

Research Article

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Reverses in Gender Salary Gaps Among STEM Faculty: Evidence from Mean and Quantile Decompositions

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Abstract: This research examines the gender salary gap in STEM and nonSTEM disciplines at a public research university. We estimate earnings regressions for female and White male faculty members as a whole as well as for those working in STEM departments. Controlling for productive characteristics and field salary differentials, we perform mean and quantile decomposition analyses to identify potential salary inequities. We observe no gender salary gap for analyses of mean or median monthly salary. However, our salary quantile analyses for STEM departments indicate there are positive effects for women in top quantiles and negative effects for women in low quantiles compared to White male peers, other things equal. This implies that highly paid female academics working in STEM departments were better rewarded than their White male peers, but female academics at the lower end of the salary distribution were not paid on par with their White male peers.

Keywords: academic salaries; gender salary gap; quantile decomposition analyses

1 Introduction

Numerous studies by economists examine the gender wage gap in the United States and other countries. The goal of studies in this voluminous literature is to ascertain

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how individual or institutional characteristics explain the observed gap. A review of the literature describing the gender wage gap in the United States is provided in Blau and Kahn (2017). The authors describe studies detailing the decrease in the gender wage gap between 1980 and 2010, noting that the convergence slowed in the 1990s.¹ Then, examining data from the Panel Survey of Income Dynamics, the authors estimate changes in key characteristics that have contributed to the slowing convergence of the gender wage gap. These characteristics include schooling, experience, industry, occupation, and union status. The findings confirm the slowing convergence of the gender wage gap in the United States during the 1990s and establish that the gender wage gap remains substantial, with women earning 8.4 % less than men even when differences in education, work experience, and occupation are taken into consideration.

Looking beyond the United States, Kunze (2018) reviews the economic literature on the gender wage gap in developed countries, predominantly focusing on studies of countries in Europe and Asia. O'Reilly et al. (2015) similarly review studies of the wage gap in the United Kingdom, Europe, and Australia. Both reviews report significant gender wage gaps favoring men. This seemingly universal observance of unexplained gender wage gaps has been attributed to both unobserved gender differences and gender discrimination.²

We next focus on studies of the gender wage gap in American academia because our data source is an American university.³ The findings of an early study of the academic gender gap in the United States are those of Toutkoushian (1998). Using data from the National Center for Education Statistics for 1988 and 1993, Toutkoushian (1998) reports that the aggregate unexplained wage gap between men and women was between 7 and 10 % for that period, which the author notes is comparable to findings from earlier national studies conducted during the 1970s and 1980s. However, the author reports that the unexplained wage gap was lower for younger female faculty members than for older female faculty members, suggesting that improvements were occurring in the academic wage gap over these years.

While studies like Toutkoushian (1998) that use national data may be more representative of academia in the United States, the precise focus of studies describing

¹ The authors provide detail describing this convergence in Blau and Kahn (2006).

² See the discussions in Fortin (2008), Casad et al. (2020), Della Giusta and Bosworth (2020), and Gamage, Sevilla, and Smith (2020).

³ There are many studies of the gender wage gap in academia in countries other than the United States. For example, recent studies of the gender wage gap at universities in the United Kingdom include Bachan and Bryson (2022), Harris and Maté-Sánchez-Val (2022), Mumford and Sechel (2020), and Woodhams, Trojanowski, and Wilkinson (2022).

gender wage gaps at specific universities often benefit from richer data describing faculty members' characteristics and productivity. Many studies use this advantage to estimate the gender salary gap at individual universities or small groups of universities.⁴ In general, these studies document the existence of unexplained gender wage gaps favoring men that vary between three and fifteen percent, although the estimates vary considerably by field, rank, and institution. The focus of these studies also varies: For example, Toumanoff (2005) reports an unexplained gender differential between 2.9 and 8.4 percent in the starting salary of faculty members at one university.

Among studies considering the gender wage gap at American universities, a more focused strand of the literature examines gender gaps in particular academic disciplines. Many disciplines are studied, including economics. However, because of the increased focus in recent years on encouraging education in science, technology, engineering, and mathematics (STEM) fields, there has been a concurrent increase in interest in promoting greater inclusion of women and members of minority populations in STEM disciplines.⁵ In their review of gender issues in STEM fields, Kahn and Ginther (2017) observe that women's underrepresentation is especially limited in math-intensive science fields and find that their observations of fewer women in math-intensive fields are consistent with preferences and psychological explanations (likely influenced by social norms).

The focus on greater inclusion in these disciplines has led to an increase in studies of gender wage gaps in STEM disciplines.⁶ The findings vary: One notable study of public universities reports that in the life and physical sciences the gender wage gap is completely explained by observed characteristics, including academic field, work experience, and research productivity (Li and Koedel 2017). However, other studies report that academic gender wage differences in STEM disciplines remain even after accounting for observed characteristics (Michelsmore and Sassler 2016). The findings of Bedard, Lee, and Royer (2021), echoing that of Toumanoff (2005), suggest that gender wage gaps are not significant in economics among assistant professors, but grow both because female faculty members move up in rank more

4 Examples of studies using data describing specific American universities include Gordon, Morton, and Braden (1974), Hoffman (1976), Hoffman (1981), Geisler and Oaxaca (2005), Toumanoff (2005), Binder et al. (2010), Lesik and Fallahi (2011), Carlin et al. (2013), and Chen and Crown (2019).

5 See National Science Foundation (2020) for a discussion of the importance of STEM education for the future labor force and the need for STEM teachers and faculty who are female, Black, and Hispanic.

6 Examples, including studies of the economics discipline, include Xu (2008), Ceci et al. (2014), Ceci et al. (2015), Michelsmore and Sassler (2016), Kahn and Ginther (2017), Li and Koedel (2017), Mumford and Sechel (2020), Ginther and Kahn (2021), Bedard, Lee, and Royer (2021), and Harris and Maté-Sánchez-Val (2022).

slowly than male faculty members and because women are more likely to leave academia.

Finally, although the vast majority of empirical studies report a gender wage gap in which male workers are paid more than their female peers, new studies report empirical evidence that diversity efforts by employers may lead to wage premia for highly productive women that reverse the wage gap. Among academics, Williams and Ceci (2015) report a two to one preference in favor of hiring women among tenure track faculty members of both genders, regardless of the math-intensiveness of the field, suggesting that diversity efforts by universities to counteract formerly sexist hiring practices lead to a more welcoming atmosphere in STEM disciplines.⁷ This evidence is consistent with efforts by universities to recruit and retain highly productive female faculty members in STEM fields. Leslie, Manchester, and Dahm (2017) suggest that the increased demand for highly productive women among employers who are seeking greater diversity in their workforce leads to higher wages for these women, other things equal.⁸ Thus, while it is typical to observe a gender wage gap favoring men, it is possible to observe a gender wage gap favoring women who are highly productive.

All of the research described above examines unexplained differences in mean wages of men and women in academia. To assess these differences, studies use multiple regression methods to control for confounding factors and many apply decomposition methods to assess the presence of potential wage discrimination.⁹ *In our study, we bring together the strands of research described above: We investigate the gender wage gap among faculty members in academic STEM fields, but extend the scope of the decomposition analyses to assess differences at several quantiles of the wage distribution.* While studies of gender wage gaps note the existence of wage premia among high-potential women at the top of the wage distribution, we know of no study that has empirically estimated gender wage gaps at both the high and low ends of the wage distribution for a single university. The advantage of using data for a single university is that the data are sufficiently rich to conduct sophisticated quantitative analyses uncovering potential wage inequities across the salary distribution.

7 The sole group not expressing a preference for hiring women were male economists, who showed no gender preference.

8 This is not limited to academic settings: Gayle, Golan, and Miller (2012) and Hill, Upadhyay, and Beekun (2015) report that female executives and CEOs earn more than their male counterparts, other things equal.

9 Decomposition methods are applied to academic gender wage gaps by Lesik and Fallahi (2011), Blau and Kahn (2017), Mumford and Sechel (2020), and Woodhams, Trojanowski, and Wilkinson (2022). Other well-known studies apply decomposition methods in nonacademic settings (Oaxaca and Ransom 2003; Geisler and Oaxaca 2005; Shatnawi, Oaxaca, and Ransom 2014).

Our goal is to analyze whether there are statistically significant gender differences in salaries at a single university given the faculty members' work characteristics, performance measures, and position in a STEM department. Unlike general studies of gender salary gaps that examine possible sources of endogenous factors causing salary differences, our goal is to ascertain whether the salary process at the university involves a gender bias. For this reason, we estimate single equation models of faculty salaries in which the explanatory variables are assumed exogenous. Because many factors that influence academic salary, such as discipline, rank, and professorship awards, may be determined in endogenous processes that are potentially gender biased, our estimates of salary gender differences are likely to underestimate the total effect.¹⁰

The application of decomposition analyses to the quantiles of the salary distribution is important because analyses at the mean may ignore significant differences that are uncovered when high and low quantiles are analyzed. Indeed, in our study we find no empirical evidence of unexplained salary differentials in our analysis of mean and median differences. One might ordinarily conclude from this that there are no gender-based inequities in salary. However, we find statistically significant unexplained gender salary differences in our analyses of both low and high salary quantiles among faculty members in STEM departments: Estimating effects for faculty members who earn relatively high salaries, we find unexplained salary differences between women and their White male peers that favor women. In contrast, when we focus on explaining the low quantiles of the salary distribution, we find there are significant unexplained differences between women and their White male peers that favor White male faculty members.

These findings indicate that female academics working in STEM departments are apparently not paid on par with their White male peers: Instead, highly paid female academics working in STEM departments earn more than their white male peers, while female academics in STEM departments who are at the lower end of the salary distribution are paid less than their white male peers, other things equal. As mentioned above, Leslie, Manchester, and Dahm (2017) suggest that high-potential women may be perceived as higher in diversity value to their organizations than high-potential men, leading to higher pay. Our findings suggest that such a gender

¹⁰ This approach is typical of studies using university data (Binder et al. 2010; Lesik and Fallahi 2011), but has also been applied in more general studies (Graves, Marchand, and Sexton 2002).

gap reversal may coexist in the same institution with a typical negative gender wage gap at the lower end of the wage distribution.

The important implication of these findings is that in examining salary policies, institutions need to look beyond the common approach of estimating only the average gender salary gap. As demonstrated in the analyses reported here, reliance on average effects means that the presence of highly paid female faculty members apparently may offset the presence of underpaid female faculty members at the lower end of the earnings distribution, so that no average gender difference is observed. However, if an institution's goal is to ensure gender salary equity for all faculty members, studies need to consider equity among female and white male faculty members of equivalent productivity at all pay levels.

We describe the study sample in Section 2 and describe the analytical variables and regression methods in Section 3. In Section 4 we report our findings and conclude the paper in Section 5 with a discussion of the findings.

2 Data

The data used for this study describe tenure-track and tenured faculty members at a large Midwestern public university, classified as a Doctoral University by the Carnegie Classifications. In the fall semester of 2015, the university enrolled 20,130 students, 25 % of whom were graduate students. This enrollment was similar to other universities classified by as Doctoral Universities for which the average enrollment in the fall semester of 2014 was 19,371 (American Council on Education 2016). The average number of tenured and tenure-track faculty members for this university was slightly smaller than the average for Doctoral Universities reported by the Carnegie Classifications.¹¹

We have 575 observations of faculty members for academic year 2015–16. We use this particular year for our study because the process of faculty unionization that occurred in the following years introduced salary policies that may have attenuated the effect of productivity measures on salary.¹² The primary source

¹¹ This university was classified as a Doctoral University: Higher Research Activity (American Council on Education 2016). Exact figures reported for this university in the Carnegie Classifications data are not reported to preserve the anonymity of the university (a condition for publication using the data).

¹² Faculty salaries for academic year 2015–16 were set prior to the beginning of the academic year. A card drive for a possible faculty union was conducted during the academic year 2015–16 and a faculty union was certified in June 2016. Contract negotiations did not begin until the summer of 2017 and the first bargaining agreement was reached in Fall 2019. Hence, the salary data used for this study amply predate union activities.

Table 1: Average monthly salary of White male and female faculty members.

	All		STEM – DHS		STEM – NSF	
	White male	Female	White male	Female	White male	Female
Average monthly salary	\$9082	\$8321 ^a	\$9473	\$8384 ^a	\$9300	\$8366 ^a
Salary gap	\$761		\$1089		\$934	
<i>N</i>	255	248	94	42	139	85
% of group	50.7 %	49.3 %	69.1 %	30.9 %	62.1 %	37.9 %

^a P -value ≤ 0.05 for a two-tailed t -test of difference between white male and female faculty members.

^b P -value > 0.05 and ≤ 0.10 for a two-tailed t -test of difference between white male and female faculty members group.

of data for the study sample was administrative data collected by the university. This was supplemented with data provided by the various units of the university and information obtained from online public data sources such as personal web-pages and LinkedIn. From this initial sample, we focus on potential differences in faculty salary by gender by comparing subsamples of 255 White male and 248 female faculty members. The White male group, the reference group against which the average salaries of female faculty members are compared, includes all male faculty members not designated in human resources records as Asian, Black, or Hispanic.¹³

In Table 1 we report the number and percentage of female and White male faculty members employed by the university, as well as those in STEM departments. We use two alternatives to define STEM fields: The first alternative, used by the United States Department of Homeland Security (DHS), is a more restrictive list of fields that includes only engineering, biological sciences, mathematics, physical sciences, and related fields. The second alternative, used by the National Science Foundation (NSF), includes many more fields, including quantitative subfields of a wide selection of disciplines such as the social sciences.¹⁴ We report faculty members' average monthly salary for both STEM field lists for academic year 2015–16 in Table 1.

¹³ To form the baseline group of White male faculty members we drop 72 observations of male faculty members identified as Asian, Black, and Hispanic. Because the small number of Black and Hispanic faculty members precludes regression and decomposition analyses of minority groups, we focus solely on the comparison of female faculty members to White male faculty members. However, descriptive statistics describing non-White male faculty members are provided in Appendix Table A-1.

¹⁴ Lists of the fields included in the two STEM groupings are in Appendix Tables A-3 and A-4.

As observed in Table 1, the percentages of female (49.3 % of the study sample) and White male (50.7 %) faculty members are similar when all units of the university are pooled.¹⁵ However, smaller percentages of STEM faculty members are female: The percentage of female STEM-DHS faculty members is only 30.9 %. This increases to 37.9 % for the STEM-NSF group, but the percentage of White male faculty members is still much higher than that of female faculty members. This gender segregation in STEM departments is well documented in the literature.¹⁶

White male faculty members earn significantly higher average monthly salaries than their female counterparts across all departments as well as across STEM departments. The average monthly salary of female faculty members is 91.6 % of the average monthly salary of white male faculty members. For faculty members in the STEM-DHS departments the percentage drops to 88.5 % and is 90.0 % for faculty in the STEM-NSF departments. The gender gap in average monthly salary ranges from \$761 for faculty members in all departments to \$934 in STEM_NSF departments and \$1089 in STEM-DHS departments. The difference in average salaries between White male and all female faculty members is statistically significant at standard levels of significance ($p\text{-value} \leq 0.05$).

3 Empirical Analyses

The comparison of salaries in Table 1 is suggestive of gender salary inequities, but does not control for relevant characteristics representing academic productivity. To better control for productivity differences between female and White male faculty members, we use regression and decomposition methods. Our null hypothesis for the empirical analyses is that there does not exist a gender salary gap among faculty members in STEM fields when we control for characteristics representing academic productivity. We test this by estimating decompositions at the mean and five quantiles of the salary distribution.

Definitions of the analytical variables are reported in Table 2 and the means and standard deviations of the variables for the pooled sample and the STEM subsamples are reported in Table 3. Similar to the findings of Table 1, the averages we report in Table 3 indicate that women comprise a lower percentage of faculty members in STEM departments. Average monthly salary is higher for faculty members working in STEM departments than for the general sample including faculty members in all departments. We also observe a higher average value in the

¹⁵ Female faculty members comprise 43.1 % and White male faculty members comprise 44.3 % of the larger sample of 575 faculty members that includes nonwhite male faculty members.

¹⁶ See, for example, Ceci et al. (2014), Li and Koedel (2017), and Xu (2008).

Table 2: Variable definitions.

Variable	Definition
Monthly salary (2016 \$US)	
MORATE	Current monthly salary (monthly rate)
STEM indicators	
STEM-DHS	=1 if faculty member's field is designated as STEM by the Department of Homeland Security, =0 otherwise (Reference group contains nonSTEM-DHS fields.)
STEM-NSF	=1 if faculty member's field is designated as STEM by the National Science Foundation, =0 otherwise (Reference group contains nonSTEM fields.)
FEM × STEM-DHS	Interaction of FEMALE and STEM-DHS
FEM × STEM-NSF	Interaction of FEMALE and STEM-NSF
Demographic characteristics	
FEMALE	=1 if female, =0 if male
ASIAN	= 1 if Asian, =0 otherwise
BLACK	= 1 if Black, =0 otherwise
HISPANIC	= 1 if Hispanic, =0 otherwise
Discipline-specific monthly salary (\$US 2016)	
CUPA	Average monthly salary by discipline from national survey (university weights)
Work characteristics	
FULL	=1 if current rank is full professor, =0 otherwise
ASSOC	=1 if current rank is associate professor, =0 otherwise
ASSIST	=1 if current rank is assistant professor, =0 otherwise
YRS	Number of years employed at the university
YRS-SQ	Squared value of number of years employed at the university
YRSOTH	Number of years employed at other university or college
YRSOTH-SQ	Squared value of number of years employed at other university or college
Performance measures	
QUINT-TOP	=1 if the faculty member's average merit rating lies in the highest quintile, =0 otherwise
QUINT-2ND	=1 if the faculty member's average merit rating lies in the 2nd quintile, =0 otherwise
QUINT-MID	=1 if the faculty member's average merit rating lies in the middle quintile, =0 otherwise

Table 2: (continued)

Variable	Definition
QUINT-4TH	=1 if the faculty member's average merit rating lies in the 4th quintile, =0 otherwise
QUINT-BOT	=1 if the faculty member's average merit rating lies in the bottom quintile, =0 otherwise
PROFSHIP	= 1 if faculty member received a professorship award, =0 otherwise
SALADJ	= 1 if received college level salary adjustment or match, =0 otherwise
SEADJ	= 1 if received university level salary adjustment, =0 otherwise
SALSTART	Faculty member's starting monthly salary (\$US 2016)
<i>Department control variables</i>	
DEPT	Set of dummy variables representing departments of the university and library

national discipline salaries for faculty members in STEM disciplines (measured by the CUPA variable). For the restrictive definition of STEM disciplines (STEM-DHS), approximately 27 % of faculty members work in STEM departments. In comparison, approximately 44.5 % of faculty members work in STEM-NSF departments. Faculty members in STEM departments are more likely to be full professors and to have longer years of employment at the university than those in the pooled sample including all departments. Similarly, faculty members in STEM departments are more likely to have been awarded professorships, to have received salary adjustments, and to be in the higher quintiles of the college merit distributions.

As described in the introduction, our focus is to assess potential gender bias in the salary practices of a single university by investigating whether there are statistically significant differences in salaries at the university given the faculty members' productivity, personal and work characteristics, and positions in STEM departments. Because our goal is to test for salary differences given existing factors, we estimate single equation models assuming that the explanatory variables are exogenous.

Table 3: Descriptive statistics for regression variables.

	All		STEM – DHS		STEM – NSF	
	Average	Standard deviation	Average	Standard deviation	Average	Standard deviation
<i>Monthly salary (\$US 2016)</i>						
MORATE	8707	2576	9137	1819	8946	1741
<i>Demographic characteristics</i>						
FEMALE	0.493	0.500	0.309	0.464	0.379	0.486
ASIAN	0.078	0.268	0.059	0.236	0.058	0.234
BLACK	0.020	0.140	0.015	0.121	0.013	0.115
HISPANIC	0.018	0.133	0.007	0.086	0.009	0.094
<i>Discipline-specific monthly salary</i>						
CUPA	9439	2290	10,222	991	9845	1154
<i>STEM indicators</i>						
STEM-DHS	0.270	0.445	1	0	0.607	0.489
STEM-NSF	0.445	0.497	1	0	1	0
<i>Work characteristics</i>						
FULL	0.334	0.472	0.404	0.493	0.388	0.488
ASSOC	0.447	0.498	0.412	0.494	0.424	0.495
ASSIST	0.219	0.414	0.184	0.389	0.188	0.391
YRS	13.19	8.61	16.1	9.76	14.67	8.95
YRS-SQ	247.97	283.21	352.5	362.9	295.0	319.7
YRSOTH	2.33	4.03	2.01	3.88	2.31	4.28
YRSOTH-SQ	21.61	72.20	19.0	63.5	23.62	90.06
<i>Performance measures</i>						
QUINT-TOP	0.155	0.362	0.169	0.376	0.161	0.368
QUINT-2ND	0.209	0.407	0.206	0.406	0.219	0.414
QUINT-MID	0.203	0.402	0.213	0.411	0.201	0.402
QUINT-4TH	0.201	0.401	0.176	0.383	0.192	0.395
QUINT-BOT	0.233	0.423	0.235	0.426	0.228	0.420
PROFSHIP	0.082	0.274	0.118	0.323	0.134	0.341
SALADJ	0.032	0.176	0.044	0.206	0.054	0.226
SEADJ	0.091	0.289	0.184	0.389	0.165	0.372
N	503		136		224	

Our models of earnings regressions are Mincer (1974) earnings regressions. Following standard practice in estimating earnings regressions, we begin with analyses of the pooled data including both female and White male faculty members and include a dummy variable (FEMALE) to indicate gender:

$$\text{MORATE} = \alpha + \beta_1 \text{FEMALE} + \text{STEM}'\beta_2 + X'\beta_3 + \varepsilon \quad (1)$$

The dependent variable is the faculty member's monthly salary (MORATE) for the 2015–16 academic year as set at the beginning of the academic year. However, because monthly salary is positively skewed, we use the natural log of monthly salary as the dependent variable, transforming the distribution to near normal. This transformation means that the coefficient estimates should be interpreted as the percentage impacts on average monthly salary of a one unit change in a continuous explanatory variable, other things equal. For dummy explanatory variables, the coefficient estimate represents the percentage change in average monthly salary of changing the value of the dummy variable from zero to one, other things equal.

FEMALE, a demographic characteristic not associated with experience, productivity, or discipline, is defined as a dichotomous variable with a value of one if human resource records indicate the faculty member is a woman and a value of zero otherwise. White male faculty members form the reference group for this variable. We include this variable in our initial analysis to ascertain if there are significant gender effects on monthly salary that are not due to factors controlled for in the analyses. Following our null hypothesis that sex is not significant in determining monthly earnings, other things equal, we expect to observe an estimate of $\beta_1 = 0$.

To identify faculty members whose department is considered to be in a STEM field, we use two alternative definitions of STEM:

STEM-NSF – A faculty member's field is defined as STEM-NSF if the department in which he or she is employed is on the list of the National Science Foundation.¹⁷

STEM-DHS – A faculty member's field was defined as STEM-DHS if the department in which he or she is employed is on the list of the Department of Homeland Security.¹⁸

We estimate alternative specifications of Equation (1) in which the STEM vector includes one or both of the above STEM variables as well as interactions of the STEM dummy variables with FEMALE.

17 National Science Foundation (2015). A copy of the NSF list is in Appendix Table A-3. The list of fields considered to be STEM by the DHS is a strict subset of the list of the NSF.

18 U.S. Department of Homeland Security (2016). A copy of the DHS list is in Appendix Table A-4.

The remaining explanatory variables in the vector X of Equation (1) represent the individual faculty member's demographic characteristics, discipline, relevant work experience, and other factors measuring the faculty member's performance.

- (a) We include **demographic characteristics** not associated with work experience, performance, or discipline to ascertain if there are significant effects on monthly salary of these factors. In addition to FEMALE, we include variables representing race and ethnicity of female faculty members:

Race – We include two variables to represent the racial identification of female faculty members. These are the only racial groups for which we have sufficient numbers of faculty members to consider in the statistical analyses. ASIAN is defined as a dichotomous variable with a value of one if the faculty member is identified in human resource records as Asian (and a value of zero if not). BLACK is defined as a dichotomous variable with a value of one if the faculty member is identified in human resource records as African-American and a value of zero if not.

Hispanicity – We define HISP as a dichotomous variable with a value of one if the faculty member is identified in human resource records as being of Hispanic ethnicity (and a value of zero if not).

Note that because the comparison group includes only White male faculty members, observations in this group have a value of zero for the race and ethnicity variables. Although the race and Hispanicity categories are not by nature mutually exclusive and our program coding did not treat them as such, the administrative data for this information indicate that these categories are in fact mutually exclusive.¹⁹

- (b) To test the effect of **work experience** on monthly salary, we hypothesize that more experienced faculty members are more productive and that this increases salary, holding other factors constant.²⁰ We include several variables representing work experience:

Years Worked at the University – This variable (YRS) represents the number of years (including leaves) since the faculty member was hired at the university. Because the effect of experience on salary is typically nonlinear in earnings regressions, we follow standard practice in earnings studies and also include the squared value of

¹⁹ We do not know how many faculty members classified in one category would also be included in a second if this information were included in the data, so we are unable to assess if this affects our findings.

²⁰ Barbezat (2004) found that both current job tenure and total years of experience had positive and statistically significant effects on faculty wages, other things equal.

years worked at the university (YRS-SQ). We expect monthly salary to increase with years of work experience, other things equal.

Prior Years at Other Academic Institutions – Years spent as faculty members in academic institutions prior to joining the university (YRSOTH) is another relevant form of professional experience. We also include a squared value of years in other positions (YRSOTH-SQ) to allow for a nonlinear effect. Similar to the effect of YRS, we expect YRSOTH to have a positive effect on monthly salary, other things equal.²¹

Current Rank – We represent the faculty member's rank with two dichotomous variables, FULL and ASSOC. Each of these variables is equal to one if the faculty member has the indicated rank and equal to zero otherwise. Assistant Professors (ASSIST) form the reference group. We interpret the estimated coefficient of FULL (or ASSOC) as the incremental effect on monthly salary of being a full (or associate) professor compared to being an assistant professor. Other things equal, we hypothesize that both full and associate professors will have higher average monthly salary than assistant professors, so we expect to observe positive coefficients for FULL and ASSOC. Further, we hypothesize that full professors will earn relatively more than associate professors, other things equal, so we expect the coefficient for FULL to have a greater magnitude than that for ASSOC. While we pose the above hypotheses, we note that sufficiently strong salary compression and inversion may counteract them.

Tenure status is not explicitly included as an explanatory variable because at this university faculty members are tenured when promoted to associate professor (or hired at associate or full rank). Consequently, all associate and full professors are tenured and no assistant professors are tenured.

- (c) To test for the effect of **performance** in research and teaching (beyond the productivity effects of experience) on monthly salary, we include several variables as potential measures of performance. None are ideal measures, but we are limited to available information.

Merit Ratings – We use the faculty member's annual merit rating, based on research productivity, teaching performance, and service, as the basis for this measure.²² Because merit ratings vary from year to year, we use a five year average

²¹ While experience in non-academic positions may also have increased a faculty member's productivity, this information is not available.

²² Performance reviews are conducted at the department level. Although review weights vary across departments, research and teaching performance are generally more heavily weighted than service. Department ratings are converted to standardized scores reported to the relevant college and merit-based salary raises are determined at the college level.

(or fewer years for recent hires) of annual merit ratings to create a variable representing the college-level quintile (lowest 0–20th percentile, 21st–40th percentile, 41st–60th percentile, 61st–80th percentile, and highest 81st–100th percentile) of each faculty member's average merit rating. We then use the quintile score of each faculty member to create three dichotomous variables representing college merit quintiles. The first variable, QUINT-TOP, has a value of one if the faculty member's average merit rating is in the highest quintile of his or her college's average ratings and a value of zero if not. The second variable, QUINT-2ND, has a value of one if the faculty member's average merit rating is in the second highest quintile of his or her college's average ratings and a value of zero if not. The third variable, QUINT-MID, has a value of one if the faculty member's average merit rating is in the third (middle) quintile of his or her college's average ratings and a value of zero if not. The reference category for these three variables contains average merit ratings in the bottom two quintiles (QUINT-4TH and QUINT-BOT) of the faculty member's college merit distribution.

If a merit score in the highest college quintile leads to larger raises over time, we will observe that faculty members who have $\text{QUINT-TOP} = 1$ have higher average monthly salaries than those in the reference category, other things equal. Similarly, faculty members with QUINT-2ND or QUINT-MID are expected to earn more than those in the reference category, other things equal. Further, we expect that the estimated effect for those in the top quintile will be the largest, followed by the effect for those in the second quintile, and those in the middle quintile, other things equal.

Professorships – PROFSHIP is a dichotomous variable with a value of one if the faculty member's record indicates that she or he was chosen by the university for a professorship award. While these awards vary in their monetary rewards, we include the variable to represent higher productivity and hypothesize that the effect on monthly salary will be positive, other things equal.

Salary Adjustments – A faculty member may have received a salary adjustment from the university. We hypothesize that this represents higher research or teaching productivity. Two variables are considered to represent salary adjustments: SALADJ is a dichotomous variable with a value of one if the faculty member received a salary adjustment via the faculty member's college (and a value of zero if not). These adjustments include (but are not limited to) salary increases granted to match outside offers of employment. SEADJ is a dichotomous variable with a value of one if the faculty member received a salary adjustment from the university (and a value of zero if not). To the extent that these variables represent a faculty member's work productivity, we hypothesize that they will have positive effects on monthly salary, other things equal.

- (d) Universities compete with other employers in hiring faculty members. Because conditions in the labor markets for some disciplines lead to higher salaries than others, the salary that the university pays to recruit a faculty member depends importantly on the faculty member's **discipline**.

Discipline-Specific Salary – To control for the effect of discipline on monthly salary, we include a variable (CUPA) which is the average national monthly salary in the faculty member's discipline. We construct the CUPA variable from data available from the College and University Professional Association for Human Resources (2015). This organization conducts annual salary surveys of colleges and universities and provides the summary data to its member organizations. Average salaries for participating colleges and universities are available by Classification of Instructional Programs code and professorial rank. In our regression analyses, we control for discipline salary effects by including the department average monthly salary for academic year 2014–15. This average is calculated using the CUPA monthly salary values for each department weighted by the composition (number of faculty members at each rank) of each department at the university.

- (e) Finally, because there may be unobserved differences across departments that are not accounted for in the explanatory variables described above, we also consider specifications of the regression analyses in which we include a dummy variable representing the faculty member's **department**. This may improve the performance of the regression model, suggesting that department should be controlled for in our analyses. However, it may also be that discrimination occurs at the department level if there is a non-neutral gender climate or bias in department practices. If this occurs, controlling for department in the analyses may incorrectly eliminate effects of discrimination. For this reason, we report estimates from regressions with and without department controls.

Department – DEPT is defined as a set of dichotomous variables (values of zero or one) representing the 42 departments of the university represented in the study sample.

Although we consider additional explanatory variables for the regression model, the variables described above are those we include in the final model. While we want the regression model to have strong explanatory power, to obtain precise and statistically unbiased estimates we carefully examined the explanatory variables of the model to minimize multicollinearity and omitted variable bias to the extent possible. In addition, because we need to analyze the smaller subsets of faculty members in STEM disciplines, it is useful to estimate a parsimonious model. Consequently, we include all important explanatory variables but

exclude unneeded variables because the greater the number of explanatory variables in the model, the lower the power for performing regressions for the separate groups.

To assess the possibility of multicollinearity, we calculate variance inflation factors for the variables in the regression models.²³ We assess the extent of omitted variable bias by carefully performing specification checks: We start with a base model and run regressions of the model adding the variable under consideration (alone and in combination with other variables). This allows us to assess the statistical significance of the added variable as well as its effect on the estimated effects of variables in the basic model. This process leads to the exclusion from the final model variables representing the faculty member's age, starting salary, starting rank, and years in current rank. We do not include these variables because they are statistically insignificant when added to the variables in the base model and, in some instances, a source of multicollinearity. However, to check the sensitivity of our findings to the exclusion of these variables, we re-run our final analyses using a model in which all of the omitted variables are included.

We also consider multiple constructions of the variables used in the analyses. For example, for faculty merit, we consider direct inclusion of a faculty member's merit score, as well as a formulation in which we add a squared value to capture potential nonlinearity. Neither of these attempts are useful, so we revert to using the set of dichotomous indicator variables reported here. Similarly, we carefully considered the construction of the CUPA variable. For the variable used in the analyses reported here, we reweighted the national data to fit the composition of the university's departments.

In summary, we consider alternative specifications of the regression model to the final model reported here. Following standard practices in labor economics, the final model was chosen because it was the 'best' in terms of consistency with the underlying theoretical framework, coefficient significance and low variance inflation factor values, relatively high R^2 values despite being parsimonious, and little evidence of omitted variable bias.

We first report estimates from pooled analyses of female and White male faculty members (with and without department controls). After reporting the estimates for a models without STEM variables, we report findings for pooled models including STEM variables and including interactions between the FEMALE and STEM variables. Because conducting pooled analyses may mask effects of gender differences if some of the explanatory variables are themselves determined by the faculty member's gender, our next step was to estimate models for the pooled data

²³ VIFs, which quantify the severity of multicollinearity in linear regression, are described in Wooldridge (2020).

including interactions between FEMALE and all of the other explanatory variables. The presence of multiple statistically significant interactions led us to estimate separate regressions for female and White male faculty members.²⁴ This is consistent with the standard approach in labor economics of estimating gender-specific models because empirical evidence indicates that the labor market experiences of men and women typically differ.²⁵

Separate regressions for White male and female faculty members allows the estimates for the explanatory variables to vary across the two groups. In the first specification for each group, we ignore whether the faculty member is in a STEM department. In the second and third specifications, we include dummy variables indicating whether the faculty member works in a STEM-NSF department or in either a STEM-NSF or STEM-DHS department. Finally, we estimate two specifications including interaction variables between FEMALE and the STEM dummy variables.

In our final analyses, we use the earnings regressions for the separate groups as the basis for decomposition analyses of the gap in logged monthly salary between female and White male faculty members for all departments and for the two groups of STEM departments. Many studies have used Oaxaca-Blinder decomposition methods to assess salary inequities between employee groups.²⁶ A decomposition of a salary gap explains the difference in the mean (or quantile) salary between two groups by decomposing the gap into two components:

$$[\text{MORATE}_{WM} - \text{MORATE}_F] = \beta_{WM}(\bar{X}_{WM} - \bar{X}_F) + (\beta_{WM} - \beta_F)\bar{X}_F \quad (2)$$

- (a) The first term on the right hand side is the portion of the monthly salary gap attributable to differences in productive characteristics (faculty experience, productivity, and discipline average salary) of the groups' members, represented by the average values of the independent variables in X . This "explained" component is not a source of potential salary discrimination.
- (b) The second term on the right hand side is the portion of the monthly salary gap that is not explained by differences in productive characteristics. The value of this component is based on the difference between the regression coefficient

²⁴ Tables of coefficients for the fully interacted models are available from the authors upon request.

²⁵ Authoritative sources in the labor economics literature describing gender-specific earnings analyses range from the surveys of Pencavel (1986) and Killingsworth and Heckman (1986) to more recent studies such as Bargain and Peichl (2016).

²⁶ Oaxaca (1973) and Blinder (1973) proposed similar methods the same year. Examples of applications include Oaxaca and Ransom (2003), Geisler and Oaxaca (2005), Shatnawi, Oaxaca, and Ransom (2014) and Blau and Kahn (2017).

estimates of White male faculty members and female faculty members, that is, on the differential returns to characteristics. If this “unexplained” component is statistically significant, it is consistent with salary inequities that may be caused by salary discrimination.

While finding a statistically significant estimate of the unexplained component is consistent with potential discrimination, this is a necessary condition rather than a sufficient condition. We cannot conclude that discrimination exists because it is possible that unexplained differences are due to unobserved productive characteristics. For this reason, statistically significant unexplained components should be treated as indicators that salary inequities are observed and further investigation is needed.

We conduct decomposition analyses for both the standard earnings regressions (at the mean) and quantile earnings regressions (at the 10th, 25th, 50th, 75th, and 90th quantiles) for the combined data set of all faculty members and for the two subsets of STEM departments (STEM-DHS and STEM-NSF). For the decomposition analysis at the mean, we also report a detailed decomposition in which the individual contributions of grouped predictors are reported.²⁷

4 Findings

Tables 4 through 7 report estimates of the effects of the various explanatory factors on the logged monthly salary of faculty members for the pooled sample of all departments as well as for the two subsets of STEM departments. The bottom rows of each table report the number of observations (N), the R^2 value for the regression reported in that column, the calculated F-statistic, and the probability of exceeding the calculated F-statistic value for the regression reported in that column.

The p -values for exceeding the calculated F-statistic were less than 0.05 for all of the models reported in Tables 4 and 6, indicating that the coefficient estimates for the models jointly differed from zero. Adding department control variables to the models reported in Tables 5 and 7 leads to higher R^2 values.²⁸ The higher R^2 values

²⁷ The mean decomposition is performed using the *oaxaca* command in Stata and the quantile decompositions are performed using the *rqdeco* command in Stata. See Jann (2008) and Melly (2005) for details of these two commands. Although detailed decomposition is not available for the quantile decompositions, we report estimates from quantile regressions of the pooled sample in Appendix Table A-2 to give the reader information describing the effects of the explanatory variables. Tables reporting quantile regression coefficient estimates for the STEM subsamples are available from the authors.

²⁸ We also run regressions with college control variables, but report the estimates from the models with department variables because these models have greater explanatory power. When

Table 4: Effects of explanatory variables on logged monthly salary.^a

Independent variables	All faculty members				
	(a) coefficient	(b) coefficient	(c) coefficient	(d) coefficient	(e) coefficient
<i>STEM indicators</i>					
STEM-DHS				−0.027	−0.026
FEM × STEM-DHS					−0.010
STEM-NSF		−0.004	0.010	0.012	0.027
FEM × STEM-NSF			−0.027		−0.027
<i>Demographic characteristics</i>					
FEMALE	0.014	0.014	0.026	0.012	0.026
ASIAN	0.042	0.043	0.042	0.043	0.044 ^c
BLACK	0.065	0.065	0.065	0.065	0.067
HISPANIC	0.010	0.010	0.008	0.010	0.008
<i>Discipline</i>					
CUPA	0.079 ^b	0.079 ^b	0.079 ^b	0.079 ^b	0.079 ^b
<i>Work characteristics</i>					
FULL	0.300 ^b	0.300 ^b	0.301 ^b	0.299 ^b	0.301 ^b
ASSOC	0.131 ^b	0.131 ^b	0.130 ^b	0.130 ^b	0.130 ^b
YRS	−0.014 ^b	−0.014 ^b	−0.014 ^b	−0.014 ^b	−0.014 ^b
YRS-SQ	0.0004 ^b	0.0004 ^b	0.0004 ^b	0.0004 ^b	0.0004 ^b
YRSOTH	0.002	0.002	0.002	0.001	0.001
YRSOTH-SQ	0.0004 ^b	0.0004 ^b	0.0004 ^b	0.0004 ^b	0.0004 ^b
<i>Performance measures</i>					
QUINT-TOP	0.026	0.026	0.027	0.023	0.025
QUINT-2ND	0.024	0.024	0.023	0.021	0.019
QUINT-MID	0.023	0.023	0.024	0.022	0.022
PROFSHIP	0.085 ^b	0.086 ^b	0.084 ^b	0.083 ^b	0.080 ^b
SALADJ	0.039	0.040	0.040	0.039	0.039
SEADJ	0.043 ^c	0.045 ^b	0.045 ^b	0.048 ^b	0.049 ^b
<i>Department controls included</i>	No	No	No	No	No
<i>N</i>	503				
<i>R</i> ²	0.7327	0.7327	0.7333	0.7337	0.7345
<i>F</i>	43.74	58.18	55.77	59.49	71.31
<i>Prob > F</i>	0.0000	0.0000	0.0000	0.0000	0.0000

^aDependent variable is ln(monthly salary). All specifications include an intercept and standard errors clustered for 42 departments. ^b*P*-value ≤ 0.05. ^c*P*-value > 0.05 and ≤ 0.10.

Table 5: Effects of explanatory variables on logged monthly salary with department controls.^a

Independent variables	All faculty members				
	(a) coefficient	(b) coefficient	(c) coefficient	(d) coefficient	(e) coefficient
<i>STEM indicators</i>					
STEM-DHS				−0.087 ^b	0.080 ^b
FEM × STEM-DHS					−0.019
STEM-NSF		−0.335 ^b	−0.285 ^b	−0.423 ^b	−0.363 ^b
FEM × STEM-NSF			−0.040 ^b		−0.029
<i>Demographic characteristics</i>					
FEMALE	0.012	0.012	0.029 ^b	0.012	0.029 ^b
ASIAN	−0.019	−0.019	−0.017	−0.019	−0.017
BLACK	−0.010	−0.010	−0.009	−0.010	−0.009
HISPANIC	−0.038	−0.038	−0.041	−0.038	−0.040
<i>Discipline</i>					
CUPA	0.021 ^b	0.021 ^b	0.026 ^b	0.021 ^b	0.025 ^b
<i>Work characteristics</i>					
FULL	0.309 ^b	0.309 ^b	0.310 ^b	0.309 ^b	0.311 ^b
ASSOC	0.129 ^b	0.129 ^b	0.128 ^b	0.129 ^b	0.129 ^b
YRS	−0.011 ^b	−0.011 ^b	−0.011 ^b	−0.011 ^b	−0.011 ^b
YRS-SQ	0.0003 ^b	0.0003 ^b	0.0003 ^b	0.0003 ^b	0.0003 ^b
YRSOTH	0.0006	0.0006	0.001	0.0006	0.001
YRSOTH-SQ	0.0004 ^b	0.0004 ^b	0.0004 ^b	0.0004 ^b	0.0004 ^b
<i>Performance measures</i>					
QUINT-TOP	0.030 ^b	0.030 ^b	0.031 ^b	0.030 ^b	0.030 ^b
QUINT-2ND	0.017	0.017	0.015	0.017	0.015
QUINT-MID	0.020 ^c	0.020 ^c	0.020 ^c	0.020 ^c	0.020 ^c
PROFSHIP	0.091 ^b	0.091 ^b	0.089 ^b	0.091 ^b	0.089 ^b
SALADJ	0.055 ^b	0.055 ^b	0.055 ^b	0.055 ^b	0.054 ^b
SEADJ	0.044 ^b	0.044 ^b	0.043 ^b	0.044 ^b	0.043 ^b
<i>Department controls included</i>	Yes	Yes	Yes	Yes	Yes
<i>N</i>	503				
<i>R</i> ²	0.9094	0.9094	0.9104	0.9094	0.9105
<i>F</i>					
<i>Prob > F</i>					

^aDependent variable is ln(monthly salary). All specifications include an intercept and standard errors clustered for 42 departments. ^b*P*-value ≤ 0.05. ^c*P*-value > 0.05 and ≤ 0.10.

Table 6: Effects of explanatory variables on logged monthly salary by gender.^a

Independent variables	White male faculty members			Female faculty members		
	(a) coefficient	(b) coefficient	(c) coefficient	(d) coefficient	(e) coefficient	(f) coefficient
<i>STEM indicators</i>						
STEM-DHS			−0.030			−0.035
STEM-NSF		0.005	0.024		−0.012	0.005
<i>Demographic characteristics</i>						
ASIAN				0.038	0.038	0.041
BLACK				0.071	0.071	0.074 ^c
HISPANIC				0.016	0.014	0.015
<i>Discipline</i>						
CUPA	0.080 ^b	0.079 ^b	0.080 ^b	0.080 ^b	0.080 ^b	0.080 ^b
<i>Work characteristics</i>						
FULL	0.287 ^b	0.288 ^b	0.285 ^b	0.305 ^b	0.303 ^b	0.306 ^b
ASSOC	0.110 ^b	0.110 ^b	0.107 ^b	0.144 ^b	0.144 ^b	0.147 ^b
YRS	−0.016 ^b	−0.016 ^b	−0.017 ^b	−0.012 ^c	−0.012 ^c	−0.013 ^c
YRS-SQ	0.0004 ^b	0.0004 ^b	0.0005 ^b	0.0003	0.0003	0.0004 ^c
YRSOTH	0.003	0.003	0.003	0.010	0.010	0.009
YRSOTH-SQ	0.0003 ^c	0.0003 ^c	0.0003	−0.0006	−0.0006	−0.0006
<i>Performance measures</i>						
QUINT-TOP	0.010	0.010	0.006	0.037	0.038	0.036
QUINT-2ND	0.008	0.007	0.001	0.039	0.039	0.037
QUINT-MID	0.0003	0.0001	−0.002	0.054	0.055	0.054
PROFSHIP	0.093 ^b	0.092 ^b	0.088 ^b	0.070 ^c	0.072 ^b	0.065 ^c
SALADJ	0.103	0.101	0.102	−0.009	−0.006	−0.009
SEADJ	0.086 ^b	0.084 ^b	0.087 ^b	−0.014	−0.009	−0.0003
<i>Department controls included</i>	No	No	No	No	No	No
<i>N</i>		255			248	
<i>R</i> ²	0.7674	0.7679	0.7688	0.6985	0.6989	0.7002
<i>F</i>	42.04	51.30	48.80	52.81	68.07	54.11
Prob > <i>F</i>	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

^aDependent variable is ln(monthly salary). All specifications include an intercept and standard errors clustered by department. ^b*P*-value ≤ 0.05. ^c*P*-value > 0.05 and ≤ 0.10.

Table 7: Effects of explanatory variables on logged monthly salary by gender with department controls.^a

Independent variables	White male faculty members			Female faculty members		
	(a) coefficient	(b) coefficient	(c) coefficient	(d) coefficient	(e) coefficient	(f) coefficient
<i>STEM indicators</i>						
STEM-DHS			−0.028			0.419 ^b
STEM-NSF		−0.118 ^b	−0.090		−1.347 ^b	−1.766 ^b
<i>Demographic characteristics</i>						
ASIAN				−0.008	−0.008	−0.008
BLACK				0.001	0.001	0.001
HISPANIC				−0.050	−0.050	−0.050
<i>Discipline</i>						
CUPA	0.046 ^b	0.046 ^b	0.046 ^b	−0.116 ^b	−0.116 ^b	−0.116 ^b
<i>Work characteristics</i>						
FULL	0.309 ^b	0.309 ^b	0.309 ^b	0.317 ^b	0.317 ^b	0.317 ^b
ASSOC	0.124 ^b	0.124 ^b	0.124 ^b	0.133 ^b	0.133 ^b	0.133 ^b
YRS	−0.011 ^b	−0.011 ^b	−0.011 ^b	−0.011 ^b	−0.011 ^c	−0.011 ^c
YRS-SQ	0.0003 ^b	0.0003 ^b	0.0003 ^b	0.0004 ^c	0.0004 ^c	0.0004 ^c
YRSOTH	−0.0001	−0.0001	−0.0001	0.006	0.006	0.006
YRSOTH-SQ	0.0004 ^c	0.0004 ^c	0.0004 ^c	−0.00005	−0.00005	−0.00005
<i>Performance measures</i>						
QUINT-TOP	0.035 ^c	0.035 ^c	0.035 ^c	0.025	0.025	0.025
QUINT-2ND	0.011	0.011	0.011	0.019	0.019	0.019
QUINT-MID	0.011	0.011	0.011	0.041 ^b	0.041 ^b	0.041 ^b
PROFSHIP	0.101 ^b	0.101 ^b	0.101 ^b	0.080 ^b	0.080 ^b	0.080 ^b
SALADJ	0.092 ^c	0.092 ^c	0.092 ^c	0.031	0.031	0.031
SEADJ	0.064 ^b	0.064 ^b	0.064 ^b	0.020	0.020	0.020
<i>Department controls included</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>		255			248	
<i>R</i> ²	0.8987	0.8987	0.8987	0.9350	0.9350	0.9350
<i>F</i>						
<i>Prob > F</i>						

^aDependent variable is $\ln(\text{monthly salary})$. All specifications include an intercept and standard errors clustered by department. ^b $P\text{-value} \leq 0.05$. ^c $P\text{-value} > 0.05$ and ≤ 0.10 .

may occur because productive characteristics of the department not controlled for by the other explanatory variables in the model are represented by the department variables. However, as mentioned in the previous section, because discrimination may occur at the department level it is possible that controlling for department in the analyses leads us to incorrectly eliminate effects of discrimination. For this reason, we report estimates from regressions with and without department control variables in Tables 4 through 7. Although the F-statistics reported in Tables 4 and 6 indicate that the earnings models are jointly statistically significant, including the large number of department dummy variables in the models in Tables 5 and 7 precludes estimation of F-statistics for these models.²⁹

For the regression model including all non-squared variables in column (a) of Table 4, the highest VIF value is 3.56 and the average VIF value is 1.44. When the squared variables (YRS-SQ and YRSOTH-SQ) are added to the model, the highly correlated YRS and YRS-SQ variables have high VIF values (20 and 16, respectively), but the VIF values for the remaining variables are all under 5. Adding the STEM-DHS and STEM-NSF dummy variables has little effect on the pattern of multicollinearity: Except for the high values of the squared variables, the maximum VIF value is 4.86 and the average is 3.72 when the STEM-DHS variable is added (4.87 and 3.67 when the STEM-NSF variable is added). Thus, multicollinearity is low overall. Because tests indicate the presence of heteroscedasticity and the importance of department controls, robust standard errors clustered by department are estimated in the models reported in Tables 4 through 7.³⁰

In Tables 4 and 5, we first add the STEM-NSF dummy variable to the base model to assess whether being in an NSF STEM department affects logged monthly salary. In the next specification (column (c)), we add an interaction between FEMALE and STEM-NSF to investigate whether the effect of working in an NSF STEM department has different effects for female and White male faculty members. In column (d) we add the STEM_DHS dummy variable to the specification in column (b). Because the fields in the DHS list are a subset of those in the NSF list, this permits us to observe whether the effect of working in the more restrictive DHS group of departments has a different effect than working in NSF departments. Finally, in column (e) of Tables 4

department variables are included in the regression, the college or discipline group variables are not statistically significant.

29 With many dummy variables added to the model, the covariance matrix of parameter estimates is not full rank, which precludes estimation of the F-statistic when the standard errors are clustered by department. We do not test any hypotheses that require this statistic and its absence does not affect the coefficient estimates and standard errors used to assess the findings.

30 Robust standard errors clustered by department are not available for the quantile decomposition analyses. Instead, these estimates are bootstrapped (100 repetitions). See Fortin, Lemieux, and Firpo (2011) for a discussion of quantile regression estimation.

and 5 we add interactions between FEMALE and both STEM variables to investigate whether the effect of working in either group of departments has different effects for female and White male faculty members.

The estimates in columns (a) through (e) of Table 4 indicate that working in a STEM department does not have a significant effect on salary. Being female does not have a statistically significant effect and race and Hispanicity do not significantly affect monthly salary for female faculty members.³¹ However, several of the explanatory variables are statistically significant and have the expected signs (average national salary in the discipline, professorial rank, years of experience, professorship awards, and salary adjustments). When rank, disciplinary salary, and productivity are controlled for, the effect of years of experience at the university is negative. Taking into account the positive effect of squared years of experience at the university, the net negative effect diminishes over time so that the minimum effect is reached at 17.5 years.

The effects of working in STEM departments reported in Table 5 differ in both magnitude and statistical significance from those of Table 4. Working in a STEM-NSF department has a negative on salary. The inclusion of an interactive effect with FEMALE in column (c) reveals that the effect among White male faculty members is approximately seven times greater (more negative) than that for female faculty members. These negative effects persist when the dummy variable for STEM-DHS is added in columns (d), except we observe that the effect of working in a STEM-DHS department has a positive effect for White male faculty members when the interactions with FEMALE are added in column (e). The interaction of FEMALE with STEM-DHS is negative, but smaller than the main effect and not statistically significant, so we conclude that working in a STEM-DHS department has a positive impact on the salaries of both White male and female faculty members, but working in STEM-NSF departments that are not STEM-DHS has a negative effect on salaries (compared to working in a nonSTEM department). While we find that controlling for the faculty member's department has an important impact on the estimated effect of STEM on logged monthly salary, we are unable to attribute these differences to productive effects or potential discrimination (or both). Finally, we note that many of the estimates of the control variables in Table 5, when department control variables were added, mirror those observed in Table 4.

Tables 6 and 7 report estimates for the gender-specific models of logged monthly salary. Similar to the findings from Table 4, the estimated effects of the STEM indicator variables reported in Table 6 do not differ significantly from zero. However, when the department dummy variables are added to the model reported

³¹ Recall that the values of Asian, Black, and Hispanic are zero for White male faculty members, so the reported effects are estimates for female faculty members only.

in Table 7, the estimated effects of the STEM-NSF variable is negative and statistically significant. When the STEM-DHS variable is added in column (c), the effects for White male faculty members of working in either type of STEM department are insignificant. In contrast, when the STEM-DHS variable is added in column (f), the effect of working in a STEM-NSF department remains negative and significant for female faculty members but the effect of working in a STEM-DHS department is positive and significant. The magnitudes of the STEM coefficients reported in Table 7 differ from those reported in Table 5: The estimates in Table 5, which were from a model in which only the STEM effects were allowed to vary with gender, indicated a larger negative effect for White male faculty members and a smaller negative effect for female faculty members. However, the estimates in Table 7, in which the effects of all the explanatory variables are allowed to vary by gender, indicate that the effects on logged monthly salary of STEM-NSF are larger among female faculty members. Further, the positive effect of STEM-DHS for female faculty members appears to be the driving force behind the positive estimate for working in a STEM-DHS department observed in Table 5 (despite the insignificant interaction with FEMALE). The differences in the estimated effects of working in STEM departments between Tables 5 and 7 suggest that there are many ways in which gender differences indirectly impact salary and the regression models in Table 7 allow these gender-specific variations in the explanatory variables to be expressed. If these differences were not important, we would observe similar findings regarding STEM effects in the two tables.

What differences do we observe in the effects of other explanatory variables? Because there are no minority faculty members in the reference group of White male faculty members, there are no estimates for these characteristics. Although the race and Hispanicity variables are included for the female subsample, the coefficients are not statistically significant. Although several of the coefficients for other explanatory variables in Tables 6 and 7 have effects similar to those in Tables 4 and 5, the magnitudes differ between the two groups: Larger effects are observed for women for discipline and professorial rank, while White males have larger effects for top merit rankings, professorship awards, and salary adjustments.

The estimates from the decomposition analyses are reported in Table 8 for regressions at the mean and in Table 9 for regressions at the 10th, 25th, 50th (median), 75th, and 90th quantiles of the logged salary distribution. In both tables, decompositions into “explained” and “unexplained” components between White male and female faculty members (per Equation (2)) are reported for the pooled sample of all faculty members and the subsets of faculty members in STEM-DHS and STEM-NSF departments. The estimates reported in Table 8 are for models without department dummy variables, but with standard errors clustered by department. Excluding department dummy variables permits rough comparability with

Table 8: Oaxaca decompositions of mean monthly salary by gender and STEM field.^a

	Estimated components at mean		
	All faculty N = 503	STEM-DHS faculty N = 136	STEM-NSF faculty N = 224
Difference predicted by model ^b	+746.91 ^c (9.32 %)	+964.58 ^c (11.60 %)	+864.14 ^c (10.45 %)
% explained	+12.27 ^c	+12.06 ^c	+9.74 ^c
% discipline-specific salary	+5.01 ^c	+4.02	+2.95 ^d
% work characteristics	+6.24 ^c	+8.14 ^c	+6.89 ^c
% performance measures	+0.06	−0.38	−0.28
% unexplained	−2.63	−0.004	+0.65
% discipline-specific salary	−0.28	+7.20	+6.38
% work characteristics	−5.52	−0.83	−3.67
% performance measures	−0.96	+1.62	+4.70 ^c

^aStandard errors are clustered by department and robust. The White male category includes all non-Asian, non-Black, and non-Hispanic male faculty members (predominantly individuals identified as White). ^bDifference in predicted (unlogged) monthly salary (White male minus female). Percentages reported in parentheses are the predicted gaps as a percentage of female average monthly salary. Detailed components for the regression intercept and the demographic variables are omitted. ^cDenotes p -value ≤ 0.05 . ^dDenotes $0.05 < p$ -value ≤ 0.10 .

the findings for the quantile decompositions in Table 9 because we are unable to estimate quantile models including department dummy variables. The standard errors for the quantile decompositions are bootstrapped (100 repetitions).³²

All of the decomposition analyses in Tables 8 and 9 are estimated using logged monthly salary as the dependent variable. This ensures the comparability of the hypothesis tests of the statistical significance of the unexplained component in the two tables. However, for convenience the estimated components reported in Table 8 are transformed (postestimation) to represent the effect on *unlogged* monthly salary.³³ The first row of Table 8 reports the differences in average monthly salaries between White male and female faculty members predicted by the models. The positive differences reported indicate that the models predict the monthly salaries of female faculty members to be significantly lower than those of their White male colleagues. The differences are greater for faculty members in STEM departments,

³² See Fortin, Lemieux, and Firpo (2011) for a discussion of estimation of quantile regression models (including bootstrapping standard errors).

³³ This option is available for the *oaxaca* command in Stata.

Table 9: Quantile Oaxaca decompositions of logged monthly salary by gender and STEM field.^a

	Estimated components at quantiles				
	10th	25th	Median	75th	90th
All (<i>N</i> = 503)					
% difference predicted by model ^b	+5.92 ^c	+6.31 ^c	+9.98 ^c	+11.86 ^c	+9.08 ^d
% explained	+8.43 ^c	+10.67 ^c	+13.28 ^c	+13.39 ^c	+11.51 ^c
% unexplained	−2.51	−4.35 ^c	−3.30	−1.53	−2.44
STEM-DHS only (<i>N</i> = 136)					
% difference predicted by model ^b	+5.09 ^d	+6.40 ^c	+8.97 ^c	+14.81 ^c	+21.06 ^d
% explained	+9.07 ^c	+9.20 ^c	+11.73 ^c	+8.27 ^c	+12.99 ^c
% unexplained	−3.98 ^c	−2.80	−2.76	+6.54 ^c	+8.07 ^c
STEM-NSF only (<i>N</i> = 224)					
% difference predicted by model ^b	+3.59 ^c	+6.05 ^c	+12.00 ^c	+13.44 ^c	+12.76 ^c
% explained	+5.84 ^c	+8.20 ^c	+10.35 ^c	+8.18 ^c	+9.47 ^c
% unexplained	−2.25	−2.16	−1.65	+5.26 ^c	+3.30

^aStandard errors are bootstrapped with reps = 100. The White male category includes non-Asian, non-Black, and non-Hispanic male faculty members. ^bDifference in predicted logged monthly salary (White male minus female). ^c*P*-value ≤ 0.05. ^d*P*-value > 0.05 and ≤ 0.10.

with the highest difference observed among faculty members working in STEM-DHS departments. The amount of the predicted gap as a percentage of female monthly salary is reported in parentheses. Again, the percentage gap is highest among faculty members in the STEM-DHS subsample.

The purpose of the decomposition analyses is to determine whether the predicted differences are due to observed characteristics of faculty members as represented by variables in the regression models (the “explained” component) or whether a significant portion is not explained by the variables in the regressions (the “unexplained” component) and may be attributed to unobserved factors or possible gender discrimination. The estimates in the second row are the percentages of the predicted salary gap that can be attributed to the explanatory variables of the models. The estimates vary from 9.75 % among STEM-NSF faculty members to 12.27 % among all faculty members. The difference in salaries due to the explained components are statistically significant for all of the decompositions. This indicates that differences in the values of observed characteristics for female and White male faculty members contribute significantly in explaining the observed gender wage gap.

To investigate which characteristics may be important in the explained component, we report estimates for three groups of variables (discipline-specific salary, work characteristics, and performance measures).³⁴ The estimates for these variable groups indicate that the explained gender differences are due primarily to the faculty members' discipline-specific salary and work characteristics (professorial rank and years of work experience). The estimated effects indicate that work characteristics have larger impacts than discipline-specific salary, especially among faculty members in STEM departments. Recall that the estimates in Table 7 reveal that these two types of variables have relatively important significant effects on salary among women. While Table 7 reports that performance measures (top merit rankings, professorship awards, and salary adjustments) are more important for White male faculty members, the estimates in Table 8 indicate that these measures of productivity do not contribute significantly to the percentage differences in monthly salary between the two groups.

The last set of estimates are the differences that are not attributable to observed variable values of female and White male faculty members. If statistically significant, these unexplained effects indicate inequities consistent with potential salary discrimination. In Table 8, unexplained differences between female and White male faculty members are not statistically significant. None of the estimates for “% unexplained” or the grouped variables has a statistically significant contribution to the salary gap. The sole exception is that differences in performance measures have a statistically significant positive contribution to unexplained differences between female and White male faculty members. However, the overall “% unexplained” between the two groups is not statistically significant.

Because the unexplained differences between female and White male faculty members reported for the decompositions in Table 8 are not statistically significant, we find no evidence of gender inequities in monthly salaries at the mean. We now estimate explained and unexplained differences at the 10th, 25th, 50th (median), 75th, and 90th quantiles of the distribution of logged salary. Quantile decompositions in Table 9 are reported between White male and female faculty members for the pooled sample of all faculty members, the subset of faculty members in STEM-DHS departments, and the subset of faculty members in STEM-NSF departments. The predicted differences reported in the first row of each section are differences

³⁴ See the groups of variables in Table 2. Demographic characteristics are included in the regression models for female faculty members in Table 8, but component estimates are omitted because the values for these variables are uniformly zero for the White male subsample. The component estimate for the regression intercept is also omitted.

in logged monthly salary (White male minus female). These predicted differences are then decomposed into the explained and unexplained components.³⁵

The positive estimates in the first row of each section of Table 9 indicate that the quantile regression models predict greater logged monthly salaries for White male faculty members than for female faculty members.³⁶ The estimates in the second row represent the percent gap that are explained by differences in White male and female faculty members' values for characteristics represented by variables in the models. These component estimates are all statistically significant, which indicates that differences in the characteristics of White male and female faculty members contribute significantly to explaining the gender salary gap. This is similar to the explained effects we observe in Table 8.

The difference in returns is represented by the unexplained component. If statistically significant, these effects indicate inequities consistent with potential salary discrimination. In Table 9, we observe five instances in which the estimates of the unexplained components are statistically significant. The first is the negative estimate for the 25th quantile of the pooled sample. The second occurs when we limit the sample to faculty members in STEM departments: We observe a statistically significant negative unexplained component at the 10th quantile. These significant estimates indicate that unexplained factors reduce the gain women would enjoy if their characteristics were rewarded at the same rate as they are for White males. These estimates are consistent with potential salary discrimination against female faculty members.

At the median we observe no statistically significant unexplained effects. This is consistent with the findings for the mean reported in Table 8, where we reported no statistically significant unexplained differences between female and White male faculty members.

However, among the estimates for the 75th and 90th quantiles, we observe three instances of statistically significant positive estimates of the unexplained component: These occur at the 75th and 90th quantiles of the distribution for female faculty members in STEM-DHS departments and at the 75th quantile for the larger subsample of faculty members in STEM-NSF departments. The positive estimates of the unexplained components imply that female faculty members in these departments earn greater logged monthly salaries than their White male counterparts for reasons not captured by the characteristics of the two groups by variables in the models. The explanation may be that these women possess characteristics that are

³⁵ The values for explained and unexplained components of the gap sum to the predicted difference in the first row of each section.

³⁶ Table A-2 reports quantile regression estimates for the pooled sample ($N = 503$).

not observed in the data but are recognized and rewarded by the university. As suggested by Leslie, Manchester, and Dahm (2017), it may be that high-potential women in highly visible STEM fields are perceived as possessing greater diversity value to their organizations than their equally high-potential White male colleagues, leading to higher pay, other things equal.

To summarize, among faculty members working in the same institution, we observe instances of gender inequities in favor of White male faculty members at low quantiles of the logged salary distribution and gender inequities in favor of female faculty members at high quantiles of the logged salary distribution. To assess the reliability of these findings, we perform decomposition analyses on two further versions of the models. In the first, we replace the merit quintile variables based on the college quintiles with merit quintile variables based on department quintiles.³⁷ We find that replacing the college quintiles with department quintiles only very slightly changes the values of the estimates in the tables and does not alter the pattern and statistical significance of the findings. In our second check on the reliability of the findings, we add the variables that were excluded from the parsimonious model (age, starting rank, starting salary, and years in current rank) and perform the decomposition analyses. We find that adding these variables to the model slightly alters the estimated effects but does not alter the pattern and statistical significance of the findings. Thus, our findings appear to be stable with respect to both of these issues.

5 Conclusions

Prior studies of the gender wage gap in academia report the presence of significant gender wage gaps even when controlling for observed characteristics. Fewer studies examine the presence of gender wage gaps in STEM disciplines and the findings vary: The findings of one study of public universities indicate that in the life sciences and physical sciences, the mean gender wage gap can be completely explained by observed characteristics (Li and Koedel 2017). However, another study of engineering and computer science departments finds that mean gender wage differences remain even after accounting for observed characteristics (Michelsmore and Sassler 2016).

³⁷ Ideally, with information describing how each college calculated merit points for determining merit raises, we would have used the appropriate merit quintile calculation for a faculty member depending upon whether his or her college actually used a college- or department-level process for determining merit raises. Without this information our strategy was to perform the decomposition analyses using the department-based scores so that the findings could be compared to those using the college-based scores.

We report findings from a study of the academic gender gap in monthly faculty salaries in STEM and nonSTEM disciplines at a public research university. While the findings of this research pertain to a single university, it is representative of many public universities of medium to large size. The advantage of using data for a single university is that the data are sufficiently rich to conduct quantitative analyses including several characteristics of the faculty members. We estimate earnings regressions for female and White male faculty members for the university as a whole as well as for those working in STEM departments. Controlling for productive characteristics and field salary differentials, we perform mean and quantile decomposition analyses of the female to White male salary gaps to assess potential salary inequities in STEM departments.

Our mean regressions for pooled (female and White male) faculty members indicate no statistically significant differences for working in STEM fields. However, the estimates in our gender-specific regressions indicate that working in a STEM department has a negative impact for both female and White male faculty members, with a larger impact among female faculty members, other things equal. We also find a positive effect of working in a selective group of STEM departments (defined by the Department of Homeland Security). To assess the magnitude of these salary differences in STEM and nonSTEM departments, we report findings from decomposition analyses at the mean and several quantiles of the salary distribution. Although observed characteristics are important in explaining salary differences for both female and White male faculty members, we find no statistically significant unexplained gender differences for our mean and median decomposition analyses. However, the findings from our quantile analyses reveal statistically significant unexplained gender differences in our pooled sample and in the STEM department subsamples. At low quantiles we observe statistically significant gender salary gaps indicating that women earning low salaries are not paid as well as their White male peers, other things equal. Gender salary gaps such as these, favoring White male faculty members, are typically observed in studies of academia. Our analyses of high quantiles of the salary distribution, however, indicate the presence of a gender salary gap favoring female faculty members: Highly paid female faculty members working in STEM departments are better paid than their White male peers, other things equal. This finding is consistent with the evidence reported by Leslie, Manchester, and Dahm (2017) in which the authors report that high-potential women were perceived as higher in diversity value to their organizations than were high-potential men, leading to higher pay.

Although we use rich data and appropriate methods and find significant effects of gender on faculty salaries, we do not have perfect measures of productivity. It is possible that relevant factors are omitted. For this reason, it is not possible to conclude that the estimated effects of unexplained factors are necessarily due to

gender discrimination. Further, because our goal was to assess whether the salary process at the university involved a gender bias, we estimated single equation models of faculty salaries in which the explanatory variables were assumed exogenous. Because we treated factors that influence academic salary, such as discipline, rank, and professorship awards, as exogenous, our estimates of salary gender differences are likely to underestimate the true gender effect.

What actions can universities or other institutions take to counteract biased academic climates and promote productive and diverse faculty, especially in STEM fields? Many factors appear to contribute to gender salary gaps and myriad interventions have been suggested to improve the situation. Studies note that the traditional academic climate in all departments, but perhaps especially in STEM departments, favors White male faculty members. This climate may lead to fewer women being hired and promoted, cause lower retention of female faculty members, and make female faculty members more reluctant to negotiate for salary increases.³⁸ As an immediate response to the existence of observed salary gaps, a university may identify faculty members for whom predicted salary is far below actual salary and grant compensating salary increments. However, more long term responses are needed to ameliorate the problematic factors causing inequities across gender and race: Diversity training promotes awareness of implicit bias and promotes healthier hiring and promotion practices. Additional efforts often include mentoring and networking to support younger faculty members for whom the climate is unfavorable. These are useful and raise awareness of implicit bias, but more specific policies are needed to encourage departments to recognize and avoid practices that harm female faculty members. Specifically, practices that disadvantage female faculty members, such as requests for extra teaching, advising, and administrative tasks that are not rewarded in promotion and merit considerations, need to be identified and rewarded in department policies for tenure, promotion, and merit increments for all faculty members. Indeed, these policies need to be transparent and the standards for tenure, promotion, and merit increments need to be objective. All of these contribute to improving the academic climate in all departments and especially in STEM disciplines.³⁹

Our findings suggest the critical importance of examining more than the mean or median gender wage gap when assessing gender salary inequities. Even when mean or median decomposition analyses suggest the absence of gender wage gaps,

³⁸ Gender bias that may create unfavorable academic climate and its impact on salary negotiations are discussed in depth in Casad et al. (2020), Bowles, Babcock, and Lai (2007), and Artz, Goodall, and Oswald (2018).

³⁹ See Casad et al. (2020) and Gamage, Sevilla, and Smith (2020).

there may be statistically significant quantile effects indicating potential gender inequities in salary. As demonstrated in the analyses reported here, the presence of highly paid female faculty members apparently may offset the presence of underpaid female faculty members at the lower end of the earnings distribution so that no average gender difference is observed. If an institution's goal is to ensure gender salary equity for all faculty members, studies need to consider equity among female and white male faculty members of equivalent productivity at *all* pay levels.

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