Is There Still a Gender Wage Gap among Assistant Professors at U.S. Public Universities?

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ABSTRACT

More than 50 years have passed since the Equal Pay Act of 1964 and women are still paid less than men are. This study sheds light on the academic gender wage gap by comparing the salaries of male and female assistant professors within 3 years of being hired at selected U.S. public universities. The data studied was collected from salary reports from public university systems in 2018 and 2019, which were obtained under the Freedom of Information Act. Due to the novel way of assigning gender using genderize.io, traditional statistical methods for comparing two populations are not appropriate. For this reason, this study uses permutation-based nonparametric tests that are valid for the data. It shows that gender wage gaps still exist among U.S. public universities. Significantly more women are receiving lower salaries compared to men. For example, the proportion of women making less than $10,000 a month is 12% higher than the proportion of men making the same amount. It concludes that gender disparities within academic disciplines are a considerable factor contributing to the wage gaps.

MATERIALS AND METHODS

1. DESCRIPTION OF DATA

Since faculty salaries in public universities are a matter of public record, the latest salary information was obtained for several large public universities. In particular, the data studied included 87,260 employees from four university systems: the University of North Carolina System (UNC) in 2019, the University of Michigan System (UMich) in 2019, the University of Wisconsin System (UWisconsin) in 2018, and the Rutgers University System (RU) in 2018. These are the latest data available when the research was conducted. The annual inflation between 2018 and 2019 was low (2.44%) and therefore it does not affect the conclusion of the study (U.S Bureau of Labor Statistics, 2022).

The data were primarily collected online from databases provided by each university. The exception is the data from UMich, which was collected by contacting its Freedom of Information Act Office. The data include variables such as name, school, campus, department, title, service day, and salary.

2. INCLUSION/EXCLUSION CRITERIA

The data were filtered to include only faculty hired within the past 3 years. Visiting assistant professors, teaching assistant professors, and clinical assistant professors were excluded from data since the primary interest is in tenure-track assistant professors. Additionally, approximately 0.6% of cases (n=21) were eliminated because of extremely low reported salaries, reported as less than $3,000 per month. Many public universities in the U.S. have salary bands with minima that are far higher than $3,000 per month. See for example the salary bands for the University of North Carolina at Charlotte (https://provost.charlotte.edu/sites/provost.charlotte.edu/files/media/Faculty%20Salary%20Ranges%201.13.22.pdf, accessed on August 2, 2022). Three faculty members randomly chosen out of the 21 were contacted and they confirmed that their reported salary was a fraction of what they actually received.

3. DATA CLEANING

Because different schools use different ways to record salary information, monthly salaries were computed to make results comparable across universities. For example, the UNC system reports full-time equivalents (FTE) and employment months for each of its employees. FTE is a unit that indicates the workload of a faculty and is calculated as a faculty's scheduled hours divided by the faculty's hours for a full-time workweek. Employment month indicates the number of months a faculty member works during a year. Typically, this is nine or twelve months. The monthly salary is then computed by the formula:

$$monthly\ salary = \frac{salary}{employment\ months * FTE} \quad (1)$$

The other schools do not report employment months; however, typical employment months are consistent within disciplines depending on the discipline culture. Therefore, an average employment month was computed for each discipline based on the UNC data and was used for the computation of monthly salary for all of the other schools. The monthly salaries for those schools were computed by dividing the salary by the corresponding discipline's mean number of employment months.

For Rutgers University, some faculty titles indicate number of employment months. For example, the title "Assistant Professor Academic year" implies that the number of employment months is 9, and "Assistant Professor Calendar year" implies that the number of employment months is 12. Therefore, the monthly salary of these observations was computed based on this information.

Since the data do not provide gender information, the genderize.io API was used to predict gender based on first names. The “guessGender” package (Caddigan, 2015) was used to connect the API to R. The result contained a person’s predicted gender and the probability of being a male or female. Then, the data from the four schools were combined. Because the names of departments at various universities are different, a new label was created grouping departments together based on both the mean salary and the name of the department (Table 2). This was stored in a variable called discipline. For example, electrical and computer engineering, information systems, and computer science all belong to computer science, so they were combined.

The final dataset contained 3,248 assistant professors and 10 variables: school, campus, name, title, department, discipline, gender, monthly salary, proportion of male, and proportion of female (Table 1).

4. STATISTICAL ANALYSIS

The empirical cumulative distribution function (empirical CDF) was plotted to visualize the gender wage difference in the combined data from the four universities. Since gender was obtained by prediction, the empirical CDF was adjusted by the gender probabilities computed by *genderize.io* using first names. Each data point was weighted by its associated probability of being male or female. Those points with higher gender probabilities overshadowed others with low gender probabilities. Below are formulas for male and female faculty salary empirical CDF.

$$F_n(t)_{male} = \frac{\sum_{j=1}^{n} I\{Z_j \le t\} * p_j}{\sum_{j=1}^{n} p_j},\ F_n(t)_{female} = \frac{\sum_{j=1}^{n} I\{Z_j \le t\} * q_j}{\sum_{j=1}^{n} q_j},$$

Where Z_js are the observed salaries, the indicator function I$\{Z_j \le t\}$ is either 1 if $Z_j \le t$ or 0 otherwise, p_j is the proportion of males associated with the jth first name, and $q_j = 1 - p_j$ is the proportion of females associated with this name.

The next question to answer is whether the difference between CDFs was statistically significant. To this end, a permutation test was used. In particular, a comparison was made between male and female empirical CDFs with the difference of the empirical CDF, where the gender proportions $p_j\ and\ q_j$ were randomly reassigned. Additionally, a second permutation test was devised to determine that the differences observed in the first test are not caused by different gender balances within various disciplines, and to avoid the Simpsons Paradox (Colin, 1972). In particular, gender proportions were randomly reassigned among faculty only within their own disciplines (Table 2), i.e., biologists' genders were replaced with those of other biologists, medical doctors' genders were replaced by those of other medical doctors, etc. In this case, only genders of faculty within the same discipline were permuted.

To measure the difference quantitatively, a p-value was computed that measures the probability that the mean of the random curve is smaller than the original curve. All points in the random curves and original curve were ranked, and the mean of the ranks for each curve was used to compute the p-value. In particular:

Define a \`$1001 * $ nx\` matrix: A = $\begin{pmatrix} y_0 \\ \vdots \\ y_{1000} \end{pmatrix} = \begin{pmatrix} a_{01} & \cdots & .2 \\ a_{11} & \cdots & .4 \\ \vdots & \ddots & \vdots \\ a_{1000,1} & \cdots & -.3 \end{pmatrix}$. Entries in each row are differences of male and female empirical CDFs for each curve: y_0 denotes the original curve and

$y_{1...}y_{1000}$ denotes the permuted curves. Each of the `nx` columns corresponds to a different monthly salary.

Define a `$1001 * $ nx` matrix of ranks: T = $\begin{pmatrix} t_{01} & \cdots & 2 \\ t_{11} & \cdots & 3 \\ \vdots & \ddots & \vdots \\ t_{1000,1} & \cdots & 1 \end{pmatrix}$, where the entries of T are the ranks of the entries of A within each column. Define the row-wise mean:

$$\text{mean}_i = \frac{1}{nx}\sum_{j=1}^{nx} t_{ij}.$$

The permutation p-value is then defined as,

$$p = proportion(mean_0 \geq \text{mean}_i) = \frac{1}{1001}\sum_{i=0}^{1000} I\{mean_0 \geq \text{mean}_i)\}.$$

RESULTS

The number of employees at each university are documented (Table 1). The aggregated disciplines were selected, their mean salaries and mean employment months were calculated (Table 2). The empirical CDF for female faculty was above its male counterpart in the range between \$6,310 and \$25,119 per month (Figure 1). After applying a permutation test on the entire population (not controlling for discipline), the non-permuted difference between male and female empirical CDFs (black curve) was far lower than the differences computed using the permuted population (blue envelope), which gives us a measure of what could be expected due to pure chance (Figure 2). The corresponding permutation p-value is 1/1001. Next, after permuting faculty genders only within each discipline (controlling for discipline), the results show that the differences of empirical CDFs based on genders permuted within discipline follow a similar pattern to the difference based on non-permuted data (Figure 3).

After analyzing all schools together, each school was analyzed individually. P-values for the second permutation test (controlling for discipline) were computed (Table 3). For Rutgers University, the p-value is less than the threshold of 0.05, while for the University of North Carolina, the p-value is less than 0.1. For these two universities, non-permuted differences remained near the bottom of the blue envelope, representing the differences of permuted curves (Figure 4). For the University of Wisconsin and the University of Michigan, the p-values were much greater than 0.1 and the non-permuted differences were well within the blue envelope (Figure 4).

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