Gender Wage Gaps in STEM Disciplines

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This study examines the academic gender wage gap in STEM and non-STEM disciplines at a public research university. We estimate earnings regressions for female and 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 male-female wage gaps to estimate potential wage discrimination in STEM departments. Our findings indicate that the gender gap in STEM departments is significantly larger than that observed over all departments. Our quantile analyses indicate that there are positive effects for women in top quantiles, but we find there is potential gender discrimination at the low end of the salary distribution among faculty members working in STEM departments. This suggests that highly paid female academics working in STEM departments are well rewarded by the competitive academic market but female academics are apparently not paid on par with their White male peers at the lower end of the salary distribution.

1. Introduction

There have been numerous studies of the gender wage gap in the United States and other countries.[1] The goal of these studies is to ascertain what portion of the observed gender wage gap may be attributable to differences in individual characteristics versus potential discrimination. Researchers have also reported empirical evidence of gender wage gaps in academia. While the goal of this research is similar to those of the general literature, these studies vary widely in their methods and focus. Many are case studies of specific universities or small groups of institutions.[2] These benefit from rich data sources although the sample may not be representative of faculty members working at other institutions. Other studies avoid this limitation by relying on national survey data, but these often suffer from a lack of useful measures of academic productivity.[3]

Another strand of the literature has focused on gender gaps in particular disciplines. Although many disciplines have been studied, in recent years there has been increased interest in science, technology, engineering, and mathematics (STEM) fields.[4] The findings of one study of 40 public universities indicate that in the life sciences and physical sciences, the gender wage gap can be completely explained by observed characteristics (academic field, work experience, and research productivity). However, in engineering and computer science gender wage differences remain even after accounting for observed characteristics (Michelmore and Sassler, 2016). To our knowledge, all of the research on this topic examines differences in average wages.

To assess differences in average wages, most studies conducted by economists use multiple regression methods to control for confounding factors and many apply decomposition methods to assess the presence of potential wage discrimination.[5] In the research reported here we bring

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[1] Blau and Kahn (2017) provide a recent survey of the literature describing the gender wage gap in the United States. There is also an extensive literature of studies focused on the gender wage gap in other countries.

[2] Examples include Gordon, Morton, and Braden (1974), Hoffman, (1976), Oaxaca and Ransom (2003), Geisler and Oaxaca (2005), Toumanoff (2005), Brown and Troutt (2017), and Chen and Crown (2019).

[3] Examples include Toutkoushian (1998), McDonald and Thornton (2001), Ehrenberg, McGraw, and Mrdjenovic (2006), Fortin (2008), Tick and Oaxaca (2010), Blau and Kahn (2017), and Li and Koedel (2017).

[4] Recent STEM studies include, for example, Xu (2008), Ceci, Ginther, Kahn, and Williams (2014), Michelmore & Sassler (2016) and Li and Koedel (2017).

[5] For example, Oaxaca and Ransom (2003), Geisler and Oaxaca (2005), Shatnawi, Oaxaca, and Ransom (2014), and Blau and Kahn (2016).

together these strands of research in our study of the gender wage gap in academic STEM fields. In our study of gender wage differences at a large Midwestern university, we conduct decomposition analyses of the gender wage gap in STEM departments. However, we extend the analyses beyond those typically conducted by assessing the gender wage difference for both the mean and for several quantiles of the wage distribution. This application of decomposition analyses to the quantiles of the wage distribution is important because analysis at the mean may overlook significant differences that exist at the low and high ends of the wage distribution. Indeed, we find little evidence of unexplained wage differentials in our analysis of mean differences but find statistically significant unexplained gender wage differences when examining both low and high wage quantiles among faculty members in STEM departments:

- Estimating effects for faculty members who earn relatively high salaries, we find positive unexplained wage effects for women, suggesting that highly paid female academics working in STEM departments are well rewarded by the competitive market for academics.
- However, when we focus on faculty members paid at the low quantiles of the salary distribution, we find there are significant unexplained differences between women and their White male peers. This suggests that female academics working in STEM departments are apparently not paid on par with their White male peers at the lower end of the salary distribution.

Findings of this research indicate that an area for investigation for this university. Further research performing quantile analyses using nationally representative data is needed to confirm the findings reported here for a more representative sample of faculty and the need for broader policy action.

In section 2 we describe the study sample and in section 3 we describe the analytical variables and regression methods. In section 4 we report our findings and conclude the paper in section 5.

2. Data

The data used for this study include tenure-track and tenured faculty members at a regional university located in the Midwest. In the fall semester of 2015, 25% of the university’s 20,130 students were graduate students. The university is categorized by the Carnegie Foundation for the Advancement of Teaching as a Doctoral University: Higher Research Activity.[6]

For academic year 2015-16, we have 575 observations of faculty members. The primary source of data for the study sample is administrative data collected by the university. This is supplemented with data provided by the various units of the university and information obtained from online data sources such as personal webpages and LinkedIn.

In Table 1 we report the number and percentage of White male and female faculty members employed by the University, as well as White male and female faculty members in STEM departments. We use two alternatives to define which departments are considered to be in STEM fields. The first alternative, used by the United States Department of Homeland Security, is a conservative listing of fields that include only engineering, biological sciences, mathematics, physical sciences, and related fields. The second alternative, used by the National Science Foundation, includes many more fields and includes quantitative subfields of a wider selection of disciplines, such as the social sciences.[7] For each group in Table 1 we report faculty members' average monthly salary in academic year 2015-16. 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.

As observed in Table 1, the percentages of male (44.3%) and female (43.1%) faculty members are similar when all units of the University are pooled. However, smaller percentages of STEM faculty members are female: The percentage of female STEM-DHS faculty member is only half that of White males. This percentage increases when we consider the STEM-NSF group, but the percentage of White male faculty members is still much higher than that for females. This apparent occupational segregation in academia is well documented.[8]

White male faculty members earn significantly higher average monthly salaries than their female counterparts across all departments as well as across STEM departments. The gender gap in

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[6] In 2017, there were 145 colleges and universities in this Carnegie Foundation group. The average enrollment for universities in this group was 11,796 students.
[7] Lists of the fields included in the two STEM groupings are included in the appendix.
[8] See Ceci et al. (2014), Li and Koedel (2017), and Xu (2008).

average monthly salary ranges from $761 when faculty members in all departments are observed to $1089 for those in only STEM-DHS departments. The difference in average salaries between White male and all female faculty members are statistically significant at standard levels of significance (p-value ≤ 0.05). For the entire study sample 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 88.9% and is 90.0% for faculty in the STEM-NSF departments.

The comparison of salaries in Table 1 is suggestive of gender salary inequities, but it is impossible to reach a conclusion concerning possible discriminatory differences across groups unless we control for relevant characteristics that may influence productivity. This is done in this paper using regression and decomposition methods.

In Table 2 we provide definitions of the analytical variables used in the analyses and the means and standard deviations of the variables are reported in Table 3. Table 3 also provides means and standard deviations for the subset of faculty members in STEM departments. The averages reported in Table 3 indicate that a lower percentage of faculty members in STEM departments are women. The average monthly salary is higher for faculty members working in STEM departments than for the entire sample. A higher average value is also observed in the national salary for faculty members in STEM disciplines (CUPA_D). For the restrictive definition of STEM disciplines (STEM-DHS), approximately 29% of faculty members work in STEM departments. For the broader definition (STEM-NSF), approximately 46% of faculty members work in STEM departments. Faculty members in STEM departments are more likely to be full professors and have longer years of employment at the university. Although faculty members in STEM departments are more likely to be awarded with professorships and receive salary adjustments, they are less likely to be in the higher quintiles of the college merit distributions.

3. Empirical Analyses

In our earnings regression model, we posit a causal relationship between the explanatory variables and the measure of earnings (monthly salary).[9] Following standard practice in estimating earnings regressions, we begin with analyses of the pooled data (including both male and female faculty members) and include a dummy variable to indicate gender:

[9] This is the standard Mincer (1974) earnings model.

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

The dependent variable is the faculty member's *monthly salary* (MORATE) for the 2015-16 academic year. Because monthly salary is positively skewed, we follow standard practice and use the natural log of monthly salary as the dependent variable, transforming the distribution to near normal. This transformation means that the estimates should be interpreted as the *percentage* impact on monthly average salary.

FEMALE is a personal characteristic not associated with experience, productivity, or discipline. This is 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. 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, including potential discrimination.

To identify faculty members whose department is considered to be a STEM (science, technology, engineering, and mathematics) field, we use two alternative definitions of STEM. The list of fields considered to be STEM by the Department of Homeland Security is a strict subset of the more liberally defined list of the National Science Foundation:

> *STEM-DHS* – A faculty member's field is defined as STEM-DHS if the department in which he or she is employed is one of those on the list of the Department of Homeland Security.[10] The list of DHS designated fields is included in the appendix.
>
> *STEM-NSF* – A faculty member's field is defined as STEM-NSF if the department in which he or she is employed is one of those on the list of the National Science Foundation.[11]

The remaining explanatory variables included in the analyses (X) represent the individual faculty member's relevant work experience, other factors that represent productivity, and the national

[10] See https://www.ice.gov/sites/default/files/documents/Document/2016/stem-list.pdf.
[11] See https://www.btaa.org/docs/default-source/diversity/nsf-approved-fields-of-study.pdf?sfvrsn=1bc446f3_2.

average of monthly salary in his or her discipline.[12] To test the effect of **experience** on monthly salary, we hypothesize that more experienced faculty members are more productive and that this increases salary, holding other factors constant. We include several variables representing 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, we follow standard practice in earnings studies and also include the squared value of years worked at the University (YRS-SQ). Monthly salary is expected 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.[13]

Current Rank - We represent the faculty member's current 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 form the reference group of faculty members (ASSIST). The estimated coefficient of FULL (or ASSOC) is interpreted as the incremental percentage 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, other things equal. 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. These hypotheses will be tested in the regressions.

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[12] Note that the faculty at this university do not have a collective bargaining agreement.
[13] While experience in non-academic positions may also increase a faculty member's productivity, This information is not available.

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

Merit ratings – We use a five year average (or fewer years for new hires) of annual merit ratings to create a variable representing the college quintile (lowest 0-20th percentile, 21st-40th percentile, 41st-60th percentile, 61st-80th percentile, and highest 81st-100th percentile) into which the faculty member's average merit falls. To avoid statistical issues involved in using a multi-level categorical variable as a regressor, we then use the quintile score of each faculty member to create three dichotomous variables to represent the college quintile merit rating. 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 lies 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 scores falling in the bottom two quintiles (QUINT-4TH and QUINT-BOT) of the faculty member's college merit distribution.

If a merit score in a highest college quintile leads to larger raises over time, we will observe that faculty members who have QUINT-TOP = 1 will 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, holding other factors constant. Further, we expect that the estimated effect for those in the top quintile should 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 was chosen by the University for a professorship award. While these awards vary in their monetary rewards, we include the variable to represent high 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 which is hypothesized to represent his or her 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 a college mechanism (and a value of zero if not). These adjustments, obtained through the faculty member's college, include (but are not limited to) salary increases given to match an outside offer. 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 productivity, we hypothesize that they will have positive effects on monthly salary, other things equal.

(3) 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 a university must pay 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_D) which is the average national monthly salary in the faculty member's discipline. The CUPA_D variable is constructed from data downloaded from the College and University Professional Association for Human Resources. 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 CIP code and professorial rank. In our regression analyses, we include the department average for academic year 2014-15 to control for discipline salary effects. This average is calculated by using the CUPA_D monthly salary values for each department weighted by the composition (number of faculty members at each rank) of each department.

(4) **Personal characteristics** that are not associated with experience, productivity, or discipline are included to indicate if there are significant effects on monthly salary that may be due to factors not controlled for in the analyses, including potential discrimination. In addition to FEMALE, we include variables to represent race and ethnicity:

Race – Two variables are included to represent racial groups among the faculty. These are the only racial minority groups for which we have sufficient numbers of faculty members to consider in the statistical analyses. ASIAN is 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 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 – HISPANIC is 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 faculty members not identified as Black, Asian, or Hispanic form the reference category (White) for these variables. Although the race and Hispanicity categories are not by nature mutually exclusive and our program coding does not treat them as such, the administrative data for this information indicate that these categories are in fact mutually exclusive.[14]

(5) 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 variables representing the faculty member's **department**. While it may be important to control for department in the regression analyses, it should also be noted that discrimination may occur at the department level. If this occurs, then 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 a set of dichotomous variables (values of zero or one) representing the 42 departments of the University represented in the study.

Although we considered additional explanatory variables for the regression model, the variables described above are those that are included in the final model. While we want the regression model to have strong explanatory power (high R^2 value and statistically significant F-statistic for the model), to obtain precise and statistically unbiased estimates we carefully examine the explanatory variables of the model to minimize multicollinearity and omitted variable bias to the extent possible. In addition, because we wish to analyze the smaller subset of faculty members

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

in STEM disciplines, it is useful to estimate a parsimonious model. That is, we wish to include all important explanatory variables, but exclude unneeded variables because the greater the number of explanatory variables in the model, the lower the power we will have for performing regressions for the separate groups.

To assess the possibility of multicollinearity for this study, we calculate variance inflation factors for the variables in the regression model.[15] We assess the extent of omitted variable bias by carefully performing specification checks: We start with the base model including variables determined by labor theory 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. Excluded from the model used for the analyses reported in this report are variables representing the faculty member's age, starting salary, starting rank, and years in current rank. These variables are not included because they were found be 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. This allows us to observe how the omission of variables from the model affects our final findings.

We also considered *multiple constructions of the variables* considered for the model. For example, for faculty merit, we considered direct inclusion of a faculty member's merit score, as well as a formulation in which we added a squared value to capture potential nonlinearity. Neither of these attempts were useful, so we reverted to a simple set of dichotomous indicator variables for the final model. Similarly, a large amount of time was given to the construction of the CUPA_D 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, alternative specifications of the regression model were carefully compared 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

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[15] VIFs quantify the severity of multicollinearity in linear regression. For further information regarding variance inflation factors, see Wooldridge (2020).

framework, coefficient significance and low VIF values, relatively high R^2 despite being parsimonious, and little evidence of omitted variable bias.

We first report estimates from pooled analyses of White male and female faculty members (with and without department controls). Because conducting pooled analyses may mask effects of gender discrimination if some of the explanatory variables are themselves determined by the faculty member's gender, our second step is to estimate separate regressions for White male and female faculty members. Separate regressions for White males and female faculty members allows the estimates for the explanatory variables to vary across the groups. In the first specification for each group, we ignore whether the faculty members is in a STEM department. In the second and third specifications, we include a dummy variable indicating that the faculty member is in a STEM-DHS or STEM-NSF department.

In our final analyses, we use the earnings regressions for the separate groups as the basis for decomposition analyses of the gap in monthly salary between White male and female faculty members (in all departments and in the two groups of STEM departments). In 1973, Ronald Oaxaca pioneered a method of estimating the effects of discrimination on wages using regression methods (Oaxaca, 1973).[16] Over the intervening years, many studies have used this method to assess salary inequities between employee groups.[17] A decomposition of a wage gap explains the difference in the mean (or other quintile) wage between two groups by decomposing the wage gap into two components:

$$\textbf{(2)}\ [\overline{\mathbf{MORATE}}_{\mathbf{WM}} - \overline{\mathbf{MORATE}}_{\mathbf{F}}] = \boldsymbol{\beta}_{\mathbf{WM}}(\overline{\mathbf{X}}_{\mathbf{N}} - \overline{\mathbf{X}}_{\mathbf{F}}) + (\boldsymbol{\beta}_{\mathbf{WM}} - \boldsymbol{\beta}_{\mathbf{F}})\overline{\mathbf{X}}_{\mathbf{F}}$$

(a) The first term on the right hand side is the portion of the monthly wage gap attributable to differences in the 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 component is *not* a source of potential salary discrimination.

(b) The second term on the right hand side is the portion of the monthly wage gap that is not explained by differences in productive characteristics. This component is calculated as the

[16] Blinder (1973) proposed a similar method the same year.
[17] Examples include Oaxaca and Ransom (2003), Geisler and Oaxaca (2005), Shatnawi, Oaxaca, and Ransom (2014) and Blau and Kahn (2017).

difference between the regression coefficient estimates of White male faculty members and female faculty members. If this term is statistically significant, it is consistent with potential salary discrimination.

We conduct the decomposition analyses for both the standard earnings regressions (average effects) and quantile earnings regressions for the combined data set of all faculty members and for the two subsets of STEM departments (STEM-DHS and STEM-NSF).[18]

4. Empirical Findings

Tables 4a and 4b report estimates of the effects of the various explanatory factors on the average monthly salary of faculty members for the pooled observations of all faculty members, as well as for faculty members in 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. Regressions also were run with college control variables, but the estimates from the models with department variables are reported because these models have greater explanatory power. (When department variables are included in the regression, the college or discipline group variables are not statistically significant.)

The p-values for exceeding the calculated F-statistic are less than .05 for all of the models reported in Tables 4a and 4b, indicating that the coefficient estimates for the models are jointly differ from zero. Adding the department control variables to the model leads to higher R^2 values in Table 4b. This may be because productive characteristics of the department that are not controlled for by the other explanatory variables in the model are represented by the department variables. However, because it may also be that discrimination occurs at the department level, it is possible that controlling for departments in the analyses may incorrectly eliminate effects of discrimination. For this reason, we report estimates from regressions with and without department control variables (Tables 4a and 4b).

For the regression model including all non-squared variables in columns (a) of Table 4a, the highest VIF value is 3.57 and the average VIF value is 1.42. When the squared variables (YRS-SQ and YRSOTH-SQ) are added to the model, the highly correlated YRS and YRS-SQ

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[18] Tables reporting quantile regression coefficient estimates are available from the authors.

variables have high VIF values (21 and 16, respectively), but the VIF values for the remaining variables are all under 5. Adding the STEM dummy variables has little effect on the pattern of multicollinearity: Except for the high values of YRS and YRS-SQ, the maximum VIF value is 4.89 and the average is 3.77. Thus, multicollinearity is low overall. Tests indicate the presence of heteroscedasticity, so robust standard errors are estimated.[19]

The estimates in columns (a) through (c) of Table 4a indicate that on average being female does not have a statistically significant effect on monthly salary, other things equal. Working in a STEM-DHS department has a negative impact on monthly salary, but the effect for working in a STEM-NSF department is not statistically significant. Several of the explanatory variables are statistically significant and have the expected signs (average national salary in the discipline, professorial rank, merit quintile, professorship awards, and salary adjustments). It is noteworthy that when rank, disciplinary salary, and productivity are controlled for the effect of years of experience at the University is negative. This negative effect diminishes over time so that a minimum is reached at approximately 20 years for White male and female faculty members.

Several of the explanatory variables have similar effects in the estimates reported in columns (d) through (i) for White male and female faculty members, although the smaller sample size leads to a loss in statistical significance. Note that none of the STEM indicators have statistically significant effects. Differential effects between the two subsamples are observed in the effect of YRSOTH-SQ, which is positive and statistically significant for White men and not statistically significant for women. Professorship awards have a larger positive effect for White males than for female faculty members. Finally, salary adjustments have a significant positive effect for White men and no effect for women.

Many of the estimates in Table 4b, when department control variables are added, mirror those observed in Table 4a, but the notable difference is that STEM-DHS and STEM-NSF have significant negative effects for the pooled sample (columns (b) and (c)). This is driven by a strong negative effect for female faculty members (columns (h) and (i)).

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[19] Robust standard errors are not available for the decomposition analyses, so the estimates are bootstrapped (100 repetitions).

The estimates from the decomposition analyses are reported in Table 5 for regressions at the mean as well as the 10th, 25th, 50th (median), 75th, and 90th quantiles of the salary distribution.[20] Although the underlying regressions use ln(monthly salary) as the dependent variable, the estimates reported in Table 5 have been transformed to represent the effect on *unlogged* monthly salary. Decompositions are provided 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 first row reports the percent difference in average monthly salaries between White male and female faculty members predicted by the models. The second row of estimates are the percent difference in monthly salaries between White male and female faculty members that is attributed to the explanatory variables of the models (i.e., professorial rank, years of work experience, squared years of work experience, the national average of the discipline salary, and the measures of productivity). The final row of estimates are the percent differences that are not attributable to the explanatory models. If statistically significant, these effects indicate potential salary discrimination.[21]

We observe a statistically significant negative effect due to unexplained factors for female faculty members at the 25th quantile of the salary distribution. When we limit the sample to faculty members in STEM-DHS departments, we observe a statistically significant negative effect due to unexplained factors for female faculty members at the 10th quantile of the salary distribution and statistically significant positive effects at the 75th and 90th quantiles of the salary distribution. The effect at the 75th quantile is preserved with the larger subsample of faculty in STEM-NSF departments is used, but the other effects are not observed.

We performed decomposition analyses on two further versions of the model to assess the reliability of our findings. In the first, we replace the merit quintile variables based on the *college quintiles* with merit quintile variables based on *department quintiles*. Ideally, with information

[20] We are unable to estimate the model with department controls for the Oaxaca quantile analysis because the large number of department indicator variables causes the computational procedure to fail.

[21] Although finding a statistically significant estimate of the unexplained component is consistent with potential discrimination, it is a necessary condition rather than a sufficient condition. We cannot conclude that discrimination exists because it is possible that the unexplained difference is due to unobserved productive characteristics. Rather, *statistically significant unexplained components are indicators that salary inequities may exist and further investigation is merited*. On the other hand, lack of a statistically significant effect indicates that there is no evidence of discrimination for the available data.

describing how each college calculated merit points for determining merit raises, we should use the appropriate merit quintile calculation for a faculty member depending upon whether his or her college actually uses a college- or department-level process for determining merit raises. Constructing the merit quintile variables in this way might improve their performance in the regression model. However, without this information, our alternative strategy is to perform the decomposition analyses using the department-based scores so that the findings may be compared to those for the college based scores. We find that replacing the college quintiles with department quintiles very slightly changes the values of the estimates in the tables and does not alter the pattern and statistical significance of the findings. Thus, the findings appear to be stable with respect to this issue.

The second check on the reliability of the findings is conducted by including the variables excluded from the model (age, starting rank, starting salary, and years in current rank) and performing 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, the findings appear to be stable with respect to this issue as well.

5. Conclusions

This study examines the academic gender gap in monthly faculty salaries in STEM and non-STEM disciplines at a public research university. We estimate earnings regressions for female and 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 male-female wage gaps to estimate potential wage discrimination in STEM departments.

Studies of the gender wage gap in academia indicate 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: 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. However, in engineering and computer science mean gender wage differences remain even after accounting for observed characteristics (Michelmore and Sassler, 2016).

In comparison, our mean regression analyses for the pooled (male and female) faculty members indicate no statistically significant differences between male and female faculty members, although we observe statistically significant negative effects of working in a STEM department. When we estimate separate regressions for male and female faculty members, we observe that being in a STEM department does not have a statistically significant effect for male faculty members but has a relatively large negative and statistically significant effect for female faculty members. Thus, it appears that working in a STEM department has a negative effect on the monthly salary of female faculty members.

To assess the magnitude of this potential gender wage discrimination in STEM departments, we conduct decomposition analyses at the mean and several quantiles of the salary distribution. We find no empirical evidence of unexplained gender differences for mean regressions. However, the findings from our quantile analyses reveal that there are statistically significant unexplained gender effects among faculty members working in STEM departments. Analyses of high quantiles of the salary distribution indicate the presence of a positive gender gap: This suggests that women who are highly paid academics working in STEM departments are well rewarded in the competitive academic market. In contrast, our analyses of low quantiles of the salary distribution indicate a negative gender wage gaps, suggesting that women who are earning lower salaries are apparently not paid on par with their White male peers. One possible explanation is that some of the women in these positions were ‘spousal hires’ who are tied to the local labor market by their partners’ employment at the university and therefore subject to monopsonistic wages.

Like many studies of academic salaries, this research is limited by the lack of strong productivity measures. The use of annual merit ratings is limited by the lack of standardization across units. While some of this is inherent because of differences in productive output across disciplines, the implementation of merit rating also appears to vary across departments and colleges. This makes it difficult to construct useful measures of merit for understanding the relationship between productivity and current salary. We found that there is little other information available describing the productivity of faculty members. To the extent that such factors are missing from our data, the estimated effects of unexplained factors that we attribute to potential discrimination may in part be due to this omitted information.

The findings reported in this paper suggest the importance of examining more than the mean gender wage gap when assessing potential discrimination in academia. Clearly, even when mean decomposition analyses suggest the absence of gender wage gaps, there may be statistically significant quantile effects indicating potential gender discrimination in monthly salary. Findings of this research suggest that potential salary discrimination is present in STEM disciplines and indicate that an area for investigation for this university. Further research performing quantile analyses using nationally representative data is needed to confirm the findings reported here for a more representative sample of faculty and the need for broader policy action.

References

Blau, FD, & Kahn, LM. 2017. The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature* 55(3), 789-865. DOI: 10.1257/jel.20160995

Blinder, A. 1973. Wage Discrimination: Reduced Form and Structural Estimates. *Journal of Human Resources* 8(4), 436–455. https://doi.org/10.2307/144855

Brown, L, & Troutt, E. 2017. Sex and Salaries at a Canadian University: The Song Remains the Same or the Times They are a Changin'? *Canadian Public Policy* 43(3), 246-60. DOI: 10.3138/cpp.2016-047

Ceci, SJ, Ginther, DK, Kahn, S, & Williams, WM. 2014. Women in Academic Science: A Changing Landscape. *Psychological Science in the Public Interest*, 1-67. https://doi.org/10.1177/1529100614541236

Chen, JJ, & Crown, D. 2019. The Gender Pay Gap in Academia: Evidence from the Ohio State University. *American Journal of Agricultural Economics* 101(5), 1337–52. https://doi.org/10.1093/ajae/aaz017

Ehrenberg, RG, McGraw, M, & Mrdjenovic, J. 2006. Why do field differentials in average faculty salaries vary across universities? *Economics of Education Review* 25 (3), 241–248. DOI: 10.1016/j.econedurev.2005.05.001

Fortin, NM. 2008. The Gender Wage Gap among Young Adults in the United States: The Importance of Money versus People. *Journal of Human Resources* XLIII(4), 884-918. DOI: 10.3368/jhr.43.4.884

Geisler, I, & Oaxaca, RL. 2005. Faculty Salary Determination at a Research I University. Working Paper, University of Arizona, Department of Economics.

Gordon, NM, Morton, TE, & Braden, IC. 1974. Faculty salaries: Is there discrimination by sex, race, and discipline? *American Economic Review*, 419–427.

Hoffman, EP. 1976. Faculty salaries: Is there discrimination by sex, race, and discipline? Additional evidence. *American Economic Review* 66 (1), 196–198.

Li, D, & Koedel, C. 2017. Representation and Salary Gaps by Race-Ethnicity and Gender at Selective Public Universities. *Educational Researcher* 6(7), 343-354. https://doi.org/10.3102/0013189X17726535

McDonald, JA, & Thornton, RJ. 2001. Comparable worth in academe: Professors at Ontario Universities. *Canadian Public Policy*, 357–73. https://doi.org/10.2307/3552474

Michelmore, K, & Sassler, S. 2016. Explaining the Gender Wage Gap in STEM: Does Field Sex Composition Matter? *Russell Sage Foundation Journal of the Social Sciences* 2(4), 194-215.

Mincer, J. 1974. *Schooling, Experience and Earnings*. New York: National Bureau of Economic Research.

Oaxaca, RL. 1973. Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review* 14(3), 693-709. https://doi.org/10.2307/2525981

Oaxaca, RL & Ransom, MR. 2003. Using Econometric Models for Intrafirm Equity Salary Adjustments. *Journal of Economic Inequality* 1(3), 221-49. https://doi-org.auth.lib.niu.edu/10.1023/B:JOEI.0000004588.24934.81

Shatnawi, D., Oaxaca, R., & Ransom, M. 2014. Movin' on up: Hierarchical occupational segmentation and gender wage gaps. *Journal of Economic Inequality* 12, 315-38. https://doi.org/10.1007/s10888-013-9257-4

Tick, SL, & Oaxaca, RL. 2010. Technological Change and Gender Wage Gaps in the US Service Industry. *Annals of Economics and Statistics* 99/100, 47-65.

Toumanoff, P. 2005. The Effects of gender on salary-at-hire in the academic labor market. *Economics of Education Review* 24, 179-88. DOI: 10.1016/j.econedurev.2004.03.008

Toutkoushian, RK. 1998. Sex Matters Less for Younger Faculty: Evidence of Disaggregate Pay Disparities from the 1988 and 1993 NCES Surveys. *Economics of Education Review* 17(1), 55-71. DOI:10.1016/S0272-7757(97)00015-0

Wooldridge, JM. 2020. *Introductory Econometrics: A Modern Approach*, 7th ed. Mason, OH: Cengage Learning.

Xu, YJ. 2008. Gender Disparity in STEM Disciplines: A Study of Faculty Attrition and Turnover Intentions. *Research in Higher Education* 49, 607-624. DOI 10.1007/s11162-008-9097-4

Table 1: Average Monthly Salary							
		ALL		**STEM - DHS**		**STEM - NSF**	
	All	**White Male**	**Female**	**White Male**	**Female**	**White Male**	**Female**
Average Monthly Salary	$8755	$9082	$8321**	$9473	$8384**	$9300	$8366**
Salary Gap		$761		$1089		$934	
Number of obs	575	255	248	94	42	139	85
% of Faculty	100%	44.3%	43.1%	16.3%	7.3%	24.2%	14.8%

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

Table 2: Variable Definitions	
Variable	**Definition**
Individual's 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
Salary Measure (2016 $US)	
MORATE	Current monthly salary (monthly rate)
Discipline-specific Monthly Salary ($US 2016)	
CUPA_D	Average monthly salary by discipline from national survey (university weights)
STEM Indicators	
STEM-DHS	=1 if faculty member's field is designated as STEM by the Department of Homeland Security, =0 otherwise
STEM-NSF	=1 if faculty member's field is designated as STEM by the National Science Foundation, =0 otherwise
Individual's Work Characteristics and Performance Measures	
FULL	=1 if current rank is full professor, =0 otherwise
ASSOC	=1 of current rank is associate professor, =0 otherwise
ASSIST	=1 of 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
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
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)
Department Control Variables	
DEPT	Set of dummy variables representing departments of the university and library

Table 3: Descriptive Statistics for Regression Variables						
	ALL		STEM - DHS		STEM - NSF	
	Average	Standard Deviation	Average	Standard Deviation	Average	Standard Deviation
Individual's Demographic Characteristics						
FEMALE	0.431	0.496	0.249	0.433	0.320	0.467
ASIAN	0.151	0.359	0.207	0.406	0.158	0.365
BLACK	0.042	0.200	0.024	0.152	0.038	0.191
HISPANIC	0.033	0.179	0.030	0.170	0.030	0.171
Current Monthly Salary ($US 2016)						
MORATE	8755	2561	9122	1831	8926	1745
Discipline-specific Monthly Salary ($US 2016)						
CUPA_D	9516	2292	10,300	962	9899	1154
STEM Indicators						
STEM-DHS	0.294	0.456	1	0	0.635	0.482
STEM-NSF	0.463	0.499	1	0	1	0
Individual's Work Characteristics and Performance Measures						
FULL	0.334	0.472	0.402	0.492	0.383	3487
ASSOC	0.445	0.497	0.391	0.489	0.417	0.494
ASSIST	0.221	0.415	0.207	0.406	0.199	0.400
YRS	13.03	8.60	15.4	9.78	14.35	8.96
YRS-SQ	243.68	281.44	332.8	356.2	285.8	315.9
YRSOTH	2.30	4.03	2.04	3.90	2.27	4.21
YRSOTH-SQ	21.47	72.01	19.3	63.4	22.80	85.64
QUINT-TOP	0.193	0.395	0.154	0.362	0.177	0.382
QUINT-2ND	0.198	0.399	0.142	0.350	0.192	0.394
QUINT-MID	0.193	0.395	0.201	0.402	0.218	0.414
QUINT-4TH	0.210	0.408	0.237	0.426	0.203	0.403
QUINT-BOT	0.205	0.404	0.266	0.443	0.211	0.408
PROFSHIP	0.080	0.272	0.118	0.324	0.132	0.339
SALADJ	0.031	0.174	0.041	0.200	0.053	0.224
SEADJ	0.089	0.285	0.166	0.373	0.150	0.358
# of obs	575		169		266	

Table 4a: Estimated Percentage Effects of Individual Characteristics on Monthly Faculty Salary[1]									
	ALL			WHITE MALE			FEMALE		
Independent Variables	**(a) Percentage Effect**	**(b) Percentage Effect**	**(c) Percentage Effect**	**(d) Percentage Effect**	**(e) Percentage Effect**	**(f) Percentage Effect**	**(g) Percentage Effect**	**(h) Percentage Effect**	**(i) Percentage Effect**
Personal Characteristics:									
FEMALE	0.021	0.015	0.018						
ASIAN	0.030*	0.034**	0.031*						
BLACK	0.047**	0.045**	0.048**						
HISPANIC	- 0.018	- 0.017	- 0.018						
Discipline:									
CUPA_D	0.079**	0.081**	0.080**	0.080**	0.080**	0.079**	0.079**	0.080**	0.080**
STEM-DHS		**- 0.030****			- 0.013			- 0.026	
STEM-NSF			- 0.014			- 0.005			- 0.012
Experience:									
FULL	0.298**	0.294**	0.295**	0.287**	0.284**	0.288**	0.301**	0.301**	0.300**
ASSOC	0.134**	0.131**	0.133**	0.110**	0.108**	0.110**	0.138**	0.140**	0.137**
YRS	- 0.015**	- 0.015**	- 0.015**	- 0.016**	- 0.016**	- 0.016**	- 0.012*	- 0.012*	- 0.012*
YRSSQ	0.0004**	0.0004**	0.0004**	0.0004**	0.0004**	0.0004**	0.0003*	0.0004*	0.0003*
YRSOTH	0.003	0.003	0.003	0.003	0.003	0.003	0.011	0.010	0.011
YRSOTHSQ	0.0003**	0.0003**	0.0003**	0.0003*	0.0003*	0.0003*	- 0.0006	- 0.0006	- 0.0007
Productivity:									
QUINT-TOP	0.031**	0.028*	0.031*	0.010	0.007	0.010	0.036	0.036	0.037
QUINT-2ND	0.028*	0.025	0.028*	0.008	0.005	0.007	0.037	0.036	0.037
QUINT-MID	0.022	0.025	0.023	0.0003	- 0.0001	0.0001	0.049*	0.049*	0.051*
PROFSHIP	0.081**	0.083**	0.084**	0.093**	0.094**	0.092**	0.070*	0.066	0.071*
SALADJ	0.033	0.037	0.038	0.103	0.109	0.101	- 0.012	- 0.011	- 0.009
SEADJ	0.057**	0.066**	0.061**	0.086**	0.090`**	0.084**	0.020	- 0.009	0.016
Department Controls Included	No	No	No	No	No	No	No	No	No
N	575			255			248		
R^2	0.7368	0.7390	0.7373	0.7674	0.7679	0.7674	0.6936	0.6948	0.6940
F	103.92	103.38	104.76	71.65	68.66	68.02	48.23	46.54	47.52
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

[1] Dependent variable is ln(monthly salary). All specifications include an intercept.

** P-value ≤ 0.05 * P-value > 0.05 and ≤ 0.10

Table 4b: Estimated Percentage Effects of Individual Characteristics on Monthly Faculty Salary[1]

	ALL			WHITE MALE			FEMALE		
Independent Variables	(a) Percentage Effect	(b) Percentage Effect	(c) Percentage Effect	(d) Percentage Effect	(e) Percentage Effect	(f) Percentage Effect	(g) Percentage Effect	(h) Percentage Effect	(i) Percentage Effect
Personal Characteristics:									
FEMALE	0.004	0.004	0.004						
ASIAN	0.001	0.001	0.001						
BLACK	0.015	0.015	0.015						
HISPANIC	- 0.037**	- 0.037**	- 0.037**						
Discipline:									
CUPA_D	0.030**	0.030**	0.030**	0.046**	0.046**	0.046**	- 0.100**	- 0.100**	- 0.100**
STEM-DHS		**- 0.241****			- 0.118			**- 1.241****	
STEM-NSF			**- 0.241****			- 0.118			**- 1.242****
Experience:									
FULL	0.309**	0.309**	0.309**	0.309**	0.309**	0.309**	0.315**	0.315**	0.315**
ASSOC	0.132**	0.132**	0.132**	0.124**	0.124**	0.124**	0.133**	0.133**	0.133**
YRS	- 0.011**	- 0.011**	- 0.011**	- 0.011**	- 0.011**	- 0.011**	- 0.011**	- 0.011**	- 0.011**
YRSSQ	0.0003**	0.0003**	0.0003**	0.0003**	0.0003**	0.0003**	0.0004**	0.0004**	0.0004**
YRSOTH	0.001	0.001	0.001	- 0.0001	- 0.0001	- 0.0001	- 0.006	0.006	0.006
YRSOTHSQ	0.0004**	0.0004**	0.0004**	0.0004**	0.0004**	0.0004**	- 0.00002	- 0.00002	- 0.00002
Productivity:									
QUINT-TOP	0.026**	0.026**	0.026**	0.035**	0.035**	0.035**	0.024	0.024	0.024
QUINT-2ND	0.011	0.011	0.011	0.011	0.011	0.011	0.020	0.020	0.020
QUINT-MID	0.013	0.013	0.013	0.011	0.011	0.011	0.039**	0.039**	0.039**
PROFSHIP	0.088**	0.088**	0.088**	0.101**	0.101**	0.101**	0072*	0072*	0072*
SALADJ	0.045**	0.045**	0.045**	0.092**	0.092**	0.092**	0.033	0.033	0.033
SEADJ	0.054**	0.054**	0.054**	0.064**	0.064**	0.064**	0.021	0.021	0.021
Department Controls Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		575			255			248	
R^2	0.9032	0.9032	0.9032	0.8987	0.8987	0.8987	0.9340	0.9340	0.9340
F	72.52	72.52	72.52	-	-	-	-	-	-
Prob > F	0.0000	0.0000	0.0000	-	-	-	-	-	-

[1] Dependent variable is ln(monthly salary). All specifications include an intercept.

** P-value ≤ 0.05   * P-value > 0.05 and ≤ 0.10

Table 5: Quantile Oaxaca Decompositions of Monthly Faculty Salary by Gender and STEM Field[1]

	Percent Effects at Quantiles					
	10th	**25th**	**median**	**mean**	**75th**	**90th**
FEMALE (vs. White male) ALL (obs=503)						
% Difference	+ 5.92**	+ 6.31**	+ 9.98**	- 9.32**	+ 11.86**	+ 9.08*
% Explained	+ 8.43**	+ 10.67**	+ 13.28**	- 12.27**	+ 13.39**	+ 11.51**
% Unexplained	- 2.51	**- 4.35****	- 3.30	+ 2.63*	- 1.53	- 2.44
FEMALE (vs. White male) STEM-DHS ONLY (obs=136)						
% Difference	+ 5.09*	+ 6.40**	+ 8.97**	- 11.60**	+ 14.81**	+ 21.06*
% Explained	+ 9.07**	+ 9.20**	+ 11.73**	- 12.06**	+ 8.27**	+ 12.99**
% Unexplained	**- 3.98****	- 2.80	- 2.76	+ 0.41	**+ 6.54****	**+ 8.07****
FEMALE (vs. White male) STEM-NSF ONLY (obs=224)						
% Difference	+ 3.59**	+ 6.05**	+ 12.00**	- 10.45**	+ 13.44**	+ 12.76**
% Explained	+ 5.84**	+ 8.20**	+ 10.35**	- 9.74**	+ 8.18**	+ 9.47**
% Unexplained	- 2.25	- 2.16	- 1.65	+ 0.65	**+ 5.26****	+ 3.30

[1] Standard errors are bootstrapped with reps=100. Percentage is white male minus female. The White male category includes all non-Asian, non-Black, and non-Hispanic male faculty members and is predominantly individuals identified as White.

** P-value ≤ 0.05

* P-value > 0.05 and ≤ 0.10