2012

Salary Equity Analysis

University of California, Santa Barbara

Office of the Executive Vice Chancellor
Introduction

In response to several previous studies on salary equity, the administration has continued to analyze academic salaries to examine issues of equity, especially with respect to gender and ethnicity. This is the 9th year of this analysis. Best practices for analyzing the data have been determined from other studies and applied here. Moreover, the salary studies have been shared with the Academic Senate’s Committee on Diversity and Equity and the Chancellor’s Advisory Committee on the Status of Women, and their feedback has been incorporated into subsequent analyses.

Salary Data

The 2012 pay equity study at UC Santa Barbara was conducted for ladder rank faculty based on October 1, 2012 Payroll/Personnel data combined with data from the Office of Academic Personnel. The Payroll/Personnel System (PPS) database represents the most accurate and up to date information on faculty salary, and the October 1, 2012 data represents a snapshot at that point in time. The data analyzed here include only ladder rank faculty members who were on active pay status, and the salaries are the annual 9-month academic salaries; they do not include summer salary or administrative stipends. Every effort is made to assure accuracy in the input data.

The data are considered for the University of California Santa Barbara as a whole; and they are also divided into Colleges/Divisions: specifically, the Divisions of Humanities and Fine Arts (HFA); Mathematics, Physical and Life Sciences (MLPS); and Social Sciences (DSS) in the College of Letters and Science; the Gevirtz Graduate School of Education (GGSE), the Donald Bren School of Environmental Science and Engineering (BREN) and the College of Engineering (ENGR).

The salary data are shown for the campus and each division/college as a function of rank and step for White Males, Women and Male Minorities in Figure 1. The use of the term "minority" here includes Black/African-American, Asian/Pacific Islander, Native American, and Hispanic regardless of citizenship or country of origin. This is consistent with federal affirmative action definitions, and with other studies referenced above. Analyzing subpopulations is complicated by increasingly smaller population sizes (and thus poorer statistics) and problems in self-reporting, including multiple affiliations.

1 In February 1996, The Associate Vice Chancellor for Academic Personnel formed a Gender Equity Advisory Group, which reviewed and reported on salary equity study methods (Zelmanowitz to Crawford, 5/28/98). In April 2002, the Associate Vice Chancellors and Divisional Chair of the Academic Senate constituted a Salary Equity Advisory Group to develop a set of recommendations on salary equity analysis, which it reported in July 2002.
The average salary for each of these groupings for the campus and for each academic division is given in Table A below.

### Table A

Average 9-Month Academic Salaries by Group and Academic Unit

<table>
<thead>
<tr>
<th>Academic Unit</th>
<th>White Males</th>
<th>Women</th>
<th>Male Minorities</th>
</tr>
</thead>
<tbody>
<tr>
<td>HFA</td>
<td>111,327</td>
<td>102,327</td>
<td>109,452</td>
</tr>
<tr>
<td>MLPS</td>
<td>139,197</td>
<td>117,212</td>
<td>117,023</td>
</tr>
<tr>
<td>DSS</td>
<td>140,248</td>
<td>112,544</td>
<td>102,218</td>
</tr>
<tr>
<td>BREN</td>
<td>154,108</td>
<td>100,120</td>
<td>N/A</td>
</tr>
<tr>
<td>GGSE</td>
<td>127,840</td>
<td>99,784</td>
<td>97,725</td>
</tr>
<tr>
<td>ENGR</td>
<td>150,236</td>
<td>132,680</td>
<td>140,700</td>
</tr>
<tr>
<td>UCSB</td>
<td>134,815</td>
<td>108,909</td>
<td>118,085</td>
</tr>
</tbody>
</table>

At first glance salaries for women and male minorities appear systematically lower than their male counterparts for the campus as a whole as well as by academic division, and the salaries vary by academic discipline as well. However, the white male population tends to be older and hence had longer to advance in the salary scale. Table B shows the same average salaries with the average birth year included.

### Table B

Average 9-Month Academic Salaries and Birth Year by Group and Academic Unit

<table>
<thead>
<tr>
<th>Academic Unit</th>
<th>White Males (Avg Birth Year)</th>
<th>Women (Avg Birth Year)</th>
<th>Male Minorities (Avg Birth Year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HFA</td>
<td>111,327 (1957)</td>
<td>102,327 (1960)</td>
<td>109,452 (1959)</td>
</tr>
<tr>
<td>MLPS</td>
<td>139,197 (1957)</td>
<td>117,212 (1962)</td>
<td>117,023 (1963)</td>
</tr>
<tr>
<td>BREN</td>
<td>154,108 (1956)</td>
<td>100,120 (1966)</td>
<td>N/A</td>
</tr>
<tr>
<td>GGSE</td>
<td>127,840 (1955)</td>
<td>99,784 (1960)</td>
<td>97,725 (1958)</td>
</tr>
</tbody>
</table>

The average salary is plotted against average birth year for each of the academic divisions below in Figure A. While the disciplinary differences reflect different salary scales (e.g., ENGR) and market forces, the data broadly show similar dependences on birth year (the lines are not regression fits, but sight guides). Hence, in examining salary differences among groups, it is important to account for differences in both discipline as well as
length in the system. This is the basis for the salary analysis methodology described below.

Figure A. Average annual salary plotted against birth year for each division/college/school

Methodology and Results

The pay equity study employed here applies the methodology recommended by the American Association of University Professors (AAUP – see, for instance, http://www.aaup.org). A similar methodology has been followed by the University of California Irvine (see, for instance, http://www.ap.uci.edu/Equity/studies/index.html). The methodology is set up to test whether women and minority faculty members are paid differently than their white male counterparts. The methodology does not include any subjective measures of quality or merit. Therefore it is expected that some faculty members will have results that are not explained well by the methodology, which relies exclusively on quantifiable objective measures. Nonetheless, it serves as a tool for identifying broad trends.

The first step is to fit the salary data for white males on the campus or in a College/Division. In previous analyses, the fit has been made by a linear regression analysis to an equation of the form:

\[
\text{SALARY} = A \times \text{(Appointment year)} + B \times \text{(Birth Year)} + C \times \text{(Degree Year)} + D
\]
where **A**, **B**, **C** and **D** are regression coefficients. However, the UC salary scale increases with rank and step (and therefore normative length of appointment/age) faster than a linear scale. Hence, a linear fit to the UC salary scale produces a slight negative bias for early and late career appointments and slight positive bias in between as shown below in Figure B:

![Figure B](image_url)

**Figure B.** Illustration of salary as a function of age for the UC salary scale versus a linear dependence.

Moreover, it was pointed out in a critique of a recent systemwide salary analysis\(^2\) that such non-linearities are better captured by using a log fit. For instance, if Salary (S) varies with age (T) in a non-linear way as:

\[
S = A T^a,
\]

where **A** and **a** are constants. Then taking log of both sides of the equation produces:

\[
\log S = \log A + a \log T
\]

The figures below (Figure C) illustrate that the Log correlation better fits the curvature of salary versus Birth Year than the Linear fit.

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\(^2\) Systemwide University Committee on Affirmative Action and Diversity (UCAAD), *Analysis of Pay Equity By Sex and , Among Men, Ethnicity, 2009-2010*
Figure C. Illustrations of linear and log fits to annual salary data as a function of birth year.

Therefore, for purposes of this analysis a fit was made to the white male salaries by a linear regression analysis to an equation of the form:

\[ \log(\text{SALARY}) = A \log(\text{Appointment year}) + B \log(\text{Birth Year}) + C \log(\text{Degree Year}) + D \]

where \(A, B, C\) and \(D\) are regression coefficients.

For most academic units, this fit does a reasonable job of correlating the salary of white males with a goodness of fit parameter, \(r^2\), of 0.45 to 0.90 (see below). The goodness of fit is a statistical parameter that comes out of the regression analysis; it demonstrates how well a correlation fits the data, with a perfect fit leading to an \(r^2\) of 1.0 and no fit at all leading to an \(r^2\) of 0.

A standard error (SE) on SALARY is also calculated as part of the regression analysis. Since the salary is not entirely captured by the three independent variables (Appointment, Birth and Degree years), the standard error reflects the uncertainty of the predicted salary.

The example below in Figure D shows a plot of PREDICTED versus ACTUAL SALARY, with the bounds (dotted lines) corresponding to the standard error (SE):
As can be seen, although the linear regression predicts the broad trend, it is imperfect, with data falling off the solid line of “ACTUAL SALARY = PREDICTED SALARY.” Most, but not all, of the data fall within one standard error of the line.

Figure 2 shows the ACTUAL SALARY vs PREDICTED SALARY for the campus as a whole and each of the divisions/colleges based on the data for white males. For comparison, the ACTUAL SALARY and PREDICTED SALARY (again based on white male data) for women and male minorities are shown on these same plots. The population of individual faculty making up each category in each division/college is given by the number N in each plot. A significant salary inequity in the women and/or male minority data would show up as a preponderance of data points on one side or the other of the “ACTUAL SALARY = PREDICTED SALARY” line. While such a preponderance is not evident for most of the data points in Figure 2, the correlation does systematically under-predict salaries of the highest-paid faculty (above $225,000), which are predominantly white males.

To further test the salary equity, residuals are calculated for the white male population, and then for women (white and minority) and male minority faculty members on the campus and in each College/Division. The residual is the difference between actual salary and salary predicted by the regression equation. A negative residual indicates that the actual salary is lower than the amount predicted for a white male faculty in the same academic unit with the same attributes. A positive residual indicates that the salary is higher than the predicted value.
The example below in Figure E shows the residual value of one data point, where the faculty member’s actual salary is $50,000 less than the predicted salary:

![Graph showing actual and predicted salaries with a residual of -$50,000](image)

Figure E. Illustration of a residual in the plot of predicted versus actual salary

As a final step, the residuals for each population (white males, women, male minorities) for UCSB and for each College/Division are plotted on a frequency histogram (the number of times a residual is calculated in a particular range of values), along with a line indicating the range of the standard error (SE) on salary. The distribution provides some measure of the salary equity – or inequity – for the campus or College/Division.

Typically, for a large population of faculty members in a College or Division, the residual distribution for the white male population will be symmetric and peaked about the origin (a residual of 0), and most of the population will fall within the standard error (SE). The residual frequency will fall off with greater residual value on both sides of the origin, and a relatively small number of faculty (low frequency) will fall outside of the SE at both the low (negative residual) and high (positive residual) ends.

If there is salary equity in the population, the residual distributions for women and minorities in the College/Division should show a similar distribution to the white male distribution. An example is given below in Figure F; here there are 26 faculty whose salaries fall within $±5000 of the predicted salary (residuals equal to or less than plus or minus $5000) and 1 each whose salaries are more than and less than $35,000 of the predicted value. Most of the faculty have salaries which fall within $18,000, the standard error (SE), of the predicted amount.
Figure F. Example of a residual frequency plot for a population in which there is no salary inequity. The distribution of residuals is symmetric about zero residual and the frequency diminishes as the residual increases.

However, in all cases (white males, women and male minorities), for a smaller population of faculty, the distributions may not be symmetric, nor peaked at the origin. Even in these cases, the degree of salary equity should be reflected by the extent to which the residuals fall within a standard error of the origin. Two examples are shown below: one in which there is no apparent salary inequity (Figure G) and one in which there is Figure H:
Figure G. Illustration of a residual frequency plot in which there is no apparent salary inequity.

Figure H. Illustration of a residual frequency plot in which there is an apparent salary inequity.
The regression analysis, standard error and goodness of fit parameter are listed for each of the academic units below in Table C.

Table C. Regression analysis parameters by academic unit

<table>
<thead>
<tr>
<th>Unit</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>(r^2)</th>
<th>SE (k$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENG</td>
<td>1.85</td>
<td>36</td>
<td>-70.5</td>
<td>111.9</td>
<td>.61</td>
<td>31</td>
</tr>
<tr>
<td>BREN</td>
<td>14.23</td>
<td>130</td>
<td>-166.6</td>
<td>80.71</td>
<td>.90</td>
<td>26</td>
</tr>
<tr>
<td>GGSE</td>
<td>-15.89</td>
<td>10</td>
<td>-36.7</td>
<td>145</td>
<td>.84</td>
<td>17</td>
</tr>
<tr>
<td>HUFA</td>
<td>13.07</td>
<td>-19</td>
<td>-28.4</td>
<td>119</td>
<td>.60</td>
<td>23</td>
</tr>
<tr>
<td>MLPS</td>
<td>25.74</td>
<td>30</td>
<td>-80.3</td>
<td>84.8</td>
<td>.45</td>
<td>39</td>
</tr>
<tr>
<td>DSS</td>
<td>17.34</td>
<td>-9.6</td>
<td>-39.2</td>
<td>108.7</td>
<td>.57</td>
<td>35</td>
</tr>
<tr>
<td>DSS (No Econ)</td>
<td>13.4</td>
<td>12.5</td>
<td>-59.4</td>
<td>115.6</td>
<td>.66</td>
<td>28</td>
</tr>
</tbody>
</table>

Residual histograms for white male, women and male minority populations for the campus as a whole and for each of the Colleges/Divisions are given in Figures 3-9. Residuals are given in units of k$ = $1000. Again, the population of individual faculty making up each category is given by the number N in each plot.

The results of this analysis are consistent with findings from previous years. No systematic changes were detected from the results reported in previous reports despite the use of a Log versus a linear relationship between salary and birth/degree/appointment years.

In Figure 3, the residual distribution for White Males for the campus as a whole is not quite symmetric, and the center of the distribution is slightly biased toward the negative residual, which biases the distributions for women and minorities as well. The slight bias in the distribution for women is also further biased by the higher salary scales for engineering and economics, which also have higher than campus average populations of white males. Figures 4-5 and 7-9 show no apparent or systemic biases in salary for women or male minorities in the respective disciplines, at least within the statistical uncertainty of this analysis. The possible bias in the social sciences indicated by the distributions for women and male minorities in Figure 6a appears to be largely the result of including economics faculty in the analysis, since this faculty is on a higher salary scale and tends to have a white male component that is higher than the average for the social sciences. As shown in Figure 6b, removing economics faculty from the analysis produces more symmetric residual distributions.
Finally, there have been suggestions to further analyze the salary data by department in the larger colleges and divisions. The difficulty of interpreting these data is illustrated for male minorities in GGSE (Figure 7), women and male minorities in BREN (Figure 8) and women in ENGR (Figure 9). In each case, the residuals are approximately distributed equally on both sides of the zero residual line, but the sample sizes are so small that it is hard to make much statistical sense beyond this. There have been additional suggestions to consider account for time-off-the clock and for other indicators, such as prizes, marital status, children, etc. These data are difficult to assemble, given the nature of our data base, so these continue to be work in progress.

The results of this analysis will continue to be used by the administration to examine reasons for large negative residuals for individual faculty as academic personnel cases are processed in future years.
Figure 1 – Salary comparisons by rank and step for UCSB and Colleges/Divisions
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Figure 1 – Salary comparisons by rank and step for UCSB and Colleges/Divisions
Figure 2—Predicted vs Actual Salary for UCSB and Colleges/Divisions
Figure 2—Predicted vs Actual Salary for UCSB and Colleges/Divisions
Figure 2—Predicted vs Actual Salary for UCSB and Colleges/Divisions
Figure 3 -- Residual histograms for UCSB for white males, women and male minority faculty.
Figure 4 – Residual histograms for HFA for white males, women and male minority faculty.
Figure 5 – Residual histograms for MLPS for white males, women and male minority faculty.
Figure 6a – Residual histograms for DSS for white males, women and male minority faculty.
Figure 6b – Residual histograms for DSS for white males, women and male minority faculty (without Economics in the white male data base)
Figure 7 – Residual histograms for GGSE for white males, women and male minority faculty.
Figure 8 – Residual histograms for BREN for white males, women and minority faculty.
Figure 9 – Residual histograms for ENGR for white males, women and male minority faculty.