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Gender Pay Gaps in the Social Sciences

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We provide a longitudinal, multi-field analysis of the gender pay gap in academia that directly links individual-level salaries to measures of scholarly productivity. Using administrative data from the ten campuses that comprise the University of California system, we combine detailed pay records with bibliometric data on publications and citations for faculty in five major social science fields. We find a raw gender pay gap of 23%, which decreases to 4.3% after controlling for field, campus, and cohort. Including controls for job title and scholarly productivity has little effect on the estimated gap, although they substantially increase explanatory power. A decomposition shows that 17% of the gap is unexplained, persisting across junior and senior faculty. We also find a large, persistent gender gap in publications, but no citation gap once output and career length are considered.

Field-level analysis reveals that pay gaps are not universal: they persist in Business, Sociology, and Anthropology, but are absent in Economics, Political Science, and smaller social science fields. Our results suggest that pay transparency is insufficient to eliminate salary disparities and that more equal representation within the field is not a prerequisite for pay equity. Our study isolates the residual gap that remains unexplained by productivity or seniority, challenging the view that these factors fully account for gender pay differences. Taken together, our findings highlight the role of field-specific norms and institutional structures, offering new directions to promote equitable compensation in academia.

gender pay gap | academia | productivity | compensation

Significance

The gender pay gap remains a persistent feature of labor markets, yet its sources are difficult to disentangle. Using detailed longitudinal data on faculty in the University of California system, we measure gender disparities in pay while holding constant academic field, campus, seniority, and scholarly productivity. We find that a raw gender pay gap of 23% falls to about 4% after accounting for observable differences. This residual gap remains unexplained. Some disciplines exhibit no gender pay gap, while others show persistent disparities, suggesting that pay inequality is not inevitable.

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All authors contributed to the writing and framing of the paper. Graff Zivin, Khanna, Lyons, and Serra-Garcia undertook research for the paper and contributed to the research design. Khanna, Lyons, and Serra-Garcia performed the data preparation and analysis. Graff Zivin provided scientific leadership.

The authors declare no competing interest.

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1. Introduction

The gender pay gap is a persistent and prominent feature of labor markets worldwide: women consistently earn less than men. In the United States, although the Equal Pay Act of 1963 prohibits gender-based wage differences for the same work, women earn about 83 cents for every dollar earned by men (1). Substantial evidence documents these disparities across sectors and throughout the wage distribution (2–8).

Extensive research exploring potential drivers of the gender pay gap highlights three main explanations. One emphasizes occupational and industrial sorting, with women disproportionately concentrated in lower-paying sectors (e.g., 9–11). Another attributes the gap to differences in human capital—such as education, work experience, and career interruptions—that influence productivity and earnings potential (e.g., 12–15). A third perspective highlights the influence of social norms, preferences, and workplace discrimination on opportunities, promotions, and compensation (e.g., 16–22). Disentangling the relative importance of these factors remains challenging due to data limitations and the multifaceted nature of the issue.

We contribute to this discussion by examining gender pay disparities among faculty across the ten campuses of the University of California system. Drawing on individual-level data from 2014 to 2021, we link publicly available administrative records on salaries, departments, job titles, campus affiliations, and cohorts with bibliometric measures of publications and citations. The resulting dataset enables a longitudinal analysis of pay, promotion, seniority, and scholarly output.

We find a raw gender pay gap of 23%. Accounting for pay year, cohort, field, and campus reduces the gap to 4.3%. Further controlling for seniority, publications, and citations has little effect on the remaining gap, although combined these variables substantially increase explanatory power (adjusted R^2 rises from 0.034 to 0.599). The residual 4.3% pay gap is present at both the assistant and full professor levels. A Kitagawa-Blinder-Oaxaca decomposition indicates that just over 17% of the gap is unexplained by observable characteristics, suggesting the

influence of other factors. We compare our magnitudes to 57 other studies in Appendix Table B4.

Our analyses also reveal notable variation across disciplines that is not explained by female representation. After conditioning on year, location, start year, field fixed effects, and measures of publications and citations, we find that the pay gap is largest in Business and Anthropology (about 7%), whereas Economics exhibits a small reversed gap favoring women. This is despite female representation in Business and Economics in our sample being at similar levels below 20%, while being closer to 50% in Anthropology. Gender gaps in publications favor men in all fields except Business, while citation gaps vary in magnitude and direction.

Unlike prior research on the gender gap in academia, which focused primarily on Economics (23–26), our research spans five major social science fields—Anthropology, Business, Economics, Political Science, Sociology, and an additional category (“Other”) that includes smaller social science fields in our data. Leveraging longitudinal panel data, we go beyond the event-study frameworks of earlier studies, which have largely focused on non-pay-related outcomes (27, 28). By comparing disciplines, we provide evidence suggesting that field-specific norms and institutional structures shape gender pay gaps in academia.

Because the UC system had pay transparency throughout our study period, our setting also sheds light on gender pay gaps in the presence of pay transparency. One frequently cited contributor to unexplained pay differences is gender variation in salary negotiations (see, e.g., 29, for a recent review). Increased pay transparency is often proposed as a potential corrective to help achieve improved outcomes (30–32), although some of these studies do not incorporate detailed measures of scholarly productivity. Our study is consistent with the fact that the mere availability of pay information does not guarantee that gender pay gaps are eliminated.

By focusing on a large, public university system with detailed, publicly available salary data, combined with comprehensive measures of scholarly productivity, our study provides a unique evaluation of the gender pay gap while accounting for both individual performance and

institutional context. In doing so, we contribute to the broader literature on the determinants of the gender pay gap, the role of negotiation and transparency, and the persistence of unexplained disparities in high-skilled labor markets.

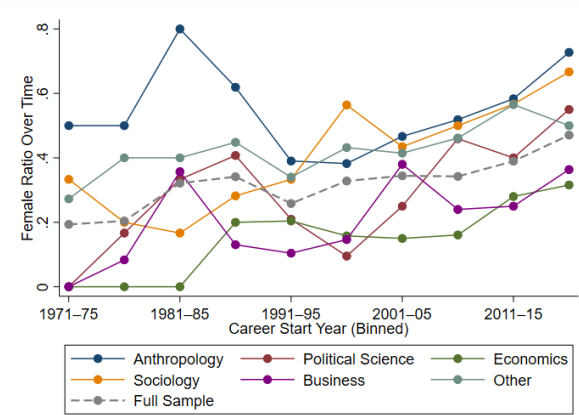
2. Results

Female representation in the Social Sciences. We begin by summarizing the representation of women among UC academic employees and how this has changed over time, starting in 1971. Panel (a) in Figure 1 provides the proportion of female faculty who joined academia in each five-year cohort. Our pay data is from 2014–2020, and we assign career start years from each researcher’s bibliographic information. As can be seen, female representation has grown across all fields in our data. By our final cohort, women account for nearly 50% (or more) of faculty in anthropology, sociology, political science, and other social sciences. In contrast, economics and business remain male-dominated.

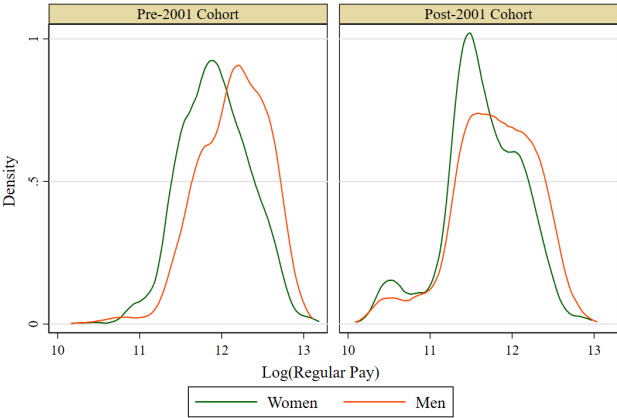
Importantly, as female representation increases, the gender pay gap appears to be declining. Raw data, presented in Panel (b) in Figure 1, demonstrates that average pay for females who entered academia before or after 2001 is meaningfully lower than it is for their male peers; however, the average gender wage gap is somewhat bridged for later cohorts. That is, the gender wage gap among post-2001 entrants is smaller on average than it is for those who entered pre-2001. The variation of pay among females who entered academia post-2001 is also lower compared to more senior females, with their male counterparts displaying a noticeable right tail in the wage distribution.*

Gender pay gaps in the Social Sciences. While unconditional pay is lower for females in the social sciences than it is for males,[†] across cohorts, this may be explained by a combination of observable differences between the two groups. For example, male academics may be more

Fig. 1. Female Representation and Pay Over Time



(a) Proportion of Females Among New Entrants by Field Over Time



Graphs by Career Start Year

(b) Wage Distributions by Gender and Cohort

Note: Panel (a) plots the share of faculty who are employed by field and career start year. Data are based on UC salary records from 2014 to 2020. Career start years are derived from researcher bibliographic information. Panel (b) shows the kernel density of Log(regular pay) by career start cohorts. During the pre-2001 cohort, mean log earnings are 11.918 and 12.127 for females and males, respectively, with a corresponding gap of 0.209. In the post-2001 cohort, mean log earnings were 11.611 and 11.775 for females and males, respectively, with a corresponding gap of 0.164.

*The wage distribution displayed in Panel (b) of Figure 1 is wide, capturing that salary in our data ranges from \$32,000 in the 1st percentile to \$390,000 in the 99th. Faculty salaries below \$50,000 are rare in our data (less than 4 percent of observations) and may be driven by partial faculty leaves. While we cannot observe the precise reasons for low salaries (e.g., leaves), we test whether dropping faculty-years with below \$50,000 in earnings affects our findings and find that it does not.

[†]The unconditional gender pay gap is the raw average difference between male and female pay in log dollars, not controlling for any explanatory variables.

productive or more likely to be senior or experienced than female academics on average.

One advantage of our data is that it simultaneously has compensation, career age, and publication information, allowing us to document the differential trajectory of wage growth with respect to measures of output, career progression, and productivity. We first examine how wages vary with publications in the top two panels of Figure 2. In Panel (a), we plot the raw relationship, with no controls. In Panel (b), we residualize both publications and compensation, controlling flexibly with indicators for year, campus, cohort, and field.

Consistent with the explanatory power of productivity for earnings, both panels demonstrate a strong positive relationship between publications and pay for both males and females. In the raw data, however, males are paid higher wages across the publication trajectory. That is, for every level of publication output, men earn higher wages. The gap is large, as the differences are in log points. Once we condition on faculty characteristics (field of study, UC campus, career start year, and year of wage observation), the male and female publication-wage relationship curves look more similar, where again there is a right tail in male earnings that is higher than their female counterparts. We find similar patterns for citations.

Similarly, Panel (c) in Figure 2 demonstrates that pay is increasing in career length for both males and females, but the gender wage gap is stark across the career trajectory. For every cohort, men are paid more, and the gap is again meaningfully large.[‡] However, once we condition on the field of study and the UC campus (Panel (d)), the gap is substantially reduced, particularly for younger academics. Relatively senior academics continue to show some gender wage gap, which seems less prominent among early-stage researchers.

Unpacking the Gender Wage Gap. The patterns shown in Figure 2 motivate our primary analysis of the gender pay gap among social scientists, where we gradually include faculty characteristics, including productivity, as controls to assess how much of the gap can be explained

by each observable, and how much remains unexplained. We estimate the following specification:

$$\begin{aligned} \log(\text{Regular Pay}_{iyflcj}) = & \beta \text{Female}_{iyflcj} + \mu_y + \mu_f + \mu_l \\ & + \mu_c + \mu_j + \gamma_1 \text{Citations}_{iyflcj} \\ & + \gamma_2 \text{Publications}_{iyflcj} + \epsilon_{iyflcj}, \end{aligned} \quad [1]$$

Where $\text{Log Regular Pay}_{iyflcj}$ are the earnings for individual i , in year y , field f , campus location l , cohort start year c , and with job title j . Our primary coefficient of interest is the coefficient on the Female_{iyflcj} indicator, conditioning on a set of fixed effects for year, field of study, campus, cohort start year, and job title. As we include campus fixed effects, we may not be picking up changes that occur as a result of inter-campus mobility. However, since the UC rules prevent inter-campus wage bidding, this is unlikely to meaningfully alter wages. Cohort start year is measured as equal to the year when a faculty member's first publication was published, or the year they entered the UC system as a faculty member.[§] We add these fixed effects incrementally to observe how the gap β changes, and the explanatory power of these controls (the R^2).

Finally, we control for lagged measures of productivity, like publications and citations. We include lagged productivity to account for time delays in pay responses to performance. As job title and productivity may, themselves, display large gender gaps, we include these factors as controls last. Indeed, seniority and rank depend on how departments promote individuals, which may be endogenous to individual characteristics. Our approach allows us to first understand how much of the gap is explained by other factors (such as the year, field, campus location, and cohort) that were not determined *after* the individual started their current job.[¶]

This analysis is presented in Table 1. On average, as the coefficient in column 1 demonstrates, females are paid about 23 percent less (0.21 log points) than males before

[§]One limitation of our definition of cohort is that, if the UC hires professors with no publications from institutions where they had professor titles, we would be erroneously classifying them as new PhD graduates. This would affect the cohort control estimates if the practice were correlated with gender and not rare.

[¶]We confirm that our estimates are not sensitive to the inclusion of an interaction between publications and citations and, thus, restrict our analyses to including the two measures of productivity separately.

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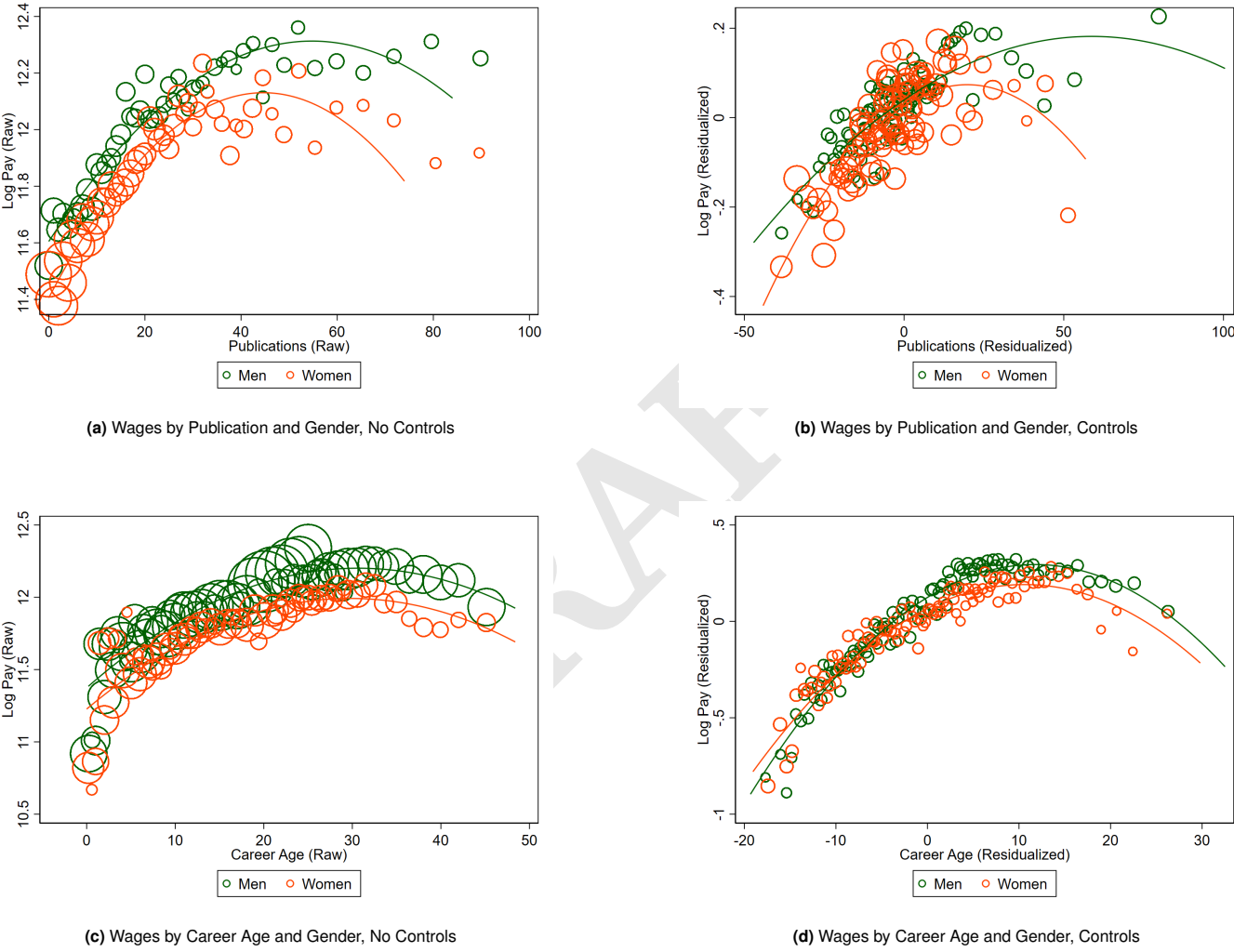


Fig. 2. Wage Gaps Across Experience and Productivity Distributions. The top two panels plot the trajectory of Log(regular pay) by publications and gender. Panel (a) plots the raw relationship, while Panel (b) includes year, location, start year, and field fixed effects. The bottom two panels show trajectories by career start date. Panel (c) is the raw relationship, and Panel (d) includes location and field fixed effects. Each plot includes 100 bins (for each gender), weighted by the number of observations in each bin.

we adjust for differences between male and female social scientists. Once we account for faculty field of study, this gap falls to 0.124 log points (column 3), providing additional evidence of the importance of differential selection into career specializations as a contributor to average gender pay gaps (33). Consistent with different campuses in the UC system having different pay strategies and with the pattern presented in Panel (b) of Figure 1, further controlling for campus and academic start year reduces the gap by another two-thirds to 4.3% (0.042 log points) in column 5. Between columns 1 and 5, the model's R^2 increases from 0.034 to 0.478, suggesting that these indicators meaningfully explain part of the variation in pay. Once academic start year is controlled for, additionally controlling for whether faculty are assistant, associate, or full professors does not meaningfully alter the gap (column 6), nor do controls for publications and citations, although both are significantly associated with pay (columns 7 and 8).

Thus, even with our full set of controls, which explain a large part of the gender pay gap (the specification in column 8 of Table 1), a Kitagawa-Blinder-Oaxaca decomposition (3, 34) suggests that 17% of the raw gender pay gap remains unexplained by observables.[¶] Interestingly, though the literature has documented meaningful gender gaps in promotion (job title) and productivity (publications and citations), these factors do not help explain the wage gap after accounting for the other factors (year, field, campus location, and cohort). In particular, once we account for these latter factors, 20% of the salary gap is left unexplained (column 5), whereas in our fully specified model (column 8), 17% remains unexplained.

We perform several analyses to examine the robustness of these estimates to potential sources of measurement error and sample attrition. First, we verify whether there is differential exit out of the sample by gender and earnings (see Appendix Table A1). Females are

not differentially likely to exit the sample. Higher-paid individuals are less likely to leave, but this does not vary by gender. We further verify that our estimates are robust to the inclusion of indicators for sample exit, late sample entry, and continuous presence in the data, even though these variables on their own are correlated with pay in expected ways (see Appendix Table A2). In Appendix Table A3 we perform a bounding exercise. In particular, we ‘retain’ workers who left the sample, and re-estimate the gender pay gap assuming that attriters would have earned the sample’s 90th percentile gender-specific salary, and assuming that attriters would have earned the sample’s 10th percentile gender-specific salary. We repeat this exercise assigning attriters the cell-lowest, and the cell-highest salary, respectively, where the cell is the location-field-start cohort by gender. All of these analyzes yield a gender pay gap that is similar to our main estimate. Then, we perform an additional exercise where we examine the consequences of having differentially low female representation in older cohorts. Appendix Table A4 restricts the sample to more recent cohorts, and Table A5 presents a weighted regression that includes probability weights of female representation in each cohort in the regression analysis. Both tables demonstrate similar gender pay gaps as in our main analysis.

To reduce concerns about differences in publication coverage in our data across fields and over time, we also confirm that the inclusion of field-campus-start year fixed effects that allow for flexibility in how field-generation-campus productivity is rewarded does not change our estimates (see Appendix Table A6). We also test whether our results are sensitive to the cut-off we use for the likelihood of our gender assignment being correct, or, in other words, whether our results are sensitive to how clearly gendered someone’s name is. In our setting, this seems unlikely given that salary negotiations typically occur following in-person interviews and because research communities tend to be relatively small and tight-knit. Consistent with these institutional features of our setting, we do not find evidence of a wage benefit from gender neutral names, or evidence that expanding our sample by including more uncertain gender assignments changes our findings (see Appendix Table A7).

[¶] The Kitagawa-Blinder-Oaxaca decomposition is a method that separates differences in outcomes (like earnings) across groups (like men and women) into explainable (e.g., productivity) and unexplainable (i.e., those not observed) differences. For example, a gap in wages across males and females may be explained by measurable productivity and seniority differences, and unmeasurable factors (e.g., discrimination). The Kitagawa-Blinder-Oaxaca decomposition quantifies the proportion of the observed wage gap attributable to each of these observed differences and, thus, traditionally provides a suggestive measure of the extent of gender discrimination in a given research setting (e.g., 3). We perform the decomposition using Stata’s “oaxaca” command, which outputs the increase in wages female faculty would experience if they had male faculty endowments (i.e., the explained portion of the salary gap) and the size of the gap that would remain if females and males had the same endowments (i.e., the unexplained portion of the salary gap) (35).

Table 1. Gender Gaps in Regular Pay

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						Log(Regular Pay)					
Sample:	Full Sample								Assistants	Associates	Full
Female	-0.210*	-0.216*	-0.124*	-0.100*	-0.042*	-0.039*	-0.038*	-0.040*	-0.039*	-0.030	-0.045*
	(0.012)	(0.025)	(0.023)	(0.021)	(0.017)	(0.014)	(0.014)	(0.014)	(0.023)	(0.024)	(0.020)
Publications							0.002*	0.001*	-0.000	-0.002	0.000
							(0.000)	(0.000)	(0.001)	(0.003)	(0.000)
IHS Citations								0.026*	0.025*	0.005	0.062*
								(0.005)	(0.008)	(0.009)	(0.009)
Year FEs	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field FEs	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Campus FEs	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FEs	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Title FEs	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
KBO											
Unexplained	100%	100%	59%	47%	20%	19%	17%	17%	30%	9%	25%
Observations	8193	8193	8193	8193	8193	8193	6654	6654	1538	1542	3456
R ²	0.034	0.065	0.203	0.261	0.478	0.541	0.595	0.599	0.555	0.490	0.516

Note: This table presents the estimated difference between female and male salaries among UC academic employees between 2014 and 2020. The Publications and IHS Citations variables are lagged one year to account for delays in wage responses. Column 9 only includes assistant professors, column 10 only includes associate professors, and column 11 only includes full professors. KBO Unexplained is the Kitagawa-Blinder-Oaxaca share of the gender pay gap unexplained by observables. A *, **, *** indicate statistical significance at 10%, 5% and 1% significance levels, respectively.

Despite evidence from Figures 1 and 2 that the pay gap is declining for newer cohorts of social science faculty, column 9 of Table 1 reveals a similar pay gap across levels of seniority, with perhaps the largest gap increase when going from Associate to Full (columns 10 and 11, respectively).^{**}

Gender performance gaps in the Social Sciences.

Given the richness of our data, we also analyze whether females and males have different output. In columns 1-4 of Table 2, we estimate whether social science faculty differ by gender in the number of publications, gradually adding controls for observables (as in Table 1).^{††} Without conditioning on observables, females have about 9 fewer publications on average than males. Adding controls for year, field of study, and campus increases this gap slightly, but controlling for academic career length and job title reduces the gap to just over 6. In our fully controlled model, the gender publication gap remains at around 5.5 publications. A Kitagawa-Blinder-Oaxaca decomposition suggests that 60% of the gap is unexplained by the observables in our data.

^{**} In estimates not reported here, we find that without the inclusion of the publications and citations controls, the gender pay gap among assistant professors is relatively small and not statistically significant. This pattern suggests that, within this group of academics for whom other drivers of inequality have declined, the pay gap may be, at least in part, driven by differential rewards for productivity between males and females.

^{††} For simplification, we don't report all specifications in Table 2, but the full set are reported in Supplementary Material Table A8.

In columns 5-8, we repeat the same analysis but using citations to measure performance. While we find a gender gap in citations on average in our sample, once we condition on our full set of controls, this gap disappears.^{‡‡} Thus, we do not find evidence that female and male social scientists are differentially cited.

Differences in gender pay gaps across fields.

To examine the extent to which the gender pay gap in the social sciences is ubiquitous, we re-run our main analyses by field of study. First, we examine just female representation by faculty groups above and below the median pay levels. The raw averages presented in Panel (a) of Figure 3 demonstrate that across all fields, female faculty are less likely to be in the pool of highly paid employees than they are to be in the pool of those paid below the sample median within their field.

Despite females having a lower likelihood of being highly paid relative to their male counterparts across fields, conditional on our full set of observables, some fields within the social sciences do not have a gender pay gap. In particular, in economics, political science, and social sciences, we group as other (because of low faculty

^{‡‡} We adjust citation counts using the inverse hyperbolic sinh transformation, and coefficients in Panel (b) of Table 2 should be interpreted as the relationship between faculty gender and the IHS of citations (for example, <https://blogs.worldbank.org/en/impactevaluations/interpreting-treatment-effects-inverse-hyperbolic-sine-outcome-variable-and/>).

Table 2. Gender Gaps in Output

	Publications				Citations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-9.060*	-9.630*	-6.415*	-5.531*	-0.529*	-0.529*	-0.125	0.060
	(0.575)	(1.354)	(1.163)	(0.996)	(0.052)	(0.123)	(0.084)	(0.075)
Lagged IHS Citations				8.262*				
				(0.601)				
Lagged Publications								0.029*
								(0.003)
Year FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Field FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Campus FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Cohort FEs	No	No	Yes	Yes	No	No	Yes	Yes
Job Title FEs	No	No	Yes	Yes	No	No	Yes	Yes
KBO Unexplained	100%	108%	71%	60%	100%	100%	24%	11%
Observations	7718	7718	7718	6654	7725	7725	7725	6654
R^2	0.023	0.102	0.287	0.447	0.013	0.064	0.595	0.691

Note: This table presents estimated gender gaps in publications and citations among UC academic employees between 2014 and 2020. KBO Unexplained is the Kitagawa-Blinder-Oaxaca share of the gender pay gap unexplained by observables. A *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

numbers in each),^{§§} there is no statistically detectable difference in pay, once observable differences are accounted for. In contrast, female faculty in business, sociology, and anthropology departments are paid significantly less than their observably similar male peers. These coefficient estimates are presented in panel (b) of Figure 3.

These findings demonstrate that gender pay gaps are not ubiquitous in academia. Moreover, while gaps appear to be decreasing as female representation is increasing, equal representation does not appear to be a necessary condition for pay equality. Economics, in which females make up less than 20% of faculty in our study period, does not have a gender pay gap, whereas in Anthropology, a field in which females and males are equally represented in our sample, females earn only about 93 cents for every dollar earned by males.

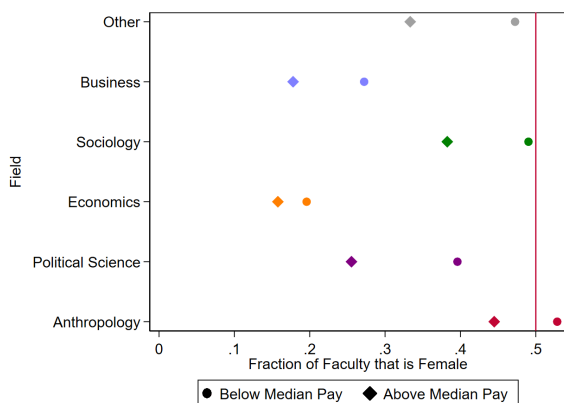
It is important to note that our analyses focus exclusively on financial compensation, as non-financial compensation is unobservable in our data. If non-financial compensation (e.g., reduced teaching loads and service burdens) varies systematically by gender, our results will not fully capture differences in total compensation. If men disproportionately obtain more favorable non-financial arrangements, our estimates constitute a lower bound on the overall gender gap in compensation. If those

non-financial elements vary significantly across fields, they may also help explain our heterogeneous pattern of results. Importantly, any impacts that these perks have on productivity will not contaminate our estimates, as we control for the publication output of each researcher.

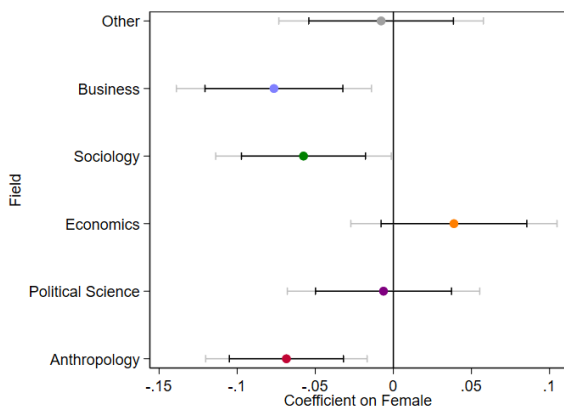
There are a few possible explanations for heterogeneity in residual gender pay gaps across fields, including differences in PhD program structures and faculty hiring due to field-specific and hard-to-document norms. A promising question for subsequent research is whether differences in market structure and evaluation practices contribute to gender pay gaps in academia. In business fields, observed gaps may partly reflect subfield composition, with men disproportionately represented in higher-paying areas such as finance. In sociology and anthropology, scholarly output more often includes books and monographs that are not in ranked journals and, thus, may be harder to evaluate. This may leave greater scope for discretion in assessing research quality and impact, potentially amplifying gender differences in how productivity is rewarded. By contrast, economics—and to a lesser extent, political science—operate in more centralized and standardized labor markets, with clearer salary anchors. Such centralization may limit idiosyncratic wage setting, helping to explain why residual pay gaps are smaller or absent in these fields.

^{§§}These fields include geography, policy, international affairs, education, and social science faculty in geographically focused or natural science research institutes.

Fig. 3. Female Pay by Field



(a) Proportion of Females Among New Entrants by Field Over Time



(b) Estimated Pay Gaps by Field

Note: Panel (a) plots the share of faculty who are women by field. Circles are for the group of faculty with below median pay, while diamonds are for the group earning above median pay, where the median is calculated by group (year, location, start year, and field). Panel (b) plots the coefficients of a regression of Log(regular pay) on a female indicator, after controlling for year, location, start year, field fixed effects, and measures of publications and citations. Black lines represent 83.4% confidence intervals and light grey lines represent 95% confidence intervals.

3. Discussion

In this paper, we evaluate the gender pay gap among social science faculty using data from all ten campuses in the University of California system. We find that controlling for field of study, academic start year, and campus reduces the gender pay gap from 23% to 4.3%, but controlling for productivity, measured as publication counts and citations, and job title do not reduce this gap any further. These findings demonstrate that even in an organization with pay transparency, gender pay gaps persist among similarly productive and ranked peers. Furthermore, we find a persistent gender gap in publication counts that is largely unexplained by observable characteristics. We find no gap in citations once observable differences between male and female social scientists are accounted for.

Importantly, we find that gender pay gaps are absent in some social science fields, suggesting that such disparities in academia are not inevitable. Moreover, this heterogeneity in gender pay gaps across fields is not explained by female faculty representation, demonstrating that equal pay does not depend on equal representation.

Our study provides a rigorous examination of the gender pay gap in academia across fields that uses longitudinal data and includes direct measures of individual productivity. These findings help reduce concerns that prior gender pay gap estimates are explainable by performance or seniority gaps, particularly given the similarity of job roles within title and field. They also demonstrate that pay transparency alone is insufficient for eliminating pay gaps. A deeper exploration of the drivers of heterogeneity in gender pay gaps across fields and potential policies to address those inequities is a fruitful area for future research.

4. Data and Materials

We combined three data sources to perform our analyses—the University of California (UC) system compensation database, Scopus, and Genderize. We summarize this process in a flow chart, Figure A1 in our Supplementary Material.

We begin by compiling faculty rosters for business schools and social science departments from public uni-

1147 versity records for the years 2014–2020. After removing
1148 duplicate entries within fields, the initial sample consists of
1149 508 business school faculty and 1,392 social science faculty,
1150 as shown in Stage 1 of the flow chart alongside. We keep
1151 only tenure-track research faculty, and drop adjunct faculty,
1152 lecturers, post-docs, and other employees.
1153

1156 In Stage 2, we merge the de-duplicated faculty lists with
1157 administrative wage records. Wage data are constructed
1158 by filtering on job title and departmental affiliation, and
1159 faculty names are matched using standardized name
1160 cleaning and fuzzy matching (36) to create a panel dataset
1161 of faculty salaries, and account for formatting changes
1162 across years. This merge yields 462 matched business
1163 school faculty (90.9% of the deduplicated list) and 1,366
1164 matched social science faculty (98.1%). As illustrated in
1165 the flow chart, attrition at this stage is modest.
1166

1170 For business schools, match rates are uniformly high
1171 across campuses, exceeding 88% at all institutions except
1172 one smaller campus (UC Riverside, with 55 faculty names
1173 has a 74.6% match rate). No campus exhibits evidence
1174 of large or systematic selection out of the wage data. For
1175 social science departments, match rates are also uniformly
1176 high across campuses, exceeding 96% in all cases.
1177

1181 In Stage 3, we merge the wage-matched faculty with
1182 publication-based productivity information obtained from
1183 Scopus author profiles. Within this stage, we collected
1184 each researcher's bibliographic information in two steps.
1185 First, we searched for their publication and citation
1186 records using [Scopus' Author Search](#). If they were found,
1187 the link to their Author Page on Scopus was collected.
1188

1192 Figure A1 in our Supplementary Material shows the
1193 layout of the Author page around the time the data was
1194 collected. The yearly publication chart, shown under
1195 document and citation trends, contains the number of
1196 documents (publications) and the number of citations per
1197 year, since the author's first publication. This yearly data,
1198 as well as the total amount of citations and documents,
1199 is collected in our data.
1200

1204 To ensure that we are accurately capturing each
1205 researcher's cohort, we complement information on when
1206 faculty started in the UC system with data on the date
1207 of their first publication using Scopus data, and use the
1208 earlier of these two dates to determine cohorts. We define
1209
1210

a cohort as the group of researchers who entered academia,
either by publishing or securing an academic job, within
a given five-year period.

The merging of Stage 3 yields 389 business school
faculty (84.2% of those in the wage data) and 1,308
social science faculty (95.8%). Attrition at this stage
reflects the absence of a Scopus profile or publication
data within a profile. This can occur more often in
business schools due to heterogeneous publishing outlets,
including practitioner-oriented journals and books, and
also happens among faculty who have not yet published.
Across campuses, the match rate is above 90% in all
campuses, except for UCLA Anderson where the match
rate is 69%. This lower rate can be explained by the
fraction of adjunct faculty at UCLA (25 of 158 in the
wage-matched data), which corresponds to 16% of faculty
names, compared to other campuses with a lower fraction
of adjunct faculty, which is below 4%. Adjunct faculty
are often industry practitioners, who do not regularly
publish in academic outlets. Critically, gender is not a
statistically or economically important determinant of our
stage 3 match rate.

Stage 4 assigns gender using the AI tool provided by
[Genderize.io](#). Genderize.io infers gender from first names
using aggregated frequencies of name–gender associations
collected from large public online sources (37). For
each first name queried, the tool returns (i) a predicted
gender (male or female) and (ii) an associated probability,
which reflects the proportion of observations in the
underlying dataset that correspond to the assigned gender.
To assess accuracy, we use the predicted gender and
compare it to the manually assigned gender by research
assistants, who collected it in the process of collecting
Scopus profile links. They assigned gender to all but 37
faculty names in the list (for whom a picture was not
available). Among the identified faculty, the manually
assigned gender and the Genderize.io gender coincide in
97% of the cases. We exclude all faculty whose name is
associated with an accuracy probability of the Genderize.io
assigned gender of 90% or less from our analyses. In
this subset, RA assignments agree with the Genderize.io
assigned gender in all cases. This step leaves us with 331
business school faculty (85.1% of those in the merged wage

1275 and productivity data) and 1,152 social science faculty
1276 (88.1%).
1277

1278 We further exclude 10 faculty who started their aca-
1279 demic careers between 1961 and 1965 because there are
1280 no females in that start year cohort. In addition, we
1281 drop 9 faculty who never have non-zero regular pay in our
1282 data. Finally, 62 faculty who are only in our pay data
1283 for the 2014 year of observation are excluded from our
1284 fully specified model because of our decision to control
1285 for lagged publications and citations. This decision is
1286 reflective of the delayed responses of salary changes to
1287 productivity increases. Thus, the final analytical sample
1288 (Stage 5) consists of 317 business school faculty and 1,084
1289 social science faculty with complete information on wages,
1290 productivity, and gender and employment at a UC campus
1291 in at least one year other than 2014.
1292

1299 Overall, the sample construction flow chart shows that
1300 sample attrition is limited. Merge rates into administra-
1301 tive wage records exceed 90% in business schools and 98%
1302 in social sciences. Subsequent reductions in sample size
1303 are driven by external data availability (Scopus profiles)
1304 rather than selective wage reporting.
1305

1308 **Data availability.** The wage records are available upon
1309 request from the University of California, Office of the
1310 President. The office maintains the right not to share
1311 private information and to charge labor fees for any new
1312 data that needs to be generated. Further details on access
1313 are available here: [https://www.ucop.edu/uc-legal/legal-](https://www.ucop.edu/uc-legal/legal-resources/information-practices/office-of-public-records-guidelines-for-access.html)
1314 [resources/information-practices/office-of-public-records-](https://www.ucop.edu/uc-legal/legal-resources/information-practices/office-of-public-records-guidelines-for-access.html)
1315 [guidelines-for-access.html](https://www.ucop.edu/uc-legal/legal-resources/information-practices/office-of-public-records-guidelines-for-access.html). The Scopus data is currently
1316 available through the Scopus API, and is available to
1317 individuals who have institutional access. At the time of
1318 data collection, we manually searched the Scopus links
1319 for all faculty names we had, and then used the resulting
1320 links and the information available on their Scopus profile
1321 at the time (summer of 2024) to construct the dataset.
1322 Since then, the website has changed, and total metrics
1323 are available, but not yearly counts.
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