likely to be driven by the fact that within universities, the variation in salaries driven by the change of school revenues may come from a small amount of faculty members and the estimated labor supply elasticity would become extremely "local". The way we construct the school revenue IV implies that we assign the same value of the school revenue IV to faculty who stay in the same school during the same period. We show in Appendix Figure A.1 that we observe mass points in the density of the school revenue IV. There is little variation in the school revenue IV within universities.

We observe a similar pattern of changes in the estimate of the exploitation rate when use the salary scale as the single IV. In Column (3), we show the result of the salary scale IV, adding field, university, and research productivity controls. We do not include title dummies in the 2SLS regression due to the concern that salary scales vary primarily by title. Appendix Figure A.2 shows the density plots of IV2 by title and university. Because salary scales can be different across pay schedule and field, i.e., not solely determined by title, we do observe some variations in the salary scale IV within titles, nonetheless, we still find mass points in the density of IV2 within titles. Column (3) shows that the rate of exploitation is estimated at 16%, a number similar to the result in Column (1) using the school revenue IV. However, adding the title dummies substantially changes the estimate of exploitation rate to 29%, as shown in Column (4). Controlling for title dummies along with field and university dummies may considerably reduce the variability in the salary scale IV, which raises the similar concern as in the case of using the school revenue IV that the variation in salaries driven by the salary scale IV comes from some "outlier" faculty.

We benefit from using both the school revenue and the salary scale as two IVs for faculty salaries because by doing so we are able to exploit changes in faculty salaries that are driven by either the exogeneous changes in the school revenue or the salary scale. Employing two IVs also allows us to include both the university and the title dummies. Adding university dummies is necessary since without the university control, we are implicitly treating the eight schools in the UC system as single "firm". However, there are reasons to think of the eight schools as individual "firms" since each school operates independently and has the autonomy to make decisions on various issues, including the salary setting.

Columns (5)-(7) report the 2SLS estimates using both two IVs. Our preferred result is in Column (7) which includes the title, university, and field dummies. The rate of exploitation is estimated at 7%. As shown in Column (5), after excluding university dummies, the rate of exploitation becomes 20%, while excluding the title dummies does not substantially change the result — Column (6) shows the exploitation rate is about 8% after removing the title dummies.