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A persistent gender pay gap among faculty in a public university system

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Despite movements towards gender parity within academia, women faculty continue to be paid less than men. While previous research has explained the gap using academic rank/seniority and productivity, existing findings are limited by either their examination of base pay or reliance on self-reported data. Here we extend the analysis beyond base pay, link faculty salary records of one public university system in the U.S. to the OpenAlex bibliometric database, and separately analyze the gender pay gap in the base (grade) and other pay (off-grade). Using stepwise regression models, we find that faculty rank accounts for a significant gap in the base pay while performance-based variables such as H-index or specialization do not play a crucial role. For other pay, no variables stand out in explaining the substantial pay gap between women and men faculty. Our results suggest that a primary source of the remaining gender pay gap is the off-grade pay. Different policy approaches are required to reduce the gender pay gap depending on the specific type of salary being targeted.

Despite clear strides towards proportionate representation of women and men among faculty in United States institutions of higher education[1], extant work shows the persistence of disparities between men and women in academic careers. Women have fewer chances to be hired as tenure-track faculty[2,3], promoted to tenure[4–6], elected to leadership roles[7], or rewarded for their impact in science[8]. This is the result of multiple and interrelated barriers placed at each stage of the academic career trajectory. To illustrate a few, women tend to spend their time on service work that goes relatively unrewarded in academic careers[9,10], their academic contributions are not always equally evaluated[11], and they face more stressors than men, for instance from family caretaking responsibilities[12,13].

Even after landing on a faculty position, women face gender disparities by receiving less monetary compensation than men[14–17]. This disparity is quite striking, as at that point there are no clear and observable distinct differences in qualifications between women and men, such as educational attainment or length of work experiences. One explanation on the salary gap is a structural one that women faculty work more than men as non-tenure track faculty, or in positions such as adjunct or visiting professor, for which salaries are lower than tenure-track faculty[18–20]. Also, within tenure-track faculty, women disproportionately occupy assistant professor positions, which are compensated less than associate or full professor positions[21–23]. Another explanation is found in a human capital view. This view argues that the salary gap reflects a gendered difference in human capital, in this case, often measured as the academic performance of faculty such as productivity (publication count) or visibility (citation count) of academic works[24,25]. In some literature in economics or business, researchers show that academic performance, measured by the prestige of the journals where publications appear, directly affects salary[26–28]. While the results of previous literature may vary in its choice of empirical sites and analytic approaches, a significant portion of the gender salary gap among faculty is attributed to two main factors: professor ranks/seniority and academic performance[21,23,24,29,30].

We revisit this question on gender pay gap among faculty in this paper. Former gender pay gap studies have primarily focused on base pay, mostly determined and fixed by the grade system[15,21,24], which sets salary scales based on a faculty member's rank and seniority. In direct contrast to base pay, off-grade pay, a way to reward high performance and extra work, has been understudied – both in the women/men difference in off-grade pay and in understanding what explains this possible off-grade gender pay gap. This type of salary, argued to be mainly based on academic merit and performance, may be an additional source of gender inequality in faculty salary[31,32]. This is because academic judgment regarding what constitutes excellence and innovation can vary greatly depending on disciplines, academic communities, and power structures[8,33–36]. Indeed, Smith-Doerr and colleagues[37] suggest that organizations value men's contributions more than women's comparable merits in determining off-grade salary. Nevertheless, there have been few attempts to understand the extent of the gender gap in off-grade pay of faculty and the factors explaining it, nor have been base and off-grade pay been directly compared within the same set of faculty. This point is essential to understand the varying causes of gender differences in base and off-grade pay.

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Also, the most frequently adopted data to study faculty salary is the National Study of Postsecondary Faculty collected by the National Center for Education Statistics[15,16,23,25,38] or a self-designed survey[24]. Although survey methods have strengths in collecting detailed information, the main *explanandum*, faculty salary, has measurement limitations because self-reported salary often overestimates one's real income[39] due to either respondent recall error or social desirability bias. The self-reported nature of surveys also poses challenges in tracking academic performance of scholars. While surveys may inquire about the number of publications, it is difficult to measure the actual content of published works and the visibility (e.g., citations) of them, which is equally, if not more, important than publication counts. Lastly, similar to salary, the self-reported academic performance of faculty is also not free from social desirability bias.

In this research, we revisit the gender gap in faculty salary by expanding two aspects of previous research: extending the analysis beyond base pay and unobtrusively measuring academic performance using bibliographic data "in the field." As a strategic case, we examined the faculty salary from ten university campuses affiliated in one U.S. public university system between 2011 and 2018. By analyzing a single public university system, we were able to reasonably exclude institutional factors and thereby control for policy variations across different institutions. Simultaneously, this approach allowed us to maintain an adequate sample size, as we were able to gather data from ten different locations within the same university system. The state where the university system is located legally mandates the disclosure of university employees' salary in the form of 'base pay' and 'other pay.' Since other universities may use a different pay system that does not align with the definition of base and other pay from the university system we consider, from now on, we capitalize 'base' and 'other pay' to indicate that we solely reflect on the particular pay system of our interest. In addition to this salary data, we uniquely linked faculty salary records with publication records in the OpenAlex bibliometric database to understand the relation between salary and academic recognition and knowledge production. We used a straightforward yet analytically sound modeling strategy that captures how the gross gender pay gap decreases or increases with the introduction of increasingly more intervening variables. We also considered how specialization of academic works[39] accounts for the variation in scholars' pay that is best explained by the standing of their niche research agendas.

Our study contributes novel evidence that gender gaps in Base and Other pay do not share the same structural underpinning of the existing pay disparity. Our study reaffirms that the structural position of women faculty is closely associated with the gap in Base pay. The final model explained 67% of the existing gender pay gap, with about two-thirds of the explanation coming from variations in faculty rank by gender. In contrast, the academic status of women and men hardly explains the gender gap in Other pay as well as other control variables. Thus, we confirm that off-grade pay, Other pay, is a major source of the remaining gender gap in faculty salary even after extensively controlling for academic performance and other structural characteristics (campus, academic age, and etc.). The results imply that the salary allotted outside the base pay grade system favors men regardless of one's academic position.

Data and methods

Data

Faculty salary

To investigate the relationship between gender and faculty salary, we compiled a large database of faculty salaries from 2010 to 2018 of all ten distinct campus locations in which faculty salaries are disclosed under the state's law. These ten campus locations are grouped in one public university system, which is a network of public universities operated and funded by a state. Ten campus locations within the university system share the same governance structure and operate under the same policy orientation including faculty hiring and promotion. The initial data contain information on full names, campus locations, rank, and the salaries of all employees, including faculty, affiliated in one of the campuses. We removed non-faculty employees (such as project managers or athletic professionals) from the data based on their job function descriptions. We selected the *latest* sampled year for each unique faculty as the year of observation if they are present in multiple years (2010–2018). We excluded cases ($N = 2{,}682$) that have total and base pay smaller than $1,000 per year or off-grade pay smaller than 0. The unique number of faculty members (excluding the cases mentioned before) from these data is 27,304.

OpenAlex bibliometric data

We then linked the faculty salary data to OpenAlex, a bibliometric database that we used to measure faculty productivity—an important confounding variable, described below. OpenAlex (https://openalex.org) is an open source database run by the nonprofit organization OurResearch[40]. The OpenAlex database built on data from its parent database Microsoft Academic Graph, which stopped their services in December 2021. From December 2021 onwards, OpenAlex aggregates multiple data sources such as CrossRef, PubMed, or ORCID on top of Microsoft Academic Graph and periodically updates its snapshot. A strength of OpenAlex and its parent database Microsoft Academic Graph is that they cover not only established journals indexed in Science Citation Index (Expanded), Social Science Citation Index, and Art & Humanities Citation, but also journals indexed in a different academic database such as Scopus[41,42]. Due to its open source nature and data quality, the OpenAlex database is increasingly used in science of science studies[43].

For those faculty members linked to the OpenAlex database, we extracted the publications that the faculty authored, along with its metadata, and any citations they received. Because we could not extract the exact information which role authors take (e.g., first author, corresponding author) in the database, we did not consider the author's publication role in counting publications and citations. We first extracted an author identifier by matching it to the faculty salary data based on a name-and-location query, and then extracted all information about their publications and citations. When one faculty member matched to more than one author ID in OpenAlex, we combined their records. This approach allowed us to trace faculty members' performance even before they landed the current position and up until the year in which we observe salaries. While OpenAlex employs a complex author disambiguation method, this method was not always fully accurate in disambiguating author records, particularly for those without ORCID IDs. Thus, it was not uncommon (62% of matched faculty in our data) that there was more than one OpenAlex author ID matched to one faculty member who had multiple publications. We hand-checked a few suspicious cases that matched more than thirty OpenAlex author IDs, but they turned out to be either empty IDs without publication records or IDs partially including some of the faculty's publications, which led us to conclude that the impact of imperfect disambiguated authors on our analysis would be minimal. The details of the matching process are described in detail in Supplementary Appendix A. We linked approximately 78% of the faculty members to OpenAlex publication records ($N=21{,}376$). As such, we compiled a database with information on individual faculty, their salaries, their ranks, and their corresponding publication records and associated metadata (cites, keywords, etc.).

Dependent variable—faculty salary

We aimed to study the role of gender in the salary a faculty received in a given year, by constructing variables based on a faculty's salary. The faculty's gross salary is composed of two parts: "Base pay" and "Other pay." "Base pay" includes base pay and its reductions. Reductions can be made voluntarily by for employee's work hour flexibility and their choice of phased retirement programs. "Other pay" includes various sources of additional payment that may have been negotiated, additional pay for summer teaching or grant supported work, and through performance-based incentive compensation. We investigated Base and Other pay separately. Yearly average Base pay from our final data set is $125,827. About 75% of faculty have Other pay, which on average is $86,496 per year. These dependent variables contain no missing values.

Independent variable—faculty gender

The salary data were compiled from web records without demographic information, and so it did not contain the (self-reports of) gender of faculty. Following prior work[35,44,45], we relied on first names in order to assign a gender. Gender association with names are simplified signals for gender identities that likely measure how individuals are perceived by others. However, we know that individuals have different ranges of (non-binary) gender identification that we were unable to pick up on in this study.

To assign gender based on names, we first inferred which population-level threshold of the gender distribution of first names in the Social Security Administration (1900–2017) best predicted self-reported gender in a separate dataset of ~36 K scholars who self-reported their genders[44,46,47]. We then matched the Social Security Administration data to the faculty salary data and used those thresholds to assign a gender. This first method led to an assigned gender for 91.1% of the scholars. Second, to further classify "unknown" genders, we used the Genderize.io[33,48,49] algorithm to assign gender (about 95% agreement between both methods). This further increased the gender recall to 95.2%. Third, if genders were still "unknown," we used the "gender" library in R. Here, when more than 80% of a name was either carried by women or men, we categorized them into either women or men. Fourth, when these aforementioned methods did not agree, we moved to hand-coding genders. Because all previous methods were mainly based on name information from western culture, they may have missed faculty with uncommon, non-standard U.S. names. For those names that we could not confidently identify their gender, we searched the full name of faculty along with the campus location in a web search. We queried reliable websites such as the official university web page introducing faculty members or Wikipedia pages of them. We considered pronouns describing faculty members or their gender expressions on university profile pictures. This further increased the gender label recall to 95.9%. When all this information did not yield a gender, we considered the observation as missing. We could not find the binary gender information of 874 observations, 4.1% of the total observations. During our hand coding of gender by Google search, we found that these missing values were mostly from short-term visiting or adjunct faculty who did not stay at a university long enough to be updated in the official homepage.

Confounding variables

Observation year

To account for yearly differences in salary (by gender), we included year fixed effects in our analyses. Some faculty may have left the public university system (and others join) in a given year. This implied we may have had multiple years of salary records for each individual. For the purpose of this study, we considered the latest observation year per faculty and did not consider within-individual salary increases/decreases over time, and observation year as the year fixed effect. This variable contained no missing data and stemmed from the faculty salary data.

One OpenAlexID (yes/no)

We added a binary indicator for whether faculty members have more than one OpenAlex identifier under the papers that we linked to their salary data. This variable was to control for any data issues that might have been driven by the author disambiguation process in OpenAlex.

Location

We included fixed effects for the ten campuses to which a faculty member was affiliated. Even though ten campuses are grouped into the one system, the status/prestige, expertise, and the cost of living are highly variable across the locations. Since salary is affected by the cost of living in the specific area, we controlled for this variable. This variable contained no missing values and originated from the faculty salary database.

Rank
We also added a categorical variable for the rank of faculty members: assistant, associate, or full professors. This variable from the faculty salary database contained no missing information.[1]

Academic age
We controlled for the academic age of faculty to take into account the length of careers. We measured the academic age by subtracting the year faculty published their first academic work in OpenAlex from the latest observation year for their salary. This variable contained no missing data when we considered the matched salary data/bibliometric data cases as the effective study sample – i.e., each publication had a publication year from which we could deduct academic age as observation year minus first publication year.

Field
Our variables of interest vary non-randomly by academic discipline. For instance, the number of papers an individual researcher produces and the number of citations each paper collects may be much larger in science, technology, engineering, and technology fields than in the Humanities[50,51], and women and men select into specific disciplines[52]. Disciplines also have different levels of consensus on key paradigms[53] implying that disciplines will vary in terms of how much the field is, on average, specialized. For example, if physics or chemistry have more consensus compared to sociology or political science[53], the level of specialization will be higher for physics or chemistry compared to sociology and political science. Additionally, how disciplines are institutionalized into departments varies by campus location. To account for this, we needed to measure scholars' fields from universities with differently institutionalized departments. Yet, this information was not present in our original faculty salary data.

As a way to collect information on faculty's fields, we used the concept-level information obtained from the OpenAlex data[40]. Concept is an assigned label to papers using an automated classifier originally trained on Microsoft Academic Graph's corpus. This classifier assigns concepts with scores to articles by machine-reading an article's title, abstract, and the name of the published journal. The score of a concept given to each article indicates the algorithm's confidence in how well the assigned concept reflects the text. Each concept ranges from 0 (no confidence) to 1 (perfect confidence). The total number of concepts is about 65,000 in a tree-like hierarchical structure. It has six layers of depth, and ultimately includes nineteen root-level concepts. For more information regarding "concepts," we refer to OpenAlex's reference page.

Using the nineteen root concepts labeled to articles, we assigned to faculty the concept that populated the highest portion of their publications as the concept with the highest confidence. As such, we ended up having nineteen different fields across faculty. During the process of assigning a field to faculty, we referred to faculty's publications for a ten-year window up to and including the salary observation year (this is consistent with the H-index and Specialization variables we discuss next). This method allowed our analyses to have precise discipline-affiliation fluidity by identifying faculty's field of expertise through their most recent academic contributions. This variable held no missing values. We used these discipline indicators as fixed-effects in our analyses.

H-index
Productivity and visibility are two dimensions of scholarly work commonly discussed in relation to the gender pay gap. Some literature draws attention to the prestige status of journals where a paper is published, a pattern that relatively stands out in business and economics fields[26,28]. However, because productivity and visibility metrics are more broadly adopted across various fields, we use H-index for our analysis. Productivity is often measured by an author's total number of publications that a researcher authored and visibility is measured by the citations that their articles garnered[39]. Productivity alone does not measure paper impact, whereas visibility, in turn, can be inflated by a single highly cited paper. Yet in our data, we found that both measures tended to be highly correlated ($r=.83$) implying. Logically so, as highly productive faculty are likely to receive many citations as well. To summarize a scholar's productivity and visibility in one measure, a conventional solution is to use an author's H-index to describe their publishing impact in a given period of time. The H-index measures the h maximum number of papers with at least h citations[54] – e.g., the H-index of ten implies that an author has ten papers with at least ten citations. We used the H-index to combine productivity and visibility in a single metric for publishing impact. When counting the number of publications and citations for H-index, we did not distinguish the first or corresponding author with other co-authors. While we were aware that the amount of input significantly varies depending on the type of author, our data did not provide the relevant information related to the author's role.

Using the OpenAlex data, we calculated the H-index of a faculty member based on their performance over the previous ten years, up to and including the year their salary was measured, assuming that the current salary is largely driven by the faculty's scholarly performance during the most recent ten years. To compute the H-index, we counted the total number of publications during the last ten years and the year of observation. For citations, we counted those eleven-year citations regardless of the publication date of the work which was cited in this period. This was because even if a faculty published a paper, for example, in 1980, if it was still cited in the 2010s, we believed these citations to old works do contribute to the faculty's current reputation. For the total number of

[1] In addition to the faculty member's rank, the salary data also included the information whether a faculty member had a clinical, visiting, tenured, or other status. We could not test the coefficient of this variable along with faculty member's rank due to the high variance inflation factors. Instead, we explored the possible confounding impact of this variable and described the details in Supplementary Appendix B.

the eleven-year citations, we then calculated the H-index – i.e., the number of works which had the number of citations of the least cited paper in that period. As the H-index was heavily right-skewed, we took a log with base ten to adjust. This variable contained no missing values.

Specialization
To measure faculty's academic specialization, prior literature occasionally counts the number of unique keywords or descriptors of an article[39,55]. However, this approach has limitations because keywords or descriptors assigned by field experts may not be able to expand into the interdisciplinary work that is becoming more common in modern science. Also, relying on hand-coded information is not scalable to consistently cover the vast amount of articles across fields and time.

We again used the 19 root-level concepts in articles, and calculated the specialization index through measuring the entropy of the distribution of concept scores of a faculty member's research articles[56]. To be consistent with our approach to H-indices, we only used faculty's works published ten years ago or less. To measure entropy for each faculty member, we summed up the scores by concept then divided them with the total of concept scores. This proportion indicated the share of a faculty member's attention to one concept shown via published works. Then, we squared the proportion and summed them up. Higher values of this measure indicated concepts concentration (i.e., higher specialization), while lower values indicated diversification of concepts (e.g., lower specialization). Because the distribution of measured specialization was also right-skewed, we took a log with base ten to adjust specialization. Even among matched samples, some faculty members did not have any matched published works in our ten-year time window and thereby missed values of specialization. It led us to delete 912 cases (4.4%) due to missing values, which led to the total effective N of 19,590. Table 1 (continuous variables) and Table 2 (categorical variables) contain descriptive statistics on all our variables.

Analytic strategy
Our twofold goal was to first model the gender pay gap and how much portion of it could be explained by our confounding variables, and then to model whether salaries were differently impacted by H-index and specialization for each gender. We used either linear regression or logistic regression models and added gender, observation year, OpenAlexID, location, rank, academic age, field, H-index, and specialization as covariates one by one. For our first goal, we estimated a series of linear regressions models for "Base pay/1K," then a series of logistic regression models for whether there was *any* "Other pay" (yes/no), and finally a series of linear regression models for "Other pay/1K" (if there is any). We divided the analysis of Other pay into two steps because a significant portion of faculty did not have any Other pay (24.1%), which introduced too many zeros in the distribution of Other pay. This zero-inflated distribution complicated the application of our regression models. Thus, we first checked the differences in the impact of explanatory variables for having any Other pay (yes/no) using logistic regression models, then tested the impact of covariates on Other pay (if there is any) using linear regression models.

In each series of models, we first described the gross gender pay gap difference, which estimated the gross gender pay gap by only including our gender covariate, then stepwise added additional explanatory variables (e.g., observation year, status, H-index, etc.) By examining the changes in the gender coefficient upon the inclusion of covariates, we were able to elucidate the residual gender pay gap, accounting for potential confounding variables. This approach was consistent with prior literature on faculty salary[21]. We did so for Base pay and Other pay with and without log base ten transformation to ascertain that our results did not differ between right-skewed (non-transformed) and relatively normally distributed variables (transformed). For logged Other pay/1K, we selected those with Other pay higher than $1,000 as the log transformation led to values less than zero otherwise (e.g., with Other pay = 900, $\log10(900/1000) = -0.046$). When we analyzed the raw salary, we dropped outliers that have values higher than two times the mean on those variables (Base pay/1K = 272; Other pay = 332), both approximately 3.8% of the cases, or $N = 774$ and $N = 582$ respectively. This analytic decision was made to render the regular Base pay and Other pay outcomes slightly *less* right-skewed. For the log transformed salary, because such outliers were pulled closer to the average due to the log base ten transformation, we did not drop outliers.

As for the second goal, we ran a series of similar linear regression models for "Base pay" and "Other pay" (not logged and logged) but then estimated gender-specific effects of H-index and specialization while keeping all other variables constant so as to study whether there were any differential returns per gender for those variables.

Variable	*N*	Mean	Standard Deviation	Min	Max
Base pay (1k)	19,590	128.6	72.7	1.03	640.1
Logged Base pay (1k)	19,590	2.0	0.4	0.01	2.8
Other pay (1k)	14,860	87.8	122.7	0.00	2074.3
Logged Other pay (1k)	14,344	1.7	0.5	0.00	3.3
Logged H-index	19,590	0.8	0.4	0.00	1.6
Logged Specialization	19,590	0.2	0.1	0.05	0.3
Academic age	19,590	23.2	13.8	0.00	68.0

Table 1. Descriptive statistics of continuous variables.

Variable		*N*	Percentage
Having other pay	Yes	14,860	75.9
	No	4730	24.1
	Total	19,590	100.0
Gender	Woman	7133	36.4
	Man	12,457	63.6
	Total	19,590	100.0
Observation year	2010	391	2.0
	2011	583	3.0
	2012	573	2.9
	2013	980	5.0
	2014	727	3.7
	2015	765	3.9
	2016	756	3.9
	2017	902	4.6
	2018	13,913	71.0
	Total	19,590	100.0
One OpenAlex ID	Yes	6804	34.7
	No	12,786	65.3
	Total	19,590	100.0
Location	J	1791	9.1
	F	2762	14.1
	C	1943	9.9
	I	252	1.3
	B	752	3.8
	E	4083	20.8
	H	946	4.8
	G	589	3.0
	A	2978	15.2
	D	3494	17.8
	Total	19,590	100.0
Rank	Assistant	4849	24.8
	Associate	3763	19.2
	Full	10,978	56.0
	Total	19,590	100.0
Field	Physics	716	3.7
	Geology	258	1.3
	Engineering	17	0.1
	Philosophy	141	0.7
	Art	386	2.0
	Sociology	452	2.3
	Business	395	2.0
	Psychology	1390	7.1
	Economics	401	2.1
	Political science	796	4.1
	Chemistry	999	5.1
	Materials science	737	3.8
	Geography	158	0.8
	Mathematics	559	2.9
	Environmental science	379	1.9
	Computer science	1375	7.0
	Medicine	7974	40.7
	Biology	2120	10.8
	History	337	1.7
	Total	19,590	100.0

Table 2. Descriptive statistics of categorical variables.

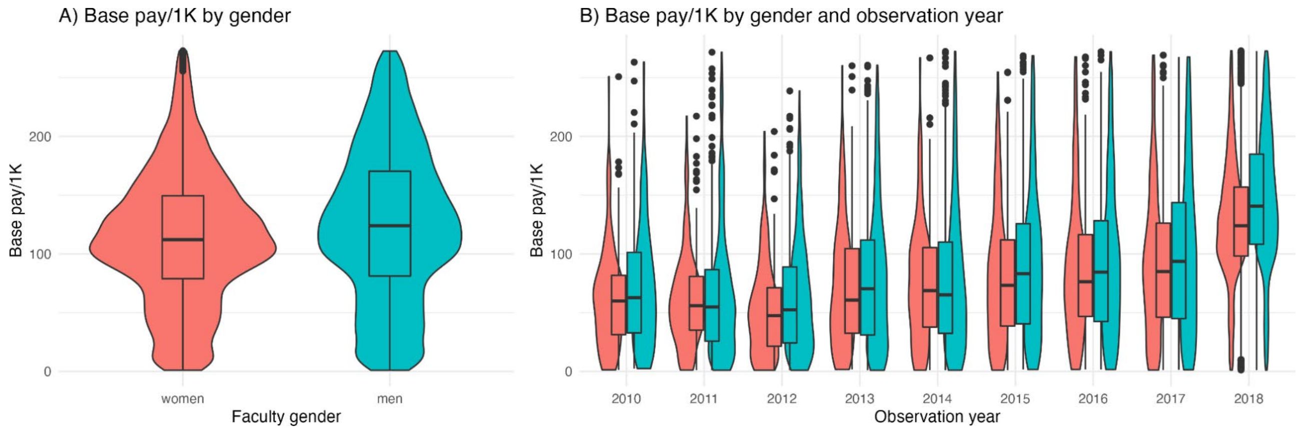

Fig. 1. Box and violin plots of Base pay/1K plotted by gender (**A**) and by gender and observation year (**B**).

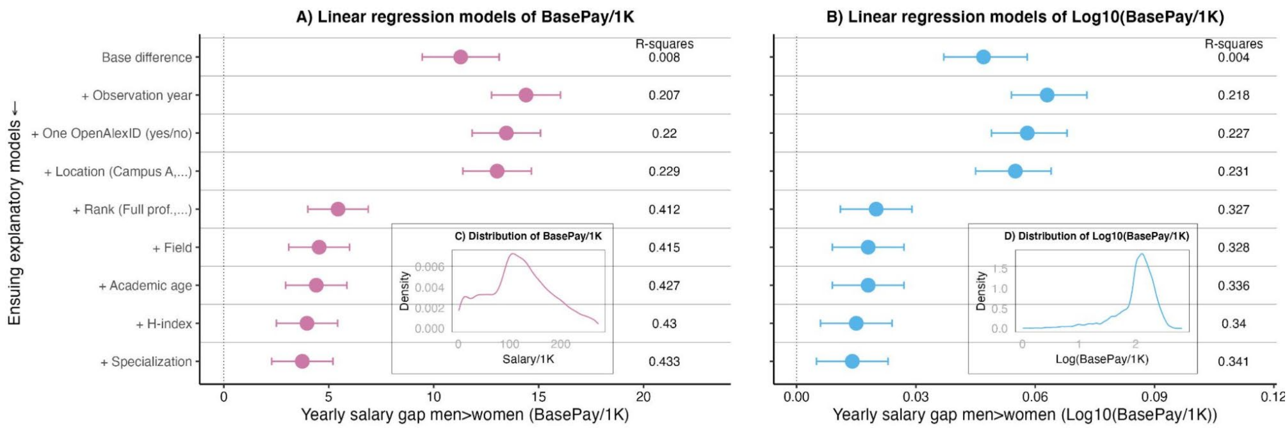

Fig. 2. Explaining gender faculty salary gap in Base pay. The left panel (**A**) examines the raw distribution and the right panel (panel B) examines the log-adjusted base pay. The horizontal line shows the 95% confidence interval. Panels C and D show the distributions of both outcome variables. Full results are in Supplementary Appendix C.1 (**A**) and C.2 (**B**).

Results
The gender pay gap in base pay
In Fig. 1, we depict the distribution of Base pay by gender (panel A) and by gender and salary observation year (panel B) as violin plots (i.e., simultaneously showing density distributions and boxplots). The uncorrected Base pay/1K is higher for men than for women (mean difference = \$11,285; $t(16367) = -12.510$; p-2sided < 0.001). There is also a mean difference between men and women in favor of men for the log-transformed Base pay/1K (mean difference = 0.047; $t(15731) = -9.830$; p-2sided < 0.001). This difference seems relatively consistent over the salary observation year. Yet, note that the year 2018 captures more than 70% of all cases in our database, and that these patterns do not necessarily depict time trends in salary but merely the latest year in which we observed a particular case. These baseline descriptive patterns suggest a higher salary for men faculty compared to women faculty.

How do these descriptive patterns hold up when we take into account various covariates? The results in Fig. 2 answer that question. Panel A shows ensuing explanatory linear regression models (N = 18,820) from a baseline men/women difference in Base pay on the X-axis to differences net of a range of variables included in each next step of the model. These ensuing variable additions to the regression model can be observed on the Y-axis. The dots are the model coefficients for men with women as reference group with 95% confidence intervals (whiskers). Figure 2, panel B depicts the same regression analysis buildup (N = 19,590), but with the log transformed Base pay as dependent variable. The number of observations in both setups differ because of the removal of outliers for the non-transformed Base pay (panel A). Panels C and D show the distributions of Base pay as the dependent variable. The major takeaway from all of these analyses is that the men/women pay gap in favor of men faculty does not disappear with the inclusion of a range of explanatory variables related to campus location, "performance" (e.g., H-index), or status (e.g., full professor or not), and is consistent across both the raw and the log-transformed Base pay variable.

Taking a closer look at each model, in the baseline model in panel A without any other explanatory variables, we observe that men earn about \$11,285 more than women (all the reported women/men differences are p-2sided < 0.001 unless stated otherwise) – i.e., the same mean difference from the descriptive results before. If we then add observation year to the model, we observe that the salary difference in favor of men faculty increases to \$14,398. This increase indicates that the raw difference in pay gap might be underestimated because more women became faculty in later years. As the pay level increases over time following the inflation rate, women's higher proportion in later years might obfuscate the gender pay gap without controlling for the observed year. Indeed, after controlling for the observation year, the gender gap turned out to be larger than the raw statistics.

Additionally, for each inclusion of an additional variable, the women/men difference in faculty salary decreases. The biggest decrease in the salary gap seems to occur with the inclusion of faculty rank (assistant, associate, or full). This implies that men are more often full professors than women and that in turn may partly explain the women/men salary gap. Around 45% of women in the data are full professors and 62% of men are, whereas full professors earn around \$33K more than associate professors and \$61K more than assistant professors. This rank variable decreases the salary pay gap from \$13K in the model that added campus location to \$5.4 K in the model that adds rank as an explanation. It also increased the explained variance of the outcome Base pay quite significantly from 22.9 to 41.2%. This finding indicates that the primary factor contributing to the lower Base pay of women faculty compared to men is their lower representation in higher faculty ranks.

We then add faculty's academic age, H-index, and specialization, respectively. Each of those variables slightly decreases the women/men faculty salary gap up to \$3,740 in favor of men faculty in the model including all variables. Interestingly, the productivity measure, H-index, does not also show a significant impact after controlling faculty rank and seniority, suggesting that the gender disparity in Base pay cannot be attributed to differences in productivity between genders. In our last model, the base salary difference of \$11,285, about \$3,740 (or 33%) remains unexplained as the net of a range of explanatory variables. In our second series of regression models (Fig. 2, panel B) of the log-transformed Base pay/1K outcome, all of these patterns provide qualitatively similar results. This implies that these results are not affected by the somewhat right-skewed distribution of Base pay.

As a post-hoc analysis, we consider whether men faculty are more likely to be among the Base pay/1K outliers (yes/no). Descriptively, 5.3% of men faculty and 1.6% of women faculty are among the Base pay outliers – i.e., those who earn more than \$272K on a yearly basis, more than twice the standard deviation from the Base pay average. When we regress this binary Base pay "elites" variable on gender and all our other explanatory variables in a logistic model, we find a similar pattern as before. Specifically, the odds for men, rather than women, to be among these outliers are 1.997 ($p < .001$). In sum, this set of results provides quite robust evidence for a persistent Base pay salary gap where men faculty earn more than women faculty.

The gender gap in receiving any other pay (or not)

Figure 3 depicts the results of a series of ensuing logistic regression models (all $N = 19{,}590$) for whether faculty receive any Other pay (yes/no), where in each next model an additional explanatory variable is added (as found

Fig. 3. Explaining the gender difference of odds in having other pay. The horizontal line shows the 95% confidence interval. Full results are in Supplementary Appendix C.3.

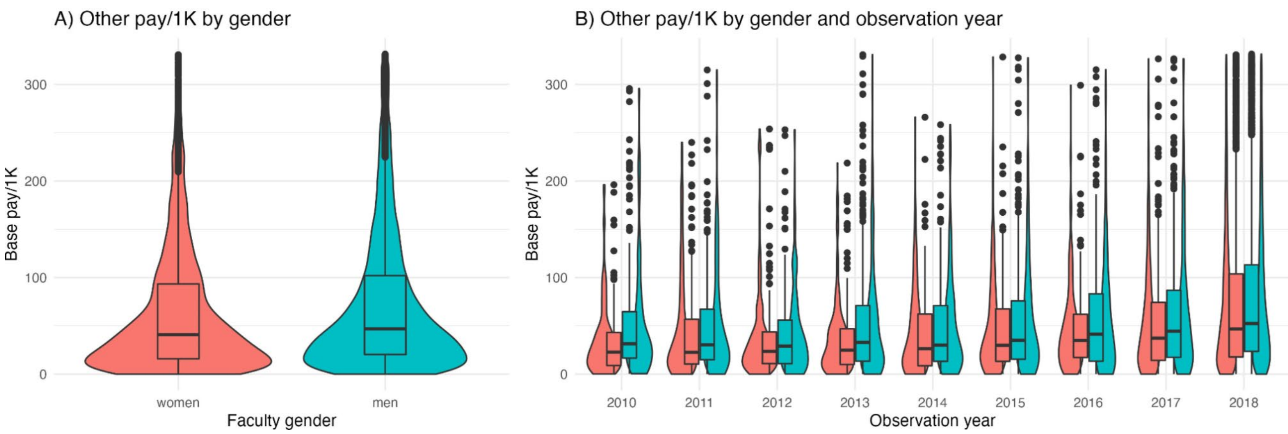

Fig. 4. Box and violin plots of Other pay/1k (if there is any) plotted by gender (**A**) and by gender and observation year (**B**).

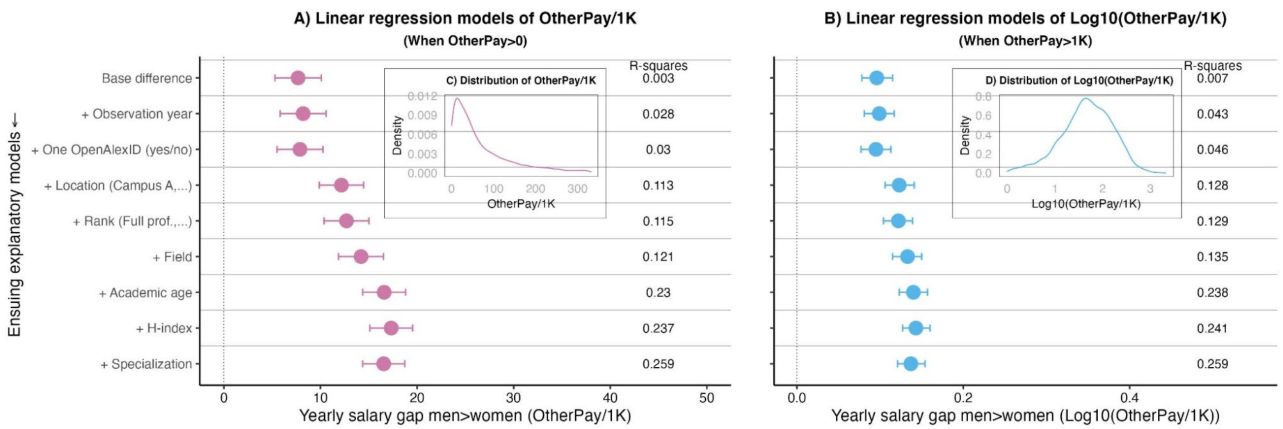

Fig. 5. Explaining gender faculty salary gap in Other pay. This analysis includes only faculty members who have other pay larger than \$0 (**A**) or larger than \$1K (**B**). The left panel (**A**) uses the raw distribution and the right panel (**B**) uses the log-adjusted other pay. The horizontal line shows the 95% confidence interval. (**C,D**) Depict the outcome variable distributions. Full results are in Supplementary Appendix C.4 (**A**) and C.5 (**B**).

on the Y-axis). Descriptively, 77.4% of women faculty and 75% of men faculty have other pay. This small difference in favor of women faculty is reflected by significantly lower odds for men to receive any Other pay in the baseline model of Fig. 3. With the addition of the observation year and whether faculty have one or more OpenAlexIDs in the second and third model, this difference does not disappear (both $p < .01$). However, with the inclusion of location, rank, field, and academic age, the difference first does not deviate from zero anymore and subsequently favors men. This suggests that men are located at certain campus locations, in ranks (higher), in fields, and have career ages (older) with higher odds of receiving Other pay. Yet, the women/men difference for receiving Other pay in the seventh model (including academic age) is barely statistically significant ($p = .028$). When we then include H-index and specialization, the women/men difference in receiving Other pay is rendered statistically insignificant. This set of results leads us to carefully assume that there is a base difference where women have slightly larger odds to have other pay, but there are no noteworthy differences in receiving Other pay between women and men faculty net of our set of confounding variables.

The gender pay gap in other pay (if there is any)

In Fig. 4, we depict the distribution of Other pay by gender (panel A) and by gender and year (panel B) as violin plots. The uncorrected Other pay/1K is higher for men than for women (mean difference = \$7,681; $t(12024) = -6.361$; p-2sided < 0.001), and the log-transformed variable shows a similar result in favor of men. Similar to Base pay, these differences seem stable across observation years. This suggests a higher Other pay salary for men faculty compared to women faculty (if there is any Other pay).

Next, we estimate salary differences between women and men faculty net of a range of confounding variables in Fig. 5. Panel A shows ensuing linear regressions ($N = 14{,}292$) from a baseline gender difference in Other pay to differences net of a range of variables included in each next step of the model (found on the Y-axis). In the analysis of raw Other pay, we removed outliers that have values higher than two times the mean. Again, dots are coefficients for men with women as reference group and with 95% confidence intervals. Figure 5, panel B ($N=14{,}344$) runs the same set of models, but with the log transformed Other pay as the outcome, and panels C and D show the distributions of Other pay. Similar to Base pay, the key finding from this set of results is that men faculty earn more Other pay than women, and that this difference does not disappear with a set of explanatory variables. These differences are unaffected by either studying the regular or the log-transformed Other pay as an outcome.

If we consider these results more closely, we observe some interesting patterns. In the baseline model in Panel A, we see that men earn about $7,681 more than women. The inclusion of observation year increases this difference to $8,204. Similar to Base pay, it indicates that when we do not control the observation year, more women faculty in later years underestimate the raw pay gap.

Additionally, with the inclusion of whether or not the observation is duplicated in OpenAlex, the difference first decreases, but then increases again with the inclusion of campus location by $12,170. This latter finding is mostly caused by the inclusion of one specific campus location where women are rather well-represented – i.e., 48% on that location compared to 36.4% across all locations – but where the Other pay gap is comparatively larger than at other campus locations ($18,037 versus $9,778). The inclusion of first faculty rank and then field of study in the next two explanatory models neither increase nor decrease the Other pay difference substantively. Next, the addition of academic age slightly increases the gender gap. This finding indicates that women who have a long career are likely to earn more other pay than men. However, similar to Base pay, the inclusion of two variables directly related with researchers' academic work, H-index and specialization, does not turn out to have the significant impact. In the final model, the gender gap escalates to $16,550, nearly doubling the initial gender gap. The regression models of the log-transformed Other pay/1K outcome (Fig. 5, panel B) show a similar pattern to raw Other pay/1K (panel A), albeit with slightly less variation, suggesting that these results are not affected by the right-skewed distribution of Other pay. This finding suggests that even the gender gap in performance-based Other pay remains unaccounted for by our productivity measure, the H-index.

Similar to our analyses of Base pay, we consider in a post-hoc analysis whether men faculty were more likely to be among the Other pay/1K outliers (yes/no). Descriptively, 5% of men faculty and 1.9% of women faculty are among the Other pay outliers – i.e., those who earn more than $332K Other pay on a yearly basis, more than twice the standard deviation from the Other pay average. When we regress this binary Other pay "elites" variable on gender and all our other explanatory variables in a logistic model, we find a similar pattern. Specifically, the odds for men rather than women to be among these outliers are 1.198 ($p<.001$). In sum, this set of results provides convincing evidence for a persistent Other pay salary gap (if there is any) where men faculty earn more off-grade pay than women faculty.

Gender-specific effects of H-index and specialization

Next, we consider whether there are any gender-specific effects of either H-index and Specialization on Base pay or Other pay. This illuminates how "performance" indicators of scholarly work vary by gender in its returns on salary. Figures 6 and 7 show the results of a series of linear regression models where we first depict predicted

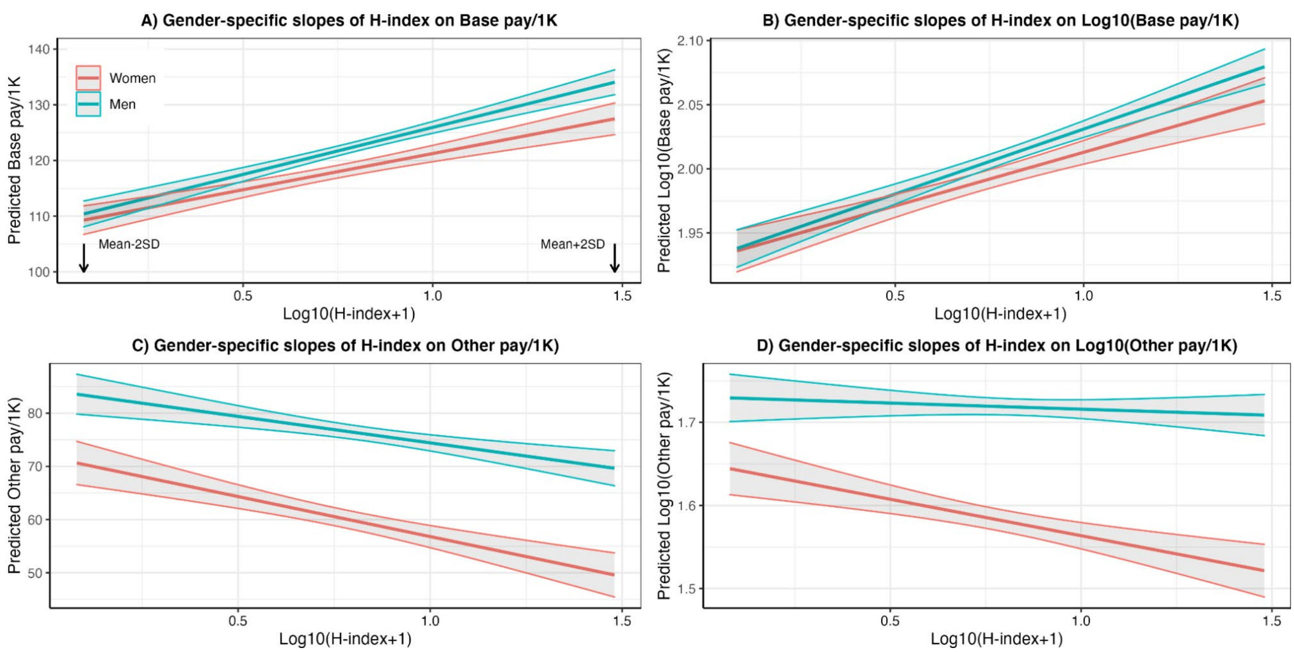

Fig. 6. Gender-specific effects of H-index on Base pay (**A**), log-transformed Base pay (**B**), Other pay (**C**), and log-transformed Other pay (**D**). The range of H-index is limited to its mean minus or plus two standard deviations, and we present predicted values of the dependent variables on the Y-axes. The shaded area shows the 95% confidence interval.

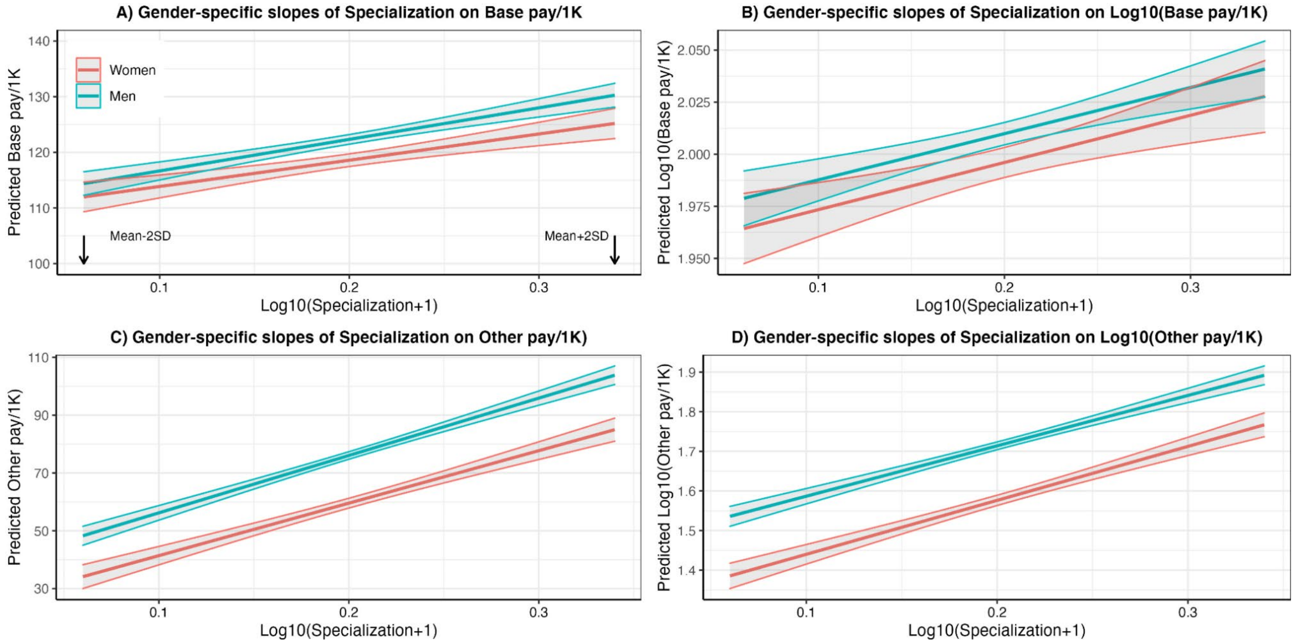

Fig. 7. Gender-specific effects of Specialization on Base pay (**A**), log-transformed Base pay (**B**), Other pay (**C**), and log-transformed Other pay (**D**). The range of H-index is limited to its mean minus or plus two standard deviations, and we present predicted values of the dependent variables on the Y-axes. The shaded area shows the 95% confidence interval.

Base and Other pay by H-index for each gender (Fig. 6) and subsequently consider gender-specific effects of Specialization on predicted Base and Other pay (Fig. 7). Each of these models includes all of the other explanatory covariates as found in the prior set of results.

H-index

Figure 6 shows whether and how H-index has gender-specific returns on Base pay (panel A), log-adjusted Base pay (panel B), Other pay (panel C), and log-adjusted Other pay (panel D). The Range of H-index is limited to plus and minus twice the standard deviation from the mean on the X-axes. The full Y-axes – i.e., starting at zero – are not shown here to highlight possible slope differences of H-index by gender in the range of predicted salaries (e.g., from 100 K to 140 K in panel A).

The analyses show that the impact of H-index on salary hardly varies by gender. H-index has a positive correlation with Base pay and logged Base pay, yet this does not differ for men and women. H-index seems negatively related to Other pay or logged Other pay (Fig. 6, panels C and D). Post-hoc analyses show, however, that an inverse u-shape effect of H-index on Other pay seems to fit the data better (i.e., a main effect and a squared effect of H-index), where H-index first has a positive correlation and then a negative relation with Other pay and logged Other pay. This inverse u-shape effect also does not differ between men and women for Other pay and logged Other pay.

As a last step, we examine whether the pattern depicted in Fig. 6 varies according to professors' ranks. The summary figure can be found in Supplementary Appendix D. Our analysis reveals that while there are no gender-specific effects of H-index among assistant and associate professors, men full professors experience greater benefits in base pay as their H-index increases compared to women full professors. This discrepancy in reward for performance accounts for the entirety of the remaining gender pay gap among full professors in Base pay. Our finding implies that the residual gender gap in base pay among full professors can be attributed to the higher recognition of high-performing men faculty members compared to their women counterparts, or vice versa, a devaluation of women full professors' contributions on Base pay.

Specialization

Figure 7 shows whether, and how, our measure of specialization has gender-specific impacts on Base pay (panel A), log-adjusted Base pay (panel B), Other pay (panel C), and log-adjusted Other pay (panel D). The range of specialization is limited to plus and minus twice the standard deviation from the mean on the X-axes. Specialization turns out to be important for faculty salary, as both Base pay and Other pay increase along with the level of specialization. Yet, we do not find gender-specific returns to specialization in any of the four analyses in Fig. 7.

Discussion and conclusion

In this study, we investigated the factors that might sustain the gender gap in faculty salary by studying approximately 19 K faculty affiliated to multiple campuses in one public university system between 2010 and

2018. We combined publicly available faculty salary information and publication records to study how the structural position of faculty and features of their academic output impacted the gender gap in faculty salary. Particularly, we separately examined the gender gap in salary by dividing gross pay into "Base pay" and "Other pay" so as to provide further nuance in understanding the gender pay gap among U.S faculty. Our results showed that distinct factors partly explain the gender gap for each type of pay. We found that 67% of the existing gender gap in Base pay was explained by confounding variables, especially, faculty status. Measures related to academic performance such as H-index and specialization, did not further explain the existing gender gap in Base pay. However, no variables, including academic performance, could explain the gender gap in Other pay. Also, we found hardly any evidence of differential returns by gender on academic performance except Base pay of full professors.

Our study reaffirms that the gap in Base pay is closely associated with the structural position of women faculty. Interpreting this result as gender equity in salary within the same faculty rank is not without issues. Rather, it should be interpreted that the promotion process is the site where gender inequality is reproduced not only in academic status[57–59], but also in monetary compensation. Additional analyses illustrate that only women with strong records survive through the ranks, which implicitly suggests that strict promotion criteria may have been imposed on women (see Supplementary Appendix E). The results also imply the existence of structural barriers for women to proportionately populate authorships and citations than men, which are much needed during the promotion process. Less productivity of women is associated with the devaluation of women's work in academia[8,35] or the concentration of service work to women faculty prohibiting their time spent on research[10]. When these factors collectively result in fewer grants and reduced research time for women, it can hinder their progress in climbing up the academic promotion ladder, leading to lower Base pay. Thus, one way to decrease the gender gap in Base pay is to clear these structural barriers against women in the academic career trajectories.

The finding that the gender gap remains substantially present in both Base and Other pay even after taking into account institutional affiliations and features of academic performance is meaningful for debates on faculty performance (or productivity) and pay. This finding suggests that women are not paid less than men due to lower academic performance or standing – i.e., keeping constant performance metrics, pay differences remain acute. Instead, limited to full professor positions, women are paid less Base pay because men receive higher pay following their academic performance than women counterparts. Our results imply that the difference in Base pay is less likely attributable to a gender productivity gap, but rather to differing levels of recognition for the academic works of established scholars.

While it is relatively understandable that academic performance may not be the primary factor explaining the gender gap in Base pay, it is surprising for Other pay, given the claim that it should focus more on meritocratic features of one's academic career. The category of Other pay includes financial sources such as negotiated raises in salary, research grants, and other funds attached to academic performance indicators. Remarkably, however, our findings suggest that the gender pay gap in Other pay is *not* highly associated with such academic performance indicators based on productivity. In fact, we found that none of our variables helped explain the existing gender gap. This finding is consistent with the previous literature that the salary allotted outside of the pay grade system favors men regardless of one's academic position[37].

This finding merits a follow-up question: where does the gap in Other pay originate from? While our current data and analysis are not sufficient to fully answer this question, we suggest several potential explanations found in prior literature. Considering that Other pay is partially funded with faculty's research grants, we conjecture that the gender gap in Other pay might result from funding acquisition. For example, men might have better funding chances than women because a significant number of reviewers and editors of journals and grants are men who are likely to favor similarly gendered research interests[60]. Yet, if we assume that research grants increase productivity, but that productivity does not associate with Other pay, there remains a puzzle to be solved. Another possible source of the gender gap in Other pay is imbalanced negotiating power because women might have less of this relational advantage than men due to their position[61] or expected gender roles[62] or due to men self-promoting more than women. Lastly, the source of gap in Other pay may extend beyond academia. Given that women have more family caregiving responsibilities and even give up academic careers often during family formation[2], women may give up the opportunity to receive summer research grants or teach classes more frequently than men. Women's decision to forgo additional tasks aligns with the explanation behind the gender pay gap among women professionals who opt out of pursuing "greedy work" and the pay following it[63].

Given the varying sources of the gender pay gap in Base and Other pay, we argue that research policies aimed at reducing this gap should be tailored differently depending on the specific type of pay being targeted. For Base pay, significant efforts should be made towards hiring and, especially promoting women to higher ranks. It is simultaneously important to ensure that the academic contributions of women full professors are appropriately recognized, on par with their men counterparts. These efforts will not only reduce the gender gap in Base pay but also help women thrive in academia and bring much-needed new perspectives in science[8,64]. However, for Other pay, the puzzle seems more complex, as academic performance in the form of productivity is inefficient to explain the Other pay gap. Rather, further investigation needs to be done to locate where specific gaps come from: negotiation, grant funding, or other sources beyond academia.

Some limitations of this study need attention. First, our approach in this study is likely to underestimate the existing gender gap in faculty salary because we assumed that the number of publications and citations represents one's academic performance well. However, a substantial amount of literature indicates that women's ideas are adopted and cited less[8,65]. Also, women's ideas are less likely to be presented in higher impact journals and higher education institutions, which might prohibit the spread of their influence[34,35]. Thus, our research is limited to the extent that we assumed that bibliographic information reflected the merit of scholars. Second, we may have found relatively less influence of productivity because it is already reflected in the promotion process. Indeed, Weisshaar[58] finds that a gender gap in promotion is partially explained by productivity differences.

Given this limitation, our results should be interpreted with caution, measuring the impact of productivity on the gender gap only within the same faculty rank. Third, our study may have underestimated the salary gap since our observation is restricted to universities affiliated with a public system. Universities majorly relying on public funding are more likely to maintain lower pay gaps between women and men, while relying on competitive research funding bring higher pay gaps[66]. Thus, our study focused on publicly funded research universities might have underestimated the overall pay gap that exists in other privately funded universities. Fourth, our study uses the conventional gender binary to focus on gender-related disparities. While we acknowledge that gender is not a binary categorization but rather a multifaceted constitution of identities[67], our work is constrained by the data limitation that did not include self-reported gender, preventing us from adopting this broader perspective on gender. Fifth, in comparison to research on gender inequity, research on ethnic inequality in the pay gap has been relatively neglected with few exceptions[68,69]. Future research may expand the scope of studying gender salary pay gap across different marginalized groups.

Data availability

We will provide the anonymized data and code upon request. Due to the sensitive nature of faculty salary data, we will provide the salary information with numbers below one thousand redacted. To request the data and code, please email the corresponding author (Lanu Kim, lanukim@kaist.ac.kr).

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Author contributions
L.K. and B.H. conceived and designed the study, and analyzed the data. L.K. collected and managed the data. L.K., B.H., S.M.G. wrote the original draft, reviewed, and edited it. B.H. visualized the results.

Declarations

Competing interests
The authors declare no competing interests.

Additional information

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