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**UNITED STATES DEPARTMENT OF LABOR**
**OFFICE OF ADMINISTRATIVE LAW JUDGES**

OFFICE OF FEDERAL CONTRACT COMPLIANCE PROGRAMS, UNITED STATES DEPARTMENT OF LABOR,

Plaintiff,

v.

ORACLE AMERICA, INC.,

Defendant.

OALJ Case No. 2017-OFC-00006

OFCCP No. R00192699

**DECLARATION OF JONATHAN RIDDELL IN SUPPORT OF DEFENDANT ORACLE AMERICA, INC.'S MOTION TO SEAL PORTIONS OF THE EVIDENCE SUBMITTED IN SUPPORT OF OFCCP'S OPPOSITION TO ORACLE'S MOTION FOR PROTECTIVE ORDER**

**EXHIBITS VOLUME 1 OF 2**

# DECLARATION OF RIDDELL ISO MOTION TO SEAL

# EXHIBIT A

**EXHIBIT A**

**EXHIBIT A**

**Analysis of Gender and Racial Differences in Compensation At Oracle, 2013-2018**

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**Econsult Corporation**

**July 19, 2019**

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## INTRODUCTION

The Office of Federal Contract Compliance Programs, U.S. Department of Labor ("OFCCP") has retained me as an expert labor economist and statistician in *OFCCP v. Oracle America, Inc.* They have asked me to provide economic and statistical analyses and opinions regarding the allegations raised in the OFCCP complaint. OFCCP has asked me to analyze whether there are gender differences in compensation in the Product Development, Information Technology, and Support job functions at Oracle America ("Oracle") at its headquarters in Redwood Shores, California for the 2013-2018 period. They have asked me to analyze whether there are racial differences in compensation in the Product Development job function, at the same location for the same period. They have also asked me to analyze the relationship of Oracle's decisions on job assignment and compensation at hire on any subsequent gender and racial compensation differentials. Finally, they asked me to estimate the economic damages incurred by women, Asian, and African American employees as of the result of gender or racial differentials in compensation.

I am a labor economist with extensive experience in the analysis of labor markets and, in particular, gender and racial differentials in labor markets. I was tenured as Professor of Regional Science, Sociology, and Real Estate at the University of Pennsylvania ("Penn"). I came to the Wharton School at Penn in 1972 after completing an M.A. and Ph.D. in economics at Duke University, following the completion of a B.A. in economics and mathematics at the University of Denver in 1969. I teach courses dealing with economics, labor markets, and the relevant statistical methodologies for both graduate and undergraduate students at Penn. I have published my research dealing with the effects of age, race, gender, and urban location on labor market outcomes and metropolitan variations in income distribution in the most prestigious economics journals. I have written five books: The Economics of Sex Discrimination (1972, reprinted 1975); Post-Industrial Philadelphia (1990); Work, Wages, and Poverty (1991); Changes in Income and Inequality within U.S. Metropolitan Areas (2000); and Mommies and Daddies on the Fast Track: Success of Parents in Demanding Professions (2004). My research has been peer reviewed and competitively funded by a variety of government agencies and private foundations, including the National Science Foundation and the National Institute of Mental Health.

My scholarly work has concentrated on the labor market for workers in science and technology. I chaired the National Research Council's Committee on Assessing the Portfolio of the Science Resources Studies Division of the National Science Foundation, resulting in the publication of a National Academy Press book, *Measuring the Science and Engineering Enterprise: Priorities of the Division of Science Resources Studies.* I also served on the National Academy of Sciences Oversight Committee for the Career Planning Center for Beginning Scientists and Engineers.

In recognition of my career research contributions, my colleagues from around the world elected me a Fellow of the Regional Science Association International in 2009 and awarded me the David E. Boyce prize for leadership in the field of regional science in 2010. I have lectured, and trained federal judges, at the Federal Judicial Center on the use of statistics in discrimination litigation. More recently, I served on the National Research Council's Committee on Measuring and Collecting Pay Information from U.S. Employers by Gender, Race and National Origin.

I am also a senior consultant with Econsult Corporation. As a consultant at Econsult, both plaintiffs and defendants have retained me as an expert in discrimination litigation involving ethnicity, race, age, and gender. I have testified as an expert witness on labor economics and statistics in more than 45 cases in federal and state courts. These cases have involved complex statistical analyses involving thousands of employees, including the settled racial discrimination allegations against The Coca-Cola Company, the Federal Deposit Insurance Company, the Eastman Kodak Company, and Merrill Lynch, as well as the gender discrimination allegations against Salomon Smith Barney, Merrill Lynch, Wet Seal, and Livermore Labs. I have reviewed and analyzed numerous computerized employee databases in the course of my work. My more detailed credentials are listed in my curriculum vitae, included as Attachment A.

This report contains the results of my study of racial and gender differences in compensation at Oracle headquarters from January 1, 2013 through December 31, 2018. The principal results of my analyses are:

- Women earn on average about 18% to 24% less than do men of comparable age, education, and seniority at Oracle. About three-quarters of this disparity arises from job assignment differences by gender for employees with comparable age, education, and seniority. Women earn significantly less than do men of comparable characteristics even when in the same jobs.

- Women's base pay rates averaged 13% less than the averages for men of comparable age, education, and seniority.

- Women received between 6 and 12 thousand fewer stock award units each year than did men of comparable age, education, and seniority.

- The global career level and the pay set for their starting jobs at Oracle account for about half of the gender disparity in pay for women. The subsequent disadvantage experienced by women in moving up from their global career levels also account for a large share of their current pay disparities.

- Oracle would have paid between $82 million and $275 million additional compensation to women if they had been paid equivalently to comparable male employees.

- Asian employees earn approximately 12% to 18% less than do white employees of comparable age, education, and seniority at Oracle. About sixty percent of this disparity arises from job assignment differences by race for employees with comparable age, education, and seniority. Asian employees earn significantly less than do white employees of comparable characteristics even when in the same jobs.

- The base pay rates of Asian employees averaged about 7% less than the averages for white employees of comparable age, education, and seniority.

- Asian employees received an average of between 2,500 and 10,500 fewer stock award units each year than did white employees of comparable age, education, and seniority.

- Oracle would have paid between $215 million and $514 million additional compensation to Asian employees if they had been paid equivalently to comparable white employees.

- The global career level and the pay set for the starting job at Oracle account for most of the racial disparity in pay for Asian employees.

- African American employees earn between 14 and 40% less than do white employees of comparable age, education, and seniority at Oracle. Over three-quarters of this disparity arises from job assignment differences by race for employees with comparable age, education, and seniority.

- The base pay rates of African American employees averaged between approximately 16% and 21% less than the averages for white employees with comparable age, education, and seniority.

- African American employees received an average of between 12,000 and 29,000 fewer stock award units each year than did white employees of comparable age, education, and seniority.

- Oracle would have paid between $1.6 thousand and $8.3 million additional compensation to African American employees if they had been paid equivalently to comparable white employees.

- For employees who came to Oracle from other jobs, race and gender differentials in pay between 2013 and 2018 reflect the race and gender differentials in their starting pay, which are highly correlated with their pay at their prior jobs.

The remainder of this report provides the bases for these conclusions. The next section discusses the conceptual basis, the statistical approaches and the results of the compensation analyses. The third section discusses the assumptions made in the analyses, focusing on the differences in assumptions for analyses of individual versus group differentials in pay. The fourth section analyzes the role of Oracle's assignments of jobs and salaries at hire on gender and racial differentials between 2013 and 2018. The fifth section discusses the conceptual bases and the computational approaches for determining the damages incurred by women, Asian, and African American employees from the racial and gender differentials in Oracle's compensation practices. The section finishes with the computation of damages.

## EVALUATING GENDER AND RACIAL DIFFERENCES IN COMPENSATION

### Compensation and Human Capital Theory

Economists expect that individual compensation will vary with the productivity of individual employees. Productivity of employees is not directly observed, however, and is difficult to measure. For that reason, economists generally focus upon the characteristics that make one employee more or less productive than another, rather than upon productivity itself. Human capital theory is a widely accepted analysis of the determinants of productivity differences, and therefore compensation differences, among individuals. The theory focuses upon the investments that individuals make that increase their skills and thus make them more productive. The following factors are particularly important:

(1) Experience, measured by tenure with an employer and age, to reflect experience at other employers; and

(2) Education.

Therefore, human capital theory leads us to some common sense conclusions. If one individual has more education, or more job experience, he or she is more likely to be entitled to higher compensation.

To quantify gender or racial differences, it is necessary to control for any *systematic* differences between men as a group and women as a group or between racial groups in their qualifications (that are the result of employee – as opposed to Oracle – actions) at the time of hire. There are, then, two important elements of employee qualifications that determine whether they should be included in the analysis of Oracle's compensation decisions: (1) the qualifications differentials are systematic by gender or race *after* the inclusion of other included credentials; and (2) the qualifications differentials are the results of decisions made by employees, not by Oracle.

I study compensation practices at Oracle in order to determine the extent to which an employee's gender or race affects outcomes. Therefore, it is *only* necessary that the analyses compare equivalently qualified *groups* of women employees and men employees, or of Asian employees and white employees or of African American employees and white employees. Any qualifications that affect compensation that are possessed by equivalent proportions, or in equal intensity, by both gender or racial groups *after* controlling for any qualification differences already included in the model or analysis, cannot affect the size of the gender or racial disparities and, therefore, cannot affect the true level of gender or racial disparity in compensation practices.

My analyses are not designed to set individual employee compensation. A statistical analysis designed to set individual compensation is fundamentally different from an analysis designed to determine differences in compensation across groups of employees (such as men and women, or Asian and white employees, or African American and white employees). In fact, adding qualifications that do not differ between the genders or races (even though they do differ among employees within each gender or race) to the analyses may render them less precise[1] and

[1] Precision refers to the ability of the analysis to make correct decisions, that is, to uncover discrimination when it exists.

more likely to lead to erroneous conclusions among employees within each gender or race) to the analyses may render them less precise[2] and more likely to lead to erroneous conclusions.

The effects of any gender or racial differences in qualifications of employees that arise from Oracle's previous or current job assignments (as opposed to the credentials and abilities that employees possessed when they started at Oracle) are part of Oracle's actions that potentially create gender and racial disparities in compensation.

Compensation differences that cannot be explained by differences in credentials that employees bring to Oracle are suspect if they are also associated with gender or race. After appropriately taking account of productivity, economists generally attribute such differences to discrimination.

I examine whether there is any difference in compensation by gender or race, after adjusting for potential racial differences in qualifications (i.e., experience and education). In order to investigate whether gender or racial differences in specific characteristics of employees may account for gender or racial differences in compensation, I compare the estimated gender or racial differentials in compensation based on a regression analysis that includes those specific characteristics with the estimated gender or racial differentials based on another regression analysis that does not include the specific characteristics. If the gender or racial differentials are the same for both analyses (those with and those without controls for the specific characteristics), then there are no gender or racial differences in the distributions of those characteristics among employees that are relevant to compensation. If the measured gender differential in compensation is smaller in analyses without controls for the specific characteristics than in those

[2] Precision refers to the ability of the analysis to make correct decisions, that is, to uncover discrimination when it exists.

with such controls, then the distributions of the specific characteristics are relevant to compensation and render women more qualified for higher compensation than men. Similarly, if the measured racial differential in compensation is smaller in analyses without controls for the specific characteristics than in those with such controls, then the distributions of the specific characteristics that are relevant to compensation render Asian employees (or African American employees) more qualified for higher compensation than white employees.

When measuring discrimination statistically, it is also important to consider the potential effects of any employment discrimination on any employee characteristics used as controls in the statistical analyses. Clearly, the characteristics which employees have determined and Oracle does not determine—such as race, ethnicity, gender, age, time at Oracle, and education—and which are also well known to affect compensation, are appropriate to use as controls in the analysis of compensation discrimination. Such characteristics are "exogenous" as they are not determined by Oracle's policies or decisions about individual employees. The preferred analyses of discrimination are those that measure the extent of discrimination using only exogenous employee characteristics as controls in the analyses.

The values of other characteristics that influence compensation—such as job and management responsibilities, or global career level—are set by Oracle in evaluating individual employees and the values of such characteristics are likely to be affected if there were discrimination. Such characteristics are "endogenous" as they are determined by Oracle's policies or decisions about individual employees. Endogenous characteristics cannot be used in any analyses of whether discrimination has occurred. Endogenous characteristics may be included in an analysis of discrimination, however, in order to assess the mechanisms by which discriminatory compensation occurs.

## Statistical Methods

I examine whether there is any difference in compensation by gender, after adjusting for potential gender differences in employee characteristics in Oracle's Product Development, Information Technology, and Support job functions. I examine whether there is any difference in compensation by race, after adjusting for potential racial differences in employee characteristics in Oracle's Product Development job function. To evaluate whether there are disparities consistent with gender or racial discrimination in compensation, I use regression analysis of Oracle's compensation records for individuals in each year. These records include measures of compensation, gender, race, ethnicity, and the skills and experience of each employee. They also include many measures of job placement.

A regression analysis evaluates the difference in pay by gender or race, after adjusting for possible differences in characteristics by gender or race that could account for the pay differences. For example, if I simply compare all Asian employees in 2016 to all white employees in Product Development, I find that Asians are paid approximately 23.6% less. It could be that Oracle places Asian employees in jobs that pay less, or that Oracle places Asian and white employees with similar skills in similar jobs but pays Asian employees less, or that Asian employees are paid less because they have less productivity (i.e., education or experience). To compare comparable Asian and white employees, it is necessary to adjust for any productivity differences that could explain compensation differences by race.

Regression analysis is the widely accepted method for analyzing the effect of one employee characteristic, such as gender or race, when skills, as measured by education and experience, are the same. My analysis uses the data provided by Oracle to evaluate whether characteristics, such as experience or education, or job placement differences by gender or race account for any differences in pay by gender or race. If there are pay differences by gender or race after controlling for any gender or racial differences in characteristics that "legitimately" affect compensation, then the results are consistent with compensation discrimination.

The regression analysis technique I employ, ordinary least squares, is commonly used by economists to measure the impact of explanatory (or independent) variables such as race or gender and other employee characteristics, such as education and experience, on a dependent variable such as compensation. In general, the regression coefficient for a particular explanatory variable measures the effect of that variable (i.e., race or gender) on the dependent variable (compensation) after adjusting (or controlling) for the effect of the other independent variables (i.e., experience and education) included in the regression equation. When a characteristic is "controlled," the statistical analysis is effectively comparing outcomes by race or gender for employees that are equal or equivalent with respect to the characteristic. For example, when work experience and education are "controlled," the statistical analysis is comparing the average difference in compensation by race (or gender) for employees who have the same level of education, have been employed at Oracle for the same length of time, and have been in the labor force for the same length of time.

In addition to providing an estimate of the size of gender or racial pay differences for comparable workers, ordinary least squares regression analysis also provides an estimate of the likelihood that the pay differential could have occurred by chance due to random variations in the data. These evaluations of the effect of random variation are referred to as statistical significance. Standard deviations are a widely used statistical metric of the likelihood that the estimated differences are the result of true differences, as opposed to random variation. The larger the absolute number of standard deviations for an estimated difference, the less likely that the difference is due to chance and the more likely it is due to a true systematic difference. For a regression estimate that is 1.96 standard deviations, the likelihood of getting that estimate if the true value or true effect of the characteristic is zero is 5%, or 0.05. Many statistical analyses label a regression estimate that is two standard deviations or greater (that is, the likelihood it could have occurred by chance is 0.05 or less) as "statistically significant." Estimates with standard deviations greater than 1.96 are less likely than 0.05 to have occurred by chance.

There are several ways to measure compensation, including Medicare-taxed compensation ("Medicare compensation") as reported to the Internal Revenue Service (IRS), base pay, bonuses, and stock awards. I use all of these measures in my analyses. Medicare compensation is the most comprehensive measure in the database as it includes bonuses, realized stock award payments, and pension contributions (but not medical insurance and other fringe benefits). Because Medicare compensation varies with weeks worked by an employee, the analyses must control for this characteristic. Base pay is the annual rate of pay assigned to each employee. Because this is the rate of pay, there is no need to adjust it for leaves of absence or work hours. Base pay does not include total compensation, however, because it does not include fringe benefits, bonuses, or stock awards. Between 2013 and 2018, Oracle awarded bonuses in [redacted]. Because many employees [redacted] a slightly different (from ordinary least squares) regression analysis, known as Tobit, is required to analyze gender and racial differentials.[3] I discuss these analyses and results below.

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[3] Numerous research articles have discussed the Tobit regression technique, following the original publication of the approach by Nobel Laureate James Tobin in 1958, "Estimation of Relationships for Limited Dependent Variables," *Econometrica* **26** (1): 24–36. For example, see Takeshi Amemiya's 1984 review, "Tobit Models: A Survey," *Journal of Econometrics* **24** (1–2): 3–61, or the econometric textbooks, Peter Kennedy's *A Guide to Econometrics* (Fifth ed.). Cambridge: MIT Press, and William H. Greene's *Econometric Analysis*. Upper Saddle River, NJ: Prentice Hall.

## Results

The (a), (b), and (c) panels of Table 1 are summaries of the analyses of measures of the effect of gender on Medicare compensation at Oracle for Product Development, Information Technology, and Support job functions between 2013 and 2018. The (a), (b), and (c) panels of Tables 2 and the (a) panel of Table 3 are summaries of the analyses of measures of the effect of race on Medicare compensation at Oracle for the Product Development job function between 2013 and 2018. Subsequent panels of these Tables are summaries of the analyses of measures of the effect of gender or race on base pay rates, and stock awards at Oracle for the same sets of jobs between 2013 and 2018.

Each table reflects measures of the gender or race pay gap as additional characteristics or controls are added to the analyses, that is, as employees who are the same with respect to the characteristics listed are compared. In these analyses, the regression coefficients for gender or race indicate the approximate percentage effects of gender or race on annual compensation, after adjusting (or controlling) for the effect of the other independent variables included in the regression equation. The next subsection reports the gender differentials; the subsequent subsection reports the race differentials for Asian employees relative to white employees; the final subsection reports the race differentials for African American employees relative to white employees.

### Gender Compensation Differentials

Table 1 includes several panels of results. The panels include different measures of pay and different groupings of employees to measure differentials. The consistency of results across the panels show that the results are not sensitive to variations in pay measures used, characteristics controlled, or differences in quality of data.[4]

### *Basic analysis*

Panel (a) of Table 1 includes all workers employed the full year who are in jobs included in the class at the end of the year.[5] Each row reflects the results for workers in the year indicated, from 2013 through 2018. I report the number of employees and the proportion of employees who are women.[6] The first column reports the gender percentage differential in Medicare compensation for each year for full year employees, with no additional controls. Women receive Medicare compensation approximately 19 to 24% less each year than men employed in the Product Development, Information Technology and Support job functions at Oracle.[7]

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[4] There were two years between 2013 and 2018 when Oracle awarded a substantial number of bonuses to employees in the Product Development, Information Technology, and Support job functions at its headquarters These were 2014 and 2018. I analyze bonus differences by gender using the same approaches as described below for stock awards. I found statistically significant lower bonuses for women in 2014 after controlling for race, ethnicity, age, education, time at Oracle, job descriptor and performance evaluation. When global career level was added, however, there were no gender differences in bonuses. For 2018, there were no gender differences in bonuses.

[5] Full year workers include all full time workers hired before the start of the year who did not terminate before the end of the year and took no leaves during the year. Medicare compensation of full year workers needs no adjustments for partial year employment.

[6] As the number of employees analyzed increases, the precision of the estimated differentials increase. Similarly, as the proportion of women increases, the precision of the estimated gender differentials in compensation increase. When precision increases, the estimate of any "true" differential has a greater number of standard deviations. Standard deviations are greater for data sets in which the differential is greater and the number of observations is constant, or when the number of observations is greater and the differential is constant.

[7] Since the dependent variable is the natural logarithm of annual Medicare compensation, each regression coefficient is customarily interpreted as the approximate percentage effect of the dependent variable of a unit change in the independent variable. However, the regression coefficient is only an approximate percentage. To get the exact percentage p, one must compute $p = e^{ß}-1$ where *ß* is the coefficient. For example, the coefficient of -0.199 yields an exact effect of -0.180, $e^{-0\ 199}-1 = -0.180$

The next step is to determine whether there are non-discriminatory bases for these gender differentials in compensation. The remaining columns in the table analyze the effects of adding various characteristics or "controls." As discussed above, the changes in the measured gender differentials in compensation, as controls or characteristics considered vary, allow me to assess whether gender differences in these controls account for, or explain, the gender differential in compensation.

The second column of Table 1(a) adds controls for race and ethnicity (measured by whether the employee is white, Asian, African American, or Hispanic). Effectively, the second column shows the differential by gender if the distributions by race and ethnicity among men and women were equivalent. The gender differential in compensation for each year in column 2 is between 17 and 24%. About one percentage point of the gender differential in compensation is associated with the greater white representation among male employees (white employees are paid more compensation than other racial and ethnic groups). Nonetheless, these differences are equivalent to those in column 1, indicating that variations by gender in race and ethnicity do not account for the gender differentials in compensation.

The third column adds controls for age (measured by years of age and the square of years of age[8] as an index of prior work experience) to the racial and ethnic controls. The third column, then, shows the differential by gender for persons of the same age within race and ethnic groups. The gender differentials in compensation for each year in column 3, which is between 17 and 23%, is substantively equivalent to the differential in columns 1 and 2, indicating that age

[8] The square of years of age is a technical correction that allows the effect of an additional year of age to vary with the age of the employee, so that an additional year of age can have a lesser effect for a 50 year old than for a 30 year old.

(reflecting prior work experience) differences by gender do not account for the gender differentials in compensation.

The fourth column adds education (measured by whether highest degree is at bachelors, masters, or doctorate levels, or unknown) to the racial, ethnic, and age controls. The fourth column, then, shows the differential by gender for persons of the same age and degree level within race and ethnic groups. The gender differentials in compensation for each year in column 4, which is between 18 and 24%, is substantively equivalent to the differentials in column 3, indicating that differences by gender in educational degrees do not account for the gender differentials in compensation.

The fifth column adds time or tenure at Oracle (measured by years employed and the square of years employed at Oracle) to the racial, ethnic, age, and education controls. The fifth column, then, shows the differential by gender for persons of the same age, degree level, and experience at Oracle within race and ethnic groups. The gender differentials in compensation for each year in column 5, which are between 18 and 24%, are substantively equivalent to the differentials in columns 3 and 4, indicating that differences by gender in time working at Oracle do not account for the gender differentials in compensation.

### *Adding endogenous characteristics*

The characteristics added as controls in columns 1 through 5 of Table 1(a) are all exogenous to Oracle, that is, none of the characteristics are affected by, or the result of, decisions made by Oracle. Gender differentials due to any of these characteristics are not the result of actions by Oracle. There are other characteristics of employees, however, that Oracle decides. Because these statistical analyses are designed to test or evaluate the gender neutrality of Oracle decisions, it is problematic to include characteristics that Oracle decides as explanatory of gender differentials in compensation. Characteristics that are determined, or influenced, by Oracle decisions are considered "endogenous," as opposed to the exogenous characteristics discussed so far. Columns 6, 7 and 8 of Table 1(a) evaluate the effects of endogenous characteristics on the gender differentials in compensation at Oracle.

The sixth column adds the current job descriptor (see Appendix A for the list of job descriptors and the corresponding job titles, based on those provided by Oracle for each employee) and exempt[9] status to the racial, ethnic, age, education, and time at Oracle controls. Oracle assigns the job title, which was the basis for the job descriptor, and exempt status to employees. The sixth column, then, shows the gender differentials in compensation for persons of the same age, degree level, experience at Oracle and in the same jobs within race and ethnic groups. The gender differentials in compensation for each year in column 6, which are between 13 and 19%, are about four to six percentage points (or 25% of the overall gap) lower than the differentials in columns 3, 4, and 5. These results show that gender differences in Oracle's job assignments are associated with some, but very far from all, of the gender differentials in compensation.

The seventh column adds a control for whether the job's global career level indicates management[10] to the racial, ethnic, age, education, time at Oracle and job controls. The column, then, shows the differential by gender for persons of the same age, degree level, experience at Oracle, job, and whether in management within race and ethnic groups. The gender differentials in compensation by year in column 7 are about three percentage points (or less than 20% of the

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9 The job classification is exempt from the Fair Labor Standards Act.

10 Global career level is an Oracle designation assigned to jobs that includes a letter and a number. The letter code of M is a management level. The number following the letter code increases with increases in responsibilities. When I control for management, as in column 7, I use the letter portion of the global career level. I code all global career level codes that begin with "M" as management.

overall gap) lower than those in column 6. These results show that Oracle's gender differences in assignments to management are associated with somewhat less than a fifth of the gender differentials in compensation.

The eighth column adds a control for the job's global career level to the racial, ethnic, age, education, time at Oracle, job, and whether the job is in management. The column, then, shows the differential by gender for persons of the same age, degree level, experience at Oracle, job, and global career level within race and ethnic groups. The gender differentials in compensation by year in column 8 are about ten percentage points (or almost 65% of the overall gap) lower than those in column 6. These results show that Oracle's gender differences in the assignment of global career levels are associated with most, but not all, of the gender differentials in compensation.

For all years and all columns of this panel, Table 1(a), the gender differentials in compensation are well over two standard deviations, regardless of which characteristics are used to define comparable groups.

### *Robustness of results*

The results in the first panel, Table 1(a), use data with some potential complications. Oracle provided no education data for more than half of the employees, forcing the grouping of these employees into an "unknown education" category for the analyses controlling for education.

In order to assess whether these missing data could account for the gender differentials in compensation, I repeat the analyses portrayed in the (a) panel of Table 1 using only those employees with education data, that is, I eliminate all employees with missing education data. To evaluate whether major areas of study and experience could account for the gender differentials in compensation, I assume for the sake of argument that job assignment at hire by Oracle represents only the subject areas of the employee's prior education and experience. This means that I assume that there were no gender differentials in the assignment of job at hire for employees with the same focus areas for their education and experience. I repeat the regression analyses using only those employees for whom I have a first job assignment at hire. I discuss these results in more detail below.

Table 1(b) repeats the analyses discussed above for Table 1(a), but uses only those employees for whom Oracle provided education data. Columns 1, 2 and 3 of this panel show that the gender differentials in compensation were about two to seven percentage points less for the employees for whom Oracle provided education data.[11] The difference arises because education was more likely to be missing for higher wage employees. Adding controls for education, time at Oracle, job descriptor, and career level, however, affect the gender differentials in compensation equivalently for those with reported educational attainment (i.e., compare Table 1(b) and for all employees (Table 1(a)). Specifically, adding controls for education and time at Oracle does not affect the size of the gender differentials in compensation. Adding controls for job descriptor reduces the gender pay gap and adding controls for global career level substantially reduces the gender gap.

Table 1(c) repeats the analyses discussed above for Tables 1(a) and 1(b), but uses only those employees for whom Oracle provided data on job at hire and who were hired into one of

[11] Because columns 1, 2 and 3 of Tables 1(a) and 1(b) measure pay differentials without controlling for education, these differentials do not come from any measurement errors in educational attainment by gender. The difference between the gender differentials reported in columns 1, 2 and 3 in Tables 1(a) and 1(b) are due to differences in the compensation levels for persons with, and without, educational data.

the six job descriptors. that include the largest number of hires.[12] Columns 1, 2, 3, 4 and 5 of this panel show gender differentials in compensation similar to those in Table 1(a) for all employees. As in Table 1(a), adding controls for age, education and time at Oracle has little effect on the size of the gender differentials in compensation. Column 6 adds the controls for job descriptors at hire. The sixth column, then, shows the differential by gender for persons of the same age, degree level, experience at Oracle and starting job within race and ethnic groups. The gender differentials in compensation by year in column 6 (between 16 and 23%) are three to four percentage points lower than the differentials in columns 3, 4, and 5. These changes in differentials indicate that gender differences in starting jobs at Oracle, if the changes were to represent differences in areas of study or experience, account for only a very small part of the gender differentials in compensation in later years.[13] If the effect of differences in starting jobs were due entirely to gender differences in educational and experience specialization areas prior to hire by Oracle, then this is an appropriate modification of the gender differentials in compensation. If this effect were the result of Oracle's gender discriminatory job assignment at hire, however, it should not decrease the estimate of gender differentials in compensation.

Column 7 shows the effects on the gender differentials in compensation of controlling for current job descriptor (as opposed to job descriptor at hire in column 6). The seventh column removes the job at Oracle hire but adds the current job (see Appendix A) to the racial, ethnic, age, education, and time at Oracle controls. The seventh column, then, shows the differential by

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12 These job descriptors are: APPS.DEVELOPER, PRODUCT MGMT/STRATEGY-PRODDEV, PROGRAMMER ANALYST-IT, QA-PRODDEV, SOFTWARE DEVELOPMENT, TECHNICAL ANALYST.

13 Because job at hire may reflect prior educational and job experience, these job controls may provide an index of educational and work experience areas. While information on major areas of study is available for most who have data on their educational attainment, it is not in a coded format. Similarly, areas of prior experience are not available in a coded or analyzable format. Alternatively, the job at hire could be different due to gender discrimination and not due to differences in areas of prior experience or education.

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gender for persons of the same age, degree level, experience at Oracle and current job within race and ethnic groups. The effects of adding controls for current job versus job at hire on the gender differential in compensation are equivalent, or very slightly increasing the differential. As in Table 1(a), adding controls for global career level in column 8, however, substantially decreases the absolute value of the gender differentials in compensation.

The ninth column adds back the job at hire to the racial, ethnic, age, education, time at Oracle, and the current job and global career level of current Oracle job. The ninth column, then, shows the differential by gender for persons of the same race, ethnicity, age, degree level, experience at Oracle, current job, global career level, and job at hire within race and ethnic groups. The gender differential in compensation for each year in column 9, which is between 4 and 7%, is substantively equivalent to the differentials in column 8, indicating that differences by gender in Oracle's hire job, or alternatively in area of prior education and experience, do not account for the gender differentials in compensation.

The gender gap in Medicare compensation at Oracle persists across a wide variety of groups of comparable employees. Regardless of the characteristics included to define comparable men and women employees, gender differentials in compensation remains statistically significant.

### *Base pay rate analyses*

I repeat all of the analyses from above replacing Medicare compensation with base pay rate as the dependent variable. These analyses of the gender differential in pay appear in Tables 1(d), 1(e), and 1(f). These analyses use a different measure of pay (base pay rate as opposed to Medicare compensation) and they use a slightly different approach to defining the employees included. For these analyses, I include all employees in each year who spent any portion of the year in a job included in the class definition. These analyses include employees who worked only part year in a position included in the class (due to transfers between jobs within Oracle, a new hire, or departure from Oracle during the year) as well as the full year employees who worked in a position included in the class at the end of the year. The analyses of Medicare compensation only included the latter group of employees.

Panel (d) of Table 1 includes all workers employed at any point in the year in a job included in the class definition.[14] Each row reflects the results of an analysis of gender differentials in base pay for the relevant job for workers in the year indicated, from 2013 through 2018. I report the number of employees and the proportion of employees who are women. The first column reports the approximate gender percentage differential in base pay rate for each year, with no additional controls. Oracle pays women at a rate about 14% lower than the rate for men employed in the Product Development, Information Technology, and Support job functions at Oracle. The gender differentials in base pay rates are less than in Medicare compensation.

The next steps proceed as for the Medicare compensation analyses to determine whether there are non-discriminatory bases for these base pay rate differentials. The remaining columns on the table analyze the various characteristics discussed above. The changes in the gender base pay rate differential with different controls allow us to assess whether gender differences in these controls, or characteristics, account for, or explain, the gender differential in the base pay rate. The second column of Table 1(d) adds controls for race and ethnicity; the third column adds controls for age to the racial and ethnic controls; the fourth column adds education; and the fifth column adds time or tenure at Oracle (measured by years employed at Oracle) to the racial, ethnic, age, and education controls. Adding race decreases the gender base pay gap by about one

[14] For these employees, I use the base pay rate listed for the last job in the class held during the year as the dependent variable.

percentage point and the remaining characteristics have no effect on the size of the gender pay gap.

As for the Medicare compensation analyses, I also consider the effects of the endogenous characteristics controlled by Oracle. The sixth column adds the current job descriptor and exempt status to the racial, ethnic, age, education, and time at Oracle controls. The seventh column adds a control for whether the current job is in management to the racial, ethnic, age, education, time at Oracle, exempt status, and job descriptor controls. The eighth column adds the current job's global career level to the racial, ethnic, age, education, time at Oracle, and job controls. As found in the analyses of gender differentials in Medicare compensation, the gender differential in base pay rate for each year in column 6 is about 25% less than the differentials in columns 2 through 5. The eighth column adds global job career level. The gender differentials in base pay in column 8 are about 60% less than in column 6, indicating that Oracle's gender differences in the assignment of global career levels contribute to a substantial part, but not all, of the gender base pay differential.

For all years and all columns of this panel, Table 1(d), the gender base pay rate differential is well over two standard deviations, regardless of how comparable groups are defined in computing the gender differentials. Following the approach used for the analyses of Medicare compensation, Table 1(e) repeats the same analyses of base pay rates excluding those with no education data and Table 1(f) adds controls for jobs assigned at hire. These last two panels yield similar patterns of results, indicating that missing education data, area of education or experience, and data irregularities do not account for the gender differential in base pay rates.

### *Stock Awards*

Table 1(g) parallels the analyses shown in Table 1(a) and in Table 1(d), but uses the number of stocks awarded, rather than Medicare compensation or base pay rate, as the dependent variable in the regression analyses. Starting in 2014, Oracle offered employees receiving stock awards three formats or alternatives for payment. Oracle offered employees stock options, restricted stocks, or a combination of both. For the period of 2014 through 2018, Oracle valued a stock option at one-fourth of a unit of restricted stock. For example, an employee offered 100 stock units could choose to receive 100 stock options or 25 units of restricted stock, in lieu of options. The employee could also choose a combination of these alternatives, receiving, for example, 50 stock options and 12.5 (rounded down to 12) units of restricted stock. Regardless of the choices made between units of restricted stock or stock options, Oracle paid the award out over four years, requiring that the employee stay at Oracle for four years to receive all of this compensation.

For the analysis reported in Table 1(g), I standardize the value of the stock award, regardless of the format actually chosen by the employee, to restricted stock unit equivalents, using Oracle's conversion ratio of four stock options equal one unit of restricted stock.

Because many employees receive [redacted] in a given year, the distribution of [redacted] [redacted] Medicare compensation and base pay rate. All employees receive compensation [redacted] in Medicare compensation or in base pay rate. There is a continuum of payment levels across employees for both Medicare compensation and base pay rates, with no large concentrations of employees at outlying values. That is [redacted] Many employees [redacted]. The analyses of racial or gender differences must consider both differences in the likelihood of [redacted] and in the size of the [redacted]. The regression technique that appropriately controls for these distributional characteristics of [redacted] is a "Tobit." I use a Tobit regression analysis of [redacted], but otherwise follow the same approaches as used in Tables 1(a) through (f). These results appear in Table 1(g).

Table 1(g) analyzes all employees in the class, as did Tables 1(a) and 1(d), using a Tobit regression to yield consistent estimates of the gender differential when there are concentrations of employees [redacted] [redacted] The first column indicates that women averaged 6,231 fewer stock unit awards in 2013 and between 7,954 and 11,980 fewer for the remaining years. The difference is statistically significant at between 2.33 and 8.86 standard deviations in each year. As with the Medicare compensation and base pay rate analyses, the next step is to determine whether there are non-discriminatory bases for this gender differential. Adding controls for race or ethnicity, age, education, and time at Oracle do not substantively change women's disadvantage in stock awards.

When I add job descriptors to the analyses, the disadvantage of women decreases by about 40% in every year but for 2013. The gender disadvantage remains statistically significant for all years but 2018.

Columns 7 and 8 add the endogenous job characteristics (that is, characteristics set by Oracle) of performance evaluations (column 7) and global career level (column 8) to the evaluation of gender differentials in stock awards. When we compare men and women with equivalent performance evaluations, women's disadvantage decreases by between 7 and 26% (comparing gender coefficients in columns 7 and 6). The gender disadvantage remains statistically significant for all years but 2018.

When we further restrict the comparisons to men and women with the same global career level (column 8), however, the average disadvantage decreases by another 69 to 80% and none of the years show a disadvantage of greater than two standard deviations. The gender disparity in stock awards is largely due to the gender disparity in global career level, followed by differences in performance evaluations, for employees who are otherwise the same in education, experience, and job descriptors.

### *Summary*

While the absolute size of gender differentials in compensation is smaller with base pay than with Medicare compensation (which includes bonuses and realized stock awards), the patterns are the same. The only controls that decrease the size of the gap are the endogenous controls, those that reflect Oracle's decisions and assignments, specifically job assigned at hire, currently assigned job and global career level of current job. The gender pay gap is statistically significant for all years, regardless of controls used to define comparison groups and of the pay measure analyzed (base pay versus Medicare compensation). Gender differentials in stock awards are also statistically significant for all years, unless I also control for Oracle's assignment of global career level.

## Asian-White Compensation Differentials

Table 2, like Table 1, includes several panels of results of comparable approaches analyzing the compensation gap between Asian and white employees of Oracle. Consistent with the class definitions, however, the only employees included are in the Product Development job function.[15] As in Table 1, the panels include different measures of pay and different groupings of employees to create alternate measures of race differentials. The consistency of results across the panels shows that the results are not sensitive to variations in pay measures used, characteristics controlled, or differences in quality of data.

*Basic Analysis*

The first panel (a) of Table 2 includes all Asian and white workers employed the full year who are in Product Development at the end of the year. This parallels the approach used for analyses of gender differentials in Table 1(a). Each row reflects the results for workers in the year indicated, from 2013 through 2018. I report the total number of white and Asian employees and the proportion of white and Asian employees who are Asian. The first column reports the Asian percentage differential in Medicare compensation for each year for full year employees, with no additional controls. Asian employees receive 22 to 30% less Medicare compensation each year than white employees in the Product Development job function at Oracle.

The next step is to determine whether there are non-discriminatory bases for these racial pay differentials. The remaining columns in the table use various characteristics to delineate comparable racial groupings. The changes in the Asian-white pay differential with different controls allow us to assess whether racial differences in these controls, or characteristics, account for, or explain, the Asian-white pay differential.

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[15] As described above, there were two years between 2013 and 2018 when Oracle awarded a substantial number of bonuses to employees in the Product Development job function at its headquarters These were 2014 and 2018. I analyzed bonus differences between Asian and white employees using the same approaches as described below for stock awards. I found no statistically significant bonuses differentials in 2014. For 2018, there were statistically significant differences in bonuses averaging about [redacted] after controlling for gender, age, education, time at Oracle, job descriptor, performance evaluation, and global career level. When I remove the two white employees who received bonuses in excess of [redacted] the Asian-white differential dropped by half and became statistically insignificant.

The second column of Table 2(a) adds a control for gender. Effectively, the second column shows the Asian pay differential if Asian employees as a group and white employees as a group had the same representation of women and men. The Asian pay differential for each year in column 2 is between 21 and 28%, Between one and two percentage points of the racial pay differential is associated with Asian employees having a greater representation of women (who are paid less than men, see Table 1). Nonetheless, these differences (or race coefficients) are similar to those in column 1, indicating that gender differences by race do not account for the racial differential in compensation.

The third column adds controls for age to the gender control. The third column, then, shows the Asian pay differential for persons of the same age and gender. The Asian pay differential for each year in column 3, which is between 12 and 18%, is around ten percentage points less in absolute value than the differential in columns 1 and 2, indicating that age differences between Asian and white employees account for almost half of the Asian pay differential. Asian employees, as a group, are younger than are white employees, as a group.[16]

The fourth column adds education to the gender and age controls. The fourth column, then, shows the Asian employees pay differentials with white employees for those with the same gender, age and degree levels. The Asian pay differentials by year in column 4, which are between 12 and 19%, are equivalent to the differentials in column 3, indicating that variations by race in education do not account for the Asian pay differential.

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[16] Age has a significant effect on individual compensation. Age, however, does not affect the gender differentials in compensation (Table 1) because men and women are of comparable age. The fact that age affects individual compensation differences does not mean it affects group differences. In the case of gender, although age affects individual differences in compensation, it does not affect differences by gender groupings. Because the average age of Asian employees is less than for white employees, age controls affect estimates of pay differences for Asian versus white groupings.

The fifth column adds time or tenure at Oracle to the gender, age, and education controls. The fifth column, then, shows the Asian pay differential for employees of the same gender, age, degree level, and experience at Oracle. The Asian pay differential for each year in column 5, which is between 12 and 18%, is equivalent to the differentials in columns 3 and 4, indicating that variations by race in time working at Oracle do not account for the Asian pay differential.

### *Adding endogenous characteristics*

As in Table 1(a), the characteristics added as controls in columns 1 through 5 of Table 2(a) are all exogenous to Oracle, that is, none of the characteristics are affected by, or the result of, decisions made by Oracle. Asian pay differentials due to any of these characteristics are not the result of actions by Oracle. Because the purpose of the analysis is to test the racial neutrality of Oracle decisions, it is problematic to include characteristics determined by Oracle decisions as explanatory of Asian pay differentials. Economists consider characteristics determined, or influenced, by Oracle decisions "endogenous," as opposed to the exogenous characteristics discussed so far. Columns 6 and 7 of Table 2(a) evaluate the effects of endogenous characteristics on the Asian-white pay differential at Oracle.

The sixth column adds the current job descriptor (Appendix A) and exempt status to the gender, age, education, and time at Oracle controls. Oracle assigns job descriptors and exempt status to employees. The sixth column, then, shows the Asian-white pay differential for persons of the same gender, age, degree level, experience at Oracle and job as assigned by Oracle. The Asian-white pay differential for each year in column 6, which is between 10 and 18%, is slightly less but substantively equivalent to the differential in column 5, indicating that racial differences in Oracle's job assignments do not account for the Asian pay differential. Regardless of whether these assignments represent the areas of education and experience of the hires or more arbitrary decisions by Oracle, they do not affect the compensation of Asian employees as a group versus white employees as a group.

The seventh column adds a control for whether the job's global career level indicates management to the gender, age, education, time at Oracle and job descriptor controls. The column, then, shows the differential by race for persons of the same gender, age, degree level, experience at Oracle, job, and whether in management within race and ethnic groups. The racial differentials in compensation by year in column 7 are substantively equivalent to those in column 6, although they are somewhat larger for the 2016 through 2018 period. These results show that Oracle's racial differences in assignments to management responsibilities are not associated with racial differentials in compensation.

The eighth column adds the current job's global career level to the gender, age, education, time at Oracle and job controls. The eighth column, then, shows the Asian-white pay differential for employees of the same gender, age, degree level, experience at Oracle, job, and global career level. The Asian pay differential for each year in column 8, which is about 6 to 10 percentage points lower (or 53 to 67% of the total differential) than those in column 6, indicates that Oracle's Asian-white variations in job global career level assignments are associated with more than half, but not all, of the racial differentials in compensation. The Asian-white pay differential remains at statistically significant levels for all years, even after controlling for the Oracle determined global career level.

For each year and column, Table 2(a) shows that the Asian-white pay differential is well over two standard deviations, regardless of how comparable groups are defined in computing the Asian-white pay differentials.

### *Robustness of results*

In order to assess whether the missing data issues discussed above for measuring gender differentials in compensation could account for the Asian-white pay differentials, I conduct the same robustness tests on the data as described above for the analysis of gender pay differentials. I repeat the analyses portrayed in the first panel of Table 2 using only those employees with education data, that is, I eliminate all employees with missing education data. To evaluate whether major area of study or of prior work experience could account for the Asian-white pay differential, I assume, again for the sake of argument, that Oracle's initial job assignments represent the subject areas of prior education and experience. I also repeat the analyses using only those employees for whom I have a first job assignment and controlling for that job. I discuss these results in more detail below.

Table 2(b) repeats the analyses discussed above for Table 2(a), but uses only those employees for whom Oracle provided education data. Columns 1, 2 and 3 of this panel show that the Asian-white pay differentials are equivalent to those for the employees for whom Oracle provided education data. Furthermore, the patterns of how adding controls for gender, age, time at Oracle, job descriptor, and global career level affect the measure of the Asian-white pay differential are equivalent to those found with an analysis including only those with reported educational attainment. Adding controls for time at Oracle and job descriptor do not affect the size of the Asian-white pay differential, while adding age (column 3) reduces the differential. Unlike Table 2(a), adding controls for education using only those with education data, results in a larger Asian pay disadvantage (between 0.5 and 2 percentage points or an increase of between 4 and 12 percent). Adding controls for global career level substantially reduces the Asian-white pay differential, as it did in the analysis of all employees in Table 2(a). The analyses of persons with education data in Table 2(b) show that the inclusion of those employees missing education data is not biasing the results towards finding a disadvantage for Asian employees, as found in Table 2(a).

Table 2(c) repeats the analyses performed in Tables 2(a) and 2(b), but uses only those employees with Oracle-provided data on job categories at hire, who were hired into the six jobs with the most hires (as was the case for Table 1(c) in the gender pay differential analysis described above). Columns 1, 2, 3, 4 and 5 of this panel show Asian-white pay differentials similar to those in Table 2(a) for all employees. As in Table 2(a), adding controls for education does not affect the size of the Asian-white pay differential, but adding age decreases the absolute size of the differential. Adding time at Oracle slightly increases the Asian disadvantage in Table 2(c), more than was the case for Table 2(a). Column 6 adds a control for job descriptor at hire. The sixth column, then, shows the differential between Asian and white employees of the same gender, age, degree level, experience at Oracle and starting job descriptor. The approximate Asian-white pay differential for each year in column 6, which is between 11 and 18%, is about two to three percentage points lower in absolute values than the differentials in column 5. While differences in starting jobs between Asian and white employees of the same education, age, and experience at Oracle do not account for most of the Asian-white pay differential, they do contribute to it. If this effect were to reflect Asian-white differences in the educational and experience areas of specialization prior to hire by Oracle, then this is an appropriate modification of the Asian-white pay differential, but if this effect were the result of Oracle's discriminatory job assignment at hire, then it should not decrease the Asian-white pay differential.

Column 7 shows the effects on the Asian-white pay differential of controlling for current job descriptor (as opposed to job descriptor at hire in column 6). The seventh column removes the job at Oracle hire but adds the current job (measured by the same categories) to the gender, age, education, and time at Oracle controls. The seventh column, then, shows the pay differential for Asian and white employees of the same gender, age, degree level, experience at Oracle, current job descriptor and exempt status. The Asian-white pay differential effects of adding controls for current job versus job at hire are equivalent (compare columns 6 and 7). The pay disadvantage for Asian employees is only somewhat less in current job, as opposed to job at hire, for 2018.

As in Table 2(a), column 8 shows that adding controls for global career level, however, substantially decreases the absolute value of the Asian-white pay differential. The pay differential decreases in absolute value by between 5 and 9 percentage points, or about 45 to 65%. These results show, as was shown above, that Oracle's racial differences in assigning current global career level account for a substantial part, but not all, of the racial pay differential. The pay differential for Asian employees in column 8 is statistically significant for each year.

The ninth column adds back the job at hire descriptor to the gender, age, education, time at Oracle, and job descriptor and global career level of current Oracle job controls. The ninth column, then, shows the approximate Asian-white pay differential for employees of the same gender, age, degree level, experience at Oracle, current job, current global career level, and job descriptor at hire. The Asian-white pay differential for each year in column 9, which is between 3.8 and 8.4%, is substantively equivalent to the differentials in column 8, indicating that differences between white and Asian employees in Oracle job descriptor at hire do not account for the current Asian-white pay differential, once current job assignment is controlled.[17]

[17] The current job descriptor and global career level may still have been determined, however, by the job descriptor and global career level of job at hire.

The racial pay gap at Oracle persists across a wide variety of alternative groupings to define comparable employees by race. Regardless of the characteristics included to define comparable Asian and white employees, the racial pay gap remains statistically significant. The only exception occurs when we control for global career level, which is the tool used to set pay. In this case, the racial pay gap remains statistically significant for each year between 2013 and 2018.

*Base pay rate analyses*

I repeat all of the analyses from Tables 2(a) through 2(c) replacing Medicare compensation with the base pay rate as the dependent variable. The analyses in Tables 2(d), 2(e), and 2(f) use base pay rate, as opposed to Medicare compensation. They also use the slightly different approach to defining the employees included from the approach used for Tables 1(d) through 1(e), as described above for the gender pay differential analyses. For these analyses, I include all employees in each year who spent any portion of the year in a job included in the class definition. These analyses include employees who worked only part year in a position included in the class (due to transfers between jobs within Oracle, a new hire, or departure from Oracle during the year) as well as the full year employees who worked in a position included in the class at the end of the year. The analyses of Medicare compensation only included the latter group of employees.

Panel (d) of Table 2 includes all workers employed at any point in the year in a job included in the class definition. Each row reflects the results of an analysis of Asian-white base pay rate differentials for the relevant jobs for workers in the year indicated, from 2013 through 2018. I report the number of employees and the proportion of Asian and white employees who are Asian. The first column shows reports the Asian-white percentage differential in base pay rate for each year, with no additional controls. Oracle pays Asian employees at a rate approximately 11 to 14% lower than the rate for white employees in the Product Development job function at Oracle.

The next steps proceed, as the Medicare compensation analyses did, to determine whether there are non-discriminatory bases for these base pay rate differentials. The remaining columns on the table analyze the effects of adding the various characteristics or controls discussed above. The changes in the Asian-white employee base pay rate differential with different controls allow an assessment of whether Asian-white employee differences in these controls, or characteristics, account for, or explain, the Asian-white employee differential in the base pay rate. The second column of Table 2(d) adds controls for gender; the third column adds controls for age to the gender controls; the fourth column adds education; and the fifth column adds time or tenure at Oracle (measured by years employed at Oracle) to the gender, age, and education controls. Adding gender decreases the race coefficient, which is an approximate estimate of the base pay percentage difference for Asian employees, by about 1.0 to 1.3 percentage points or by about ten percent. Adding age decreases the racial base pay rate differential further by between 3.5 and 6.1 percentage points, or by about another 40 percent. Adding time at Oracle also decreases the differential, but by a fraction of a percentage point. Nonetheless, all racial differentials on column 5 of Table 2(d) are highly statistically significant.

As for the Medicare compensation analyses, I also consider the effects of the endogenous characteristics controlled by Oracle. The sixth column adds current job descriptor and whether the job is exempt to the gender, age, education, and time at Oracle controls. The seventh column adds whether the current job is in management to the gender, age, education, time at Oracle, job controls. The eighth column adds the current global career level to the gender, age, education, time at Oracle, job descriptor, exempt status, and whether the job is in management. As found in the analyses of Asian-white employee differentials using Medicare compensation, the Asian-white employee base pay rate differential for each year (column 8) is less than half of the differential in column 6. Racial differences in Oracle's assignments of global career levels contribute to a substantial part, but not all, of the Asian-white employee base pay rate differential. For all years and all columns of this panel, Table 2(d), the Asian-white base pay rate differential is well over two standard deviations, regardless of how comparable groups are defined in computing the racial differentials.

Table 2(e) repeats the same analyses excluding those for whom education data were not provided and Table 2(f) adds controls for starting jobs using only those employees with data on starting jobs who were in one of the six jobs most assigned at hire. The results in Table 2(e) including only those with education data are equivalent to those in Table 2(d), which included employees with no available education data.

Table 2(f), which analyzes base pay rate differentials by race after controlling for starting job descriptors, shows comparable patterns for base pay rate differentials to those in Table 2(a) when the same controls are used in the analysis. Gender and job descriptor at hire have a small effect; age has a larger effect, and differentials in global career level of current job (for Asian and white employees of comparable gender, age, education, time at Oracle, job at hire or current job) has the largest association with the size of the racial base pay rate gap.

These (d) and (f) panels of Table 2 yield similar patterns of results to the (a) panel, indicating that missing education data area of education, or experience, and data irregularities, do not account for the Asian-white differential in base pay rates.

### *Stock Awards*

Table 2(g) parallels the analyses shown in Table 2(a) and 1(g). Table 2(g) uses the number of stock units awarded as the dependent variable in the regression analyses. As in Table 1(g), I standardize the value of the stock award, regardless of the format actually chosen by the employee, using Oracle's conversion ratio of four stock options equal one unit of restricted stock. I use Tobit regression analyses for the reasons discussed above.

Table 2(g) analyzes all employees in the class, as did Tables 2(a) and 2(d). The first column indicates that Asian employees averaged [redacted] fewer stock unit awards than did white employees in 2013. The difference is statistically significant (at 4.51 standard deviations). The Asian disadvantage in stock awards in subsequent years is between [redacted] stock units a year and statistically significant for each year. As with the Medicare compensation and base pay rate analyses, the next step is to determine whether there are non-discriminatory bases for the racial differentials. Adding controls for gender, age, education, and time at Oracle (column 5 of Table 2(g)) yields a similar Asian disadvantage in stock awards as were found with no controls (column 1 of Table 2(g)) and the disadvantage remains statistically significant for each year.

When I add job descriptors to the analyses, the disadvantage of Asian employees decreases by about 40% in every year but for 2017. The disadvantage of Asian employees remains statistically significant, however, for each of these years except for 2018. In 2017, the addition of a control for job descriptors decreases the Asian disadvantage by almost 60% and the disadvantage is not statistically significant.

Columns 7 and 8 add the endogenous job characteristics (that is, characteristics set by Oracle) of performance evaluations (column 7) and global career level (column 8) to the evaluation of gender differentials in stock awards. While adding controls for performance evaluations changes the relative disadvantage of Asian employees, the change increases the disadvantage in some years (2014, 2015, and 2016) and decreases the disadvantage in other years (2013, 2017, and 2018). The Asian-white disadvantage, after controlling for job descriptor and performance rating, is statistically significant for all years but 2017 and 2018.

When we further restrict the comparisons to Asian and white employees with the same global career level (column 8), however, the average disadvantage decreases greatly and none of the years show a disadvantage of greater than two standard deviations. The Asian-white disparity in stock awards is largely due to the Asian-white disparity in global career level, followed by differences in job descriptors, for employees who are otherwise the same in gender, education, experience, and performance ratings.

### *Summary*

For each panel, each year and each column, Table 2 shows that the Asian-white pay differential is well over two standard deviations, regardless of how comparable groups are defined or how compensation is measured in computing the Asian-white pay differentials. Asian employees of the same gender, age, education, and time at Oracle as white employees receive statistically significantly fewer stock awards. There is no racial differential in stock awards, however, if Oracle's assigned jobs and global career levels were to define comparison groups.

## African American-White Compensation Differentials

Table 3, comparable to Tables 1 and 2, includes three panels of results of the same approaches as in panels a, d, and g of Tables 1 and 2 to analyzing the compensation gap between African American and white employees of Oracle.[18] Consistent with the class definitions, the only employees included are in the Product Development job function. As for Tables 1 and 2, the panels include different measures of pay and different groupings of employees to measure differentials.

### *Basic analysis*

The first panel (a) of Table 3 includes all African American and white workers employed the full year who are in Product Development job function at the end of the year. The analyses presented in Table 3(a) parallel those used for Asian-white employee comparisons in Table 2(a). Each row reflects the results for workers in the year indicated, from 2013 through 2018. I report the total number of white and African American employees and the proportions of white and African American employees. The numbers of African American employees are small, totaling between 23 and 30 for each of the individual years, far less than were included for Asian employees or for women employees in Tables 1 and 2. The small numbers mean that the statistical analyses must be imprecise.[19]

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18 As described above, there were two years between 2013 and 2018 when Oracle awarded a substantial number of bonuses to employees in the Product Development job function at its headquarters These were 2014 and 2018. I analyzed bonus differences between African American and white employees using the same approaches as described below for stock awards. I found no statistically significant bonuses differentials in 2014 or 2018.

19 The lack of precision means that the true differentials between African American and white employees must be much larger than in the case of gender or Asian-white differentials for the differential to be more than two standard deviations.

The first column reports the African American workers' approximate percentage differential in Medicare compensation relative to white workers for each year for full year employees, with no additional controls. The Medicare compensation for African American employees is approximately 23 to 54% less each year than for white employees in the Product Development job function at Oracle. The racial differential is statistically significant for each year.

The next step is to determine whether there are non-discriminatory bases for these pay differentials. The remaining columns in the table analyze various characteristics. The changes in the African American-white pay differential with different controls allow us to assess whether racial differences in these controls, or characteristics, account for, or explain, the racial pay differential.

The second column of Table 3(a) adds a control for gender. Effectively, the second column shows the average African American pay differential by gender for white and African American employees. The African American pay differential for each year in column 2, which is between 22 and 51%, is substantively the same as in column 1, indicating that gender composition differences by race do not account for the African American pay differential.

The third column adds controls for age to the gender control. The third column, then, shows the African American pay differential by gender for persons of the same age. The African American pay differential for each year in column 3, which is between 15 and 45%, generally around seven to nine percentage points difference from the differential in columns 1 and 2, indicates that age differences between African American and white employees account for about a fifth of the African American pay differential. African American employees are on average younger than are white employees.

The fourth column adds education to the gender and age controls. The fourth column, then, shows the African American employee pay differential with white employees for those with the same gender, age and degree levels. The African American pay differential for each year in column 4, which is between 16 and 44%, is substantively similar to the differentials in column 3, indicating that racial differences in educational degrees do not account for the African American pay differential.

The fifth column adds time or tenure at Oracle to the gender, age, and education controls. The fifth column, then, shows the African American pay differential for employees of the same gender, age, degree level, and experience at Oracle. The African American pay differential for each year in column 5, which is between 14 and 41%, is a bit less, but substantively the same as the differentials in columns 3 and 4, indicating that variations by race in time working at Oracle do not account for the African American pay differential. After controlling for gender, age, education, and time at Oracle, the racial compensation differential remains statistically significant for 2014 through 2018

*Adding endogenous characteristics*

As for Tables 1(a) and 2(a), the characteristics added as controls in columns 1 through 5 are all exogenous to Oracle, that is, none of the characteristics are affected by, or the result of, decisions made by Oracle. African American pay differentials due to any of these characteristics are not the result of actions by Oracle. The other characteristics of employees, which Oracle decides, are considered in Columns 6 and 7. Columns 6 and 7 of Table 3(a) evaluate the effects of endogenous characteristics on the African American-white pay differential at Oracle. The sixth column adds the current job descriptor and exempt status to the gender, age, education, and time at Oracle controls. The African American-white pay differentials for each year in column

6, which are between 10 and 32%, are less than the differentials in column 5, indicating that racial differences in Oracle's job assignments between African American and white employees of the same gender, age, education, and time at Oracle are associated with between 12 and 40 percent of the African American-white pay differential. The racial pay differential remains statistically significant, after adding job descriptor and exempt status to define comparator groups, for 2014 through 2018.

The seventh column adds a control for whether the job's global career level indicates management to the gender, age, education, time at Oracle and job descriptor controls. The column, then, shows the differential by race for persons of the same gender, age, degree level, experience at Oracle, job, and whether in management. The racial differentials in compensation by year in column 7 are absolutely less than in column 6, but the African American-white pay differential remains statistically significant for each year from 2015 through 2018.

The eighth column adds the global career level to the gender, age, education, time at Oracle, job descriptor controls, and whether the job is in management. The eighth column, then, shows the African American-white pay differential for employees of the same gender, age, degree level, experience at Oracle, job, whether in management and global career level. The African American pay differential for each year in column 8, which is much lower than in column 6, indicates that differences in Oracle's global career level assignments contribute to a substantial part of the racial pay differential. The African American-white pay differential is not statistically significant for any year after these controls are added. The pay differences remain substantial, however, and are of comparable magnitudes to those for Asian employees and for women. The small number of African American employees make it difficult for differentials even of these magnitudes to be statistically significant.

### *Robustness of results*

Because there are so few African-American employees in Product Development at Oracle, it is impossible to conduct the robustness tests described above (for gender and Asian-white pay disparities) in order to assess the effects of missing education data and job at hire. The number of African American employees with education data or with initial job data are simply too few for statistical analyses.

### *Base pay rate analyses*

I repeat all of the analyses from Table 3(a) replacing Medicare compensation with base pay rate as the dependent variable. These analyses appear in Table 3(b). These analyses use base pay rate, as opposed to Medicare compensation. They also use the slightly different approach to defining the employees included. The included employees are based on the same criteria used for Tables 1(d) through 1(f) and Tables 2(d) through 2(f). For these analyses, I include all employees in each year who spent any portion of the year in a job included in the class definition. Panel (b) of Table 3 includes all African American and white workers employed at any point in the year in a job included in the class definition. Each row reflects the results of an analysis of African American-white differentials in base pay for the relevant job for workers in the year indicated, from 2013 through 2018. I report the number of employees and the proportion of African American and white employees who are African American. Because this panel includes all employees in the class at any point during the year, the number of observations is greater, yielding 30 to 34 African American employees included each year between 2013 and 2018. The first column reports the African American-white percentage differential in base pay rate for each year, with no additional controls. Oracle pays African American employees a base pay rate that is approximately 24 to 31% lower than the rate for white employees in the Product

Development job function at Oracle. The racial differential in base pay rates is statistically significant for all years.

The next steps proceed as for the Medicare compensation analyses to determine whether there are non-discriminatory bases for these base pay rate differentials. The remaining columns on the table analyze the various characteristics discussed above. The changes in the African American-white base pay rate differential with different controls allow an assessment of whether African American-white differences in these controls, or characteristics, account for, or explain, the African American-white differential in the base pay rate. The second column of Table 3(b) adds controls for gender; the third column adds controls for age to the gender controls; the fourth column adds education; and the fifth column adds time or tenure at Oracle (measured by years employed at Oracle) to the gender, age, and education controls. Adding controls for age reduces the racial differential about 30% reflecting that African Americans are younger than white employees. The racial differential remains statistically significant, however, after controlling for age. Adding education (column 4) and time at Oracle (column 5) does not affect the size or statistical significance of the racial pay differential. The African American-white base pay differential is statistically significant in each year, after controlling for the exogenous characteristics of gender, age, education, and experience at Oracle.

As for the Medicare compensation analyses, I also consider the effects of the endogenous characteristics controlled by Oracle. The sixth column adds the current job descriptor and exempt status to the gender, age, education, and time at Oracle controls. The seventh column adds whether the job is in management to the gender, age, education, time at Oracle and job descriptor controls. The eighth column adds the job's global career level to the gender, age, education, time at Oracle, and job descriptor controls. The African American-white differential in base pay rate for each year in column 8 (race coefficient) is less than half of the differentials in column 6, indicating that Oracle's African American-white variations in global career level assignments contribute to a substantial part, but not all, of the African American-white pay differential. The racial differentials in base pay rates remain statistically significant in 2017 and 2018 and are negative but statistically insignificant in the other years. The levels of the differentials or race coefficients are comparable to the levels found for women in Table 1(d) and for Asians relative to whites in Table 2(d). The results in Table 3(b) follow the same pattern with respect to characteristics included as found for the Medicare compensation analyses reported for African American and white employees in Table 3(a).

### *Stock Awards*

Table 3(c) parallels the analyses shown in Tables 1(g) and 2(g). Table 3(c) uses the number of stock units awarded as the dependent variable in the regression analyses. As in Tables 1(g) and 2(g), I standardize the value of the stock award, regardless of the format actually chosen by the employee, using Oracle's conversion ratio of four stock options equal one unit of restricted stock. I use Tobit regression analyses for the reasons discussed above.

Table 3(c) analyzes all employees in the class, as did Tables 1(a), 2(a), 3(a), 1(d), 2(d), 3(b), 1(g), and 2(g). The first column indicates that African American employees averaged [redacted] fewer stock unit awards annually than white employees in 2013. The difference is statistically significant (at two standard deviations). The African American annual disadvantage in stock awards in subsequent years is between [redacted] stock units and is statistically significantly lower than the number received by white employees for each year except for 2018. As with the Medicare compensation and base pay rate analyses, the next step is to determine whether there are non-discriminatory bases for the racial differentials. Adding controls for gender, age, education, and time at Oracle only slightly decrease the African American employee disadvantage in stock awards, but the disadvantage remains statistically significant in 2013 and 2014, but ending up only marginally statistically significant in 2015 through 2017, as controls are added in column 5. While the racial coefficient remains large in each year, the small numbers of African American employees lead to imprecise measures of the racial coefficient. The small numbers mean that racial differential must be very large to be statistically significant. The last three columns of Table 3(c) show that adding controls for the jobs to which white employees and African American employees were assigned by Oracle reduces the African American employee disadvantage substantially. There are no statistically significant differences in Column 8 of Table 3(c). The differentials, nonetheless, remain large in columns 6, 7, and 8 implying that the lack of statistical significance arises in a large part from the small number of African American employees.

### *Summary*

For each panel, each year and each column, Table 3 shows that the African American-white pay differential is mostly over two standard deviations. In the instances when the differential falls below two standard deviation, the differentials remain large relative to those statistically significant differentials by gender and for Asian employees. The lack of statistical significance arises in large part from the small number of African American employees, and not because they experience less differential treatment than women or Asian employees. African Americans of the same gender, age, education, and time at Oracle as white employees receive statistically significantly fewer stock awards.

## ASSUMPTIONS

I study the compensation practices at Oracle in order to determine whether an employee's gender or race affect the outcomes. Therefore, it is *only* necessary that the analyses compare similarly situated *groups* of employees by gender and race. Any characteristics that affect individual employee compensation levels but are possessed by equivalent proportions, or at equal levels, by both genders or races do not matter in the analysis of whether gender or race affects compensation.

In the absence of evidence to the contrary, I assume that employees are equivalently qualified by gender and race. No presumption that one group's "unmeasured" qualifications, or jobs, are on average "inferior" to those of another group should be made, when the groups have, on average, equivalent measured qualifications. I assume that employees of the same age, time at Oracle, educational level and work area do not systematically differ by race or gender in their qualifications. Therefore, to quantify racial or gender disparities in compensation, it is only necessary that we control for *systematic* differences by race or gender that remain after we have controlled for all other differences that exist by group.

This is fundamentally different from an analysis of individual outcomes or differences. If we want to determine what any individual should be paid, we must control for every characteristic by which any individual differs from others. An analysis of differences in group outcomes requires that we control for the characteristics by which the groups as a whole differ, but not those by which all individuals differ. For example, if being taller allows individuals to more easily dunk a basketball, but the average and the variance in height is the same for African American and white players, controlling for height will not affect the measurement of racial differences in successful dunks. Height will be associated, however, with the differences in successful dunks across individuals.

The premise that individual differences that alter treatment outcomes for individuals do not matter in the evaluation of the treatment using average group outcomes is the basis for modern clinical trial research. This premise underlies the evaluation of the effectiveness of pharmaceutical and other medical treatments. For example, difficult to observe or measure behaviors such as diet or conscientiousness may affect outcomes for a particular drug. By randomly distributing individuals into two treatment groups (receiving the treatment and not receiving the treatment), we do not have to worry about, or control for, the individual differences in the responses to drugs or treatments caused by unmeasured behaviors such as diet or conscientiousness because both treatment groups would have equivalent representations of such behaviors in the groups. (This is comparable to not controlling for height when comparing successful basketball dunks by race, even though height affects dunk success, when the mean and variance in height is equivalent by race.) We can simply judge whether the drug or treatment has an effect by comparing the group average outcome for those receiving the clinical intervention with those who do not. If those receiving the clinical intervention experience better average outcomes than those who do not, the treatment is determined to be effective. If those who do not receive the clinical intervention experience equivalent outcomes to those who do, the treatment is determined to be ineffective. This is the case even though individuals within the treatment groups have different outcomes, prompted by differences in their characteristics such as diet or conscientiousness or genetic differences.

The approach commonly used in discrimination studies is equivalent to that used for clinical trials. First, we control for measured qualifications (that is, we group employees who are the same by measured "control" characteristics such as experience and education that may differ systematically or on average by gender or between racial groups.) Second, we test whether the "treatment," (in this case race or gender) affects outcomes by dividing each group of individuals with equivalent education and experience into two subgroups such as men versus women or Asians versus whites or Asians versus African American, or Asians versus Hispanics. The "control" characteristics (such as education and experience) used to define the groups randomly sort individuals into a group that should experience the same average outcomes if the basis for defining the subgroups (race or gender) is not affecting the outcome. While we fully expect that individuals within each group will have varying outcomes, we do not expect the group averages to differ when the treatment is the same (or in the clinical context when the drug is ineffective). We evaluate whether outcomes differ by race or gender in the same way we evaluate whether those who receive a treatment have a different outcome than those who do not.

*Any characteristics that affect whether individual employees are paid more, but that are possessed by equivalent proportions, or at equal levels, by both races, or by both genders, do not matter in the analysis of whether race or gender affects compensation.* An analysis of racial or gender disparities in compensation must control for overall racial or gender differences in productivity, which are not caused by employer decisions.

In summary, the analyses do not require controls for all factors by which individuals differ, only those by which the groups differ. Because we are evaluating whether employer decisions differ by race or gender of employees, the analyses must not control for those factors or characteristics that the employer affects, such as job assignments.

## SALARY AND JOB ASSIGNMENT AT HIRE

Finally, I examine whether the gender and racial salary differentials for Oracle employees in 2013 through 2018 relate to Oracle's decisions about salary and job placement at the time the employees were hired. If Oracle is continuing the gender or racial differentials that their employees experienced prior to their Oracle employment, I expect the gender and racial differentials in salaries at last jobs and in starting salaries to be similar.

### Base Salary at Hire

To determine the gender and racial salary differentials at hire, I turn to those employees for whom Oracle has provided me data on the prior salary. There are 4868 employees whose prior salaries are reported. After I remove those employees with unusable data,[20] 1387 remain. Salary at an employee's prior employer closely predicts their starting pay at Oracle. A regression of prior salary on starting salary shows that prior salary explains most (61%) of the variation in starting base pay rates at Oracle.

Table 4 reports the results of my analyses of the ties between starting pay gender and racial differentials and prior pay gender and racial differentials. The first column shows the gender or racial differentials in starting pay for all class members relative to comparators (i.e., men or white employees) between 2013 and 2018. The first panel provides the differentials with

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[20] There were 2234 employees who were dropped because their records did not indicate a "NEW HIRE-REGULAR" and 1070 employees were dropped because they had a "0," a blank, or unknown indicated in the prior salary field of the database. 227 were dropped because they only reported hourly pay. Another 27 had notes, rather than salaries, reported in this field of the database. One person had a foreign currency salary that could not be identified. Finally, we dropped employees for whom we were unable to match to an initial hire record, which yielded the 1258 employees in the regression analyses.

controls for exogenous characteristics only; the second panel adds a control for the job descriptor at hire, as assigned by Oracle; the third panel adds a control for Oracle's assignment of global career level at hire. The results show the same patterns as shown in Tables 1(d), 2(d), and 3(b), which analyzed base pay rates for 2013 through 2018. Table 4 reports the gender and racial differentials in starting base pay salaries and restricts the analyses to those with starting pay data. As with 2013 through 2018 base pay rates, the gender and racial differentials largely arise from gender and racial differentials in Oracle's assignment of global career level to employees of equivalent education and experience.

The next four columns show the results of parallel analyses of the subset of employees for whom usable data on prior pay are available. The second column shows the gender and racial differentials in starting pay when I repeat the analysis of starting pay reported in the first column, but only for those with prior pay data. The third column shows the gender and racial differentials in prior pay, that is, pay at the last employer before coming to Oracle. The fourth column shows the extent of gender and racial differentials in the discrepancy between prior pay and starting pay. The last column shows the gender and racial differentials in current base pay.

The gender and racial differentials in prior pay and in starting pay (columns 3 vs. 2) are similar. The results reported in column 4 show that there is no statistically significant difference by gender or race between starting pay and prior pay. These results are consistent with Oracle setting starting pay based on prior pay and, as a result, "mimicking" the racial and gender differentials in the wider labor market.

### Job Assignments at Hire

To determine the effects of gender and racial differentials in job assignments at hire, I turn to analyses of those employees for whom Oracle provided data on their starting jobs. There are 8126 employees whose starting jobs are reported. Tables 5, 6, and 7 reports the results of my analyses of the role of job assignments at hire on gender and racial differentials in compensation.

The first column of Table 5(a) reports the gender differentials in Medicare earnings, and the first column of Table 5(b) reports the gender differentials in base pay rates, when I control for exogenous worker employee characteristics (race, ethnicity, age, education, experience,) and Oracle's assignment of job descriptor and of global career level at time of hire. Both Medicare earnings and base pay are statistically significantly lower for women in each year in column 1. The gender differentials in the second column of these tables are the result of adding current job descriptor as a control to the previous controlled characteristics; the third column of these tables are the result of adding current global career level to the controls in the second column. While the current job descriptor decreases the gender gap by about one percentage point, the addition of current global career level (the third column) reduces the Medicare earnings gap by more than half (Table 5(a) and the base pay gap (Table 5(b)) by about half.

Between 2013 and 2018, Oracle was less likely to award women than to award men, who were in global career level of IC3 and IC4, higher global career levels (see regression analyses in Appendix B). Because of this disparity in the assignment of global career levels, current global career level also contributes to half of the current gender disparities in pay

Tables 6(a) and 6(b) show a different pattern for Asian employees relative to white employees. For both Medicare compensation (Table 6(a)) and base pay rate (Table 6(b)), the race coefficients in columns 1, 2, and 3 are very similar. Job assignments at hire account for most of the Asian-white compensation differential. In contrast to the results for the gender pay gap in Table 5(a) and (b), current global career level has little effect on the size of the Asian-white pay differential.

Tables 7(a) and 7(b) show the pattern for African American employees relative to white employees. Because there are so few African American employees, the measures of the African American pay gap are imprecise. As a result, they show a great deal of volatility from year to year and across the columns, making it very difficult to sort out the effects of the additional controls in columns 2 and 3. Nonetheless, it does appear that current global career level does account for a part of the pay gap.

**LOST EARNINGS: DAMAGES**

## Damages Experienced by Women

Table 1(a) shows gender differences in Medicare compensation of women employed at Oracle headquarters from January 1, 2013 through December 31, 2018. The table presents approximate percentage compensation differentials that arise from pay differences by gender for each year, as measured controlling for different sets of variables. I now use those differentials to calculate total lost earnings controlling for three sets of male comparators:

- Race, ethnicity, age, education, and time employed at Oracle (column 5 of Table 1(a));[21]
- Race, ethnicity, age, education, time employed at Oracle, exempt status, and job descriptor (column 6 of Table 1(a)); and
- Race, ethnicity, age, education, time employed at Oracle, exempt status, job descriptor, and global career level column 8 of Table 1(a)).

[21] I transform the regression coefficients for gender coefficients reported in column 5 of Table 1(a), which are approximate percentage differences, to the precise percentage difference using the approach described in footnote 6 above.

Table 8 reports the additional pay due to women were they to have Medicare compensation equivalent to that of men with the same characteristics. I present three different estimates based on different sets of characteristics used to define male comparators, as represented in columns 5, 6, and 8 of Table 1(a). Table 8 reports three estimates of the total damages, from 2013 through 2018, arising from differences in Medicare compensation, not including lost fringe benefits or interest. These totals are reported in the last row of Table 8.

In addition to losing earnings, women lost the contributions that Oracle should have made to their 401(k) accounts. I assume that Oracle's contributions to the employees' 401(k) plans equal 3% of earnings.[22] I present three different estimates of the value of lost 401(k) benefits based on the comparators, as represented in columns 5, 6, and 8 of Table 1(a). They appear in the second column of the columns for each set of comparators. Sums of those benefits over the years yield three estimates of the total lost benefits arising from differences in Medicare compensation, not including interest. These totals are reported in the last row of Table 8.

In order to make the women employees whole, it is necessary to convert the nominal losses of Medicare compensation and fringe benefits into real losses, or losses that reflect the current buying power of the lost compensation. To do this, I add in the interest lost due to the delayed payment of these losses. The interest rates on lost compensation are set at the historical IRS late payment interest rates compounded quarterly. For the purpose of the interest calculations, I assume that earnings and benefits are paid in the middle of each year. I have assumed a judgment date of December 31, 2019, so I have computed interest through that date. The implied interest on lost earning and benefits is shown in the third column of the columns for each set of comparators. Sums of the interest due over the years yield three estimates of the total

[22] See Oracle U.S. Benefits, 2014 U.S. Benefits, page 10 (ORACLE_HQCA_0000022068).

lost benefits arising from differences in Medicare compensation including interest. These totals are reported in the last row of Table 8.

As Table 8 shows, women in Product Development, Information Technology, and Support at Oracle lost between $82 million and $275 million between 2013 and 2018 due to their lower compensation rates relative to comparable men.

## Damages Experienced by Asian Employees

Table 2(a) shows racial differences in Medicare compensation of Asian employees at Oracle headquarters from January 1, 2013 through December 31, 2018. The table presents approximate percentage compensation differentials that arise from pay differences by race for each year, as measured controlling for different sets of variables. I now use those differentials to calculate total lost earnings controlling for three sets of white comparators:

- Gender, age, education, and time employed at Oracle (column 5 of Table 2(a));
- Gender, age, education, time employed at Oracle, exempt status, and job descriptor (column 6 of Table 2(a)); and
- Gender, age, education, time employed at Oracle, exempt status, job descriptor, and the job's global career level (column 8 of Table 2(a)).

In Table 9, I report the additional pay due to Asian employees were they to have Medicare compensation equivalent to that of white employees with the same characteristics or control variables. I present three different estimates based on the comparators, as represented in columns 5, 6, and 8 of Table 2(a). They appear in the second column of the columns for each set of comparators of Table 9. Sums of those benefits over the years yield three estimates of the total lost benefits arising from differences in Medicare compensation, not including interest. These totals are reported in the last row of Table 9.

In addition to losing earnings, Asian employees lost part of the contributions that Oracle should have made to their 401(k) accounts. As in the case of women's damages, I assume that Oracle's contributions to the employees' 401(k) plans equal 3% of earnings. I present three different estimates of the value of lost 401(k) benefits based on the comparators, as represented in columns 5, 6, and 8 of Table 2(a). They appear in the second column of the columns for each set of comparators in Table 9. Sums of those benefits over the years yield three estimates of the total lost benefits arising from differences in Medicare compensation, not including interest. These totals are reported in the last row of Table 9.

In order to make the Asian employees whole, it is necessary to convert nominal losses of Medicare compensation and fringe benefits into real losses, or losses that reflect the current buying power of the monies lost. As in the case of women discussed above, I add in the interest lost due to the delayed payment of these losses as I discussed above. Sums of the interest due over the years yield three estimates of the total lost benefits arising from differences in Medicare compensation including interest. These totals are reported in the last row of Table 9.

As Table 9 shows, Asian employees in Product Development at Oracle lost between $215 million and $514 million between 2013 and 2018 due to their lower compensation rates relative to comparable white employees.

## Damages Experienced by African American Employees

Table 3(a) shows racial differences in Medicare compensation between African American and white employees in Product Development at Oracle headquarters from January

1, 2013 through December 31, 2018. The table presents approximate percentage compensation differentials that arise from differences in pay between African American and white employees for each year, as measured controlling for different sets of variables. I now use those differentials to calculate total lost earnings controlling for three sets of white comparators:

- Gender, age, education, and time employed at Oracle (column 5 of Table 3(a));
- Gender, age, education, time employed at Oracle, exempt status, and job descriptor (column 6 of Table 3(a)); and
- Gender, age, education, time employed at Oracle, exempt status, job descriptor, and global career level (column 8 of Table 3(a)).

Table 10 reports the additional pay due to African American employees were they to have Medicare compensation equivalent to that of white employees with the same characteristics. I present three different estimates based on the comparators, as represented in columns 5, 6, and 8 of Table 3(a). They appear in the second column of the columns for each set of comparators of Table 10. Sums of those benefits over the years yield three estimates of the total lost benefits arising from differences in Medicare compensation, not including interest. These totals are reported in the last row of Table 10.

In addition to losing earnings, African American employees lost part of the contributions that Oracle should have made to their 401(k) accounts. As in the case of damages for women and for Asian employees, I assume that Oracle's contributions to the employees' 401(k) plans equal 3% of earnings. I present three different estimates of the value of lost 401(k) benefits based on the comparators, as represented in columns 5, 6, and 8 of Table 3(a). They appear in the second column of the columns for each set of comparators in Table 10. Sums of those benefits over the years yield three estimates of the total lost benefits arising from differences in Medicare compensation, not including interest. These totals are reported in the last row of Table 10.

In order to make the African American employees whole, it is necessary to convert nominal losses of Medicare compensation and fringe benefits into real losses, or losses that reflect the current buying power of the compensation lost. As in the case of women and Asian employees discussed above, I add in the interest lost due to the delayed payment of these losses as I discussed above. Sums of the interest due over the years yield three estimates of the total lost benefits arising from differences in Medicare compensation including interest. These totals are reported in the last row of Table 10.As Table 10 shows, African American employees in Product Development at Oracle lost between $1.6 million and $8.3 million between 2013 and 2018 due to their lower compensation rates relative to comparable white employees.

## CONCLUSIONS

The economic and statistical evidence presented in this report is consistent with gender differences in compensation in the Product Development, Information Technology, and Support job functions at Oracle America ("Oracle") at its headquarters in Redwood Shores, California for the 2013-2018 period. The economic and statistical evidence is consistent with racial differences in compensation in the Product Development job function, at the same location for the same period. The economic and statistical evidence is also consistent with Oracle's decisions on job assignment and compensation at hire leading to subsequent gender and racial compensation differentials. Oracle would have paid between $82 million and $275 million additional compensation to women if they had been paid equivalently to comparable male employees; Oracle would have paid between $215 million and $514 million additional compensation to

Asian employees if they had been paid equivalently to comparable white employees; and Oracle would have paid between $1.6 million and $8.3 million additional compensation to African American employees if they had been paid equivalently to comparable white employees.

JANICE F. MADDEN, Ph.D.
July 19, 2019

# TABLES

| Table 1(a) | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Gender Differences in Medicare Earnings at Oracle Headquarters by Year, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | Gender Only (1) | | Adds Race/Ethnicity (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Women | Gender Coefficient | ST DEV* | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV |
| 2013 | 4327 | 26.3% | -0.213 | -11.96 | -0.199 | -11.33 | -0.200 | -12.07 | -0.201 | -12.17 | -0.199 | -12.40 | -0.157 | 10.50 | -0.128 | -9.21 | -0.055 | -4.96 |
| 2014 | 4279 | 26.4% | -0.232 | -11.69 | -0.217 | -11.09 | -0.221 | -11.85 | -0.223 | -12.05 | -0.221 | -12.29 | -0.166 | -10.07 | -0.134 | -8.70 | -0.063 | -5.21 |
| 2015 | 4225 | 26.1% | -0.188 | -10.60 | -0.173 | -9.94 | -0.174 | -10.61 | -0.176 | 10.80 | -0.177 | -11.06 | -0.132 | -8.95 | -0.105 | -7.57 | -0.046 | -4.27 |
| 2016 | 4273 | 25.5% | -0.199 | -10.63 | -0.189 | -10.23 | -0.198 | -11.35 | -0.203 | -11.70 | -0.199 | -11.72 | -0.150 | -9.68 | -0.119 | -8.23 | -0.052 | -4.74 |
| 2017 | 4241 | 25.8% | -0.237 | -11.05 | -0.228 | -10.72 | -0.231 | -11.46 | -0.238 | -11.91 | -0.239 | -12.15 | -0.178 | -9 92 | -0.146 | -8.80 | -0.058 | -4.71 |
| 2018 | 4019 | 26.2% | -0.242 | -11.23 | -0.235 | -11.02 | -0.231 | -11.38 | -0.238 | -11.78 | -0.239 | -12.04 | -0.187 | -10.19 | -0.151 | -8.91 | -0.058 | -4.71 |
| * ST DEV stands for Standard Deviation | | | | | | | | | | | | | | | | | | |

| Table 1(b) | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Gender Differences in Medicare Earnings at Oracle Headquarters by Year, Employees with Recorded Education Characteristics, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | Gender Only (1) | | Adds Race/Ethnicity (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Women | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV |
| 2013 | 1448 | 26% | -0.146 | -5 93 | -0.138 | -5.73 | -0.143 | -6.38 | -0.143 | -6.41 | -0.146 | -6.64 | -0.130 | -5.90 | -0.105 | -5.16 | -0 039 | -2.28 |
| 2014 | 1530 | 25% | -0.166 | -6.77 | -0.163 | -6.82 | -0.167 | -7.41 | -0.167 | -7.45 | -0.171 | -7.69 | -0.145 | -6.63 | -0.113 | -5.64 | -0 051 | -3.16 |
| 2015 | 1626 | 24% | -0.140 | -6.49 | -0.137 | -6.45 | -0.144 | -7.22 | -0.145 | -7.28 | -0.145 | -7.33 | -0.116 | -5.96 | -0 085 | -4.78 | -0 037 | -2.62 |
| 2016 | 1814 | 23% | -0.159 | -7.11 | -0.161 | -7.31 | -0.180 | -8.85 | -0.183 | -9.01 | -0.183 | -9.00 | -0.153 | -7.73 | -0.117 | -6.39 | -0 052 | -3.72 |
| 2017 | 1974 | 24% | -0.194 | -7 56 | -0.195 | -7.73 | -0 200 | -8.72 | -0 200 | -8.77 | -0 206 | -9.00 | -0.171 | -7.60 | -0.135 | -6.44 | -0 053 | -3.02 |
| 2018 | 1737 | 24% | -0.207 | -7 89 | -0.211 | -8.14 | -0 215 | -8.80 | -0 220 | -9.03 | -0 226 | -9.31 | -0.194 | -8.10 | -0.163 | -7.34 | -0 064 | -3.77 |

| Table 1(c) | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Gender Differences in Medicare Earnings at Oracle Headquarters by Year,<br>Employees with Recorded Characteristics of Job Assigned at Hire, with Various Characteristics Considered | | | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | | | |
| | | | Gender Only<br>(1) | | Adds Race/Ethnicity<br>(2) | | Adds Age<br>(3) | | Adds Education<br>(4) | | Adds Time at Oracle<br>(5) | | Adds<br>Job Descriptor at Hire<br>(6) | | Removes Job Descriptor At Hire and Adds Exempt/Non Exempt and Current Job Descriptor<br>(7) | | Adds<br>Global Career Level<br>(8) | | Adds<br>Job Descriptor at Hire<br>(9) | |
| Year | Number of Workers | % Women | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV |
| 2013 | 3266 | 25.7% | -0.237 | -12.12 | -0.216 | -11.10 | -0 212 | -11.74 | -0.212 | -11.77 | -0.207 | -11.73 | -0.171 | -9 83 | -0.173 | -10.18 | -0 059 | -4.58 | -0.052 | -4.07 |
| 2014 | 3229 | 25 8% | -0.262 | -12.08 | -0.236 | -11.01 | -0 234 | -11.60 | -0.237 | -11.76 | -0.232 | -11.79 | -0.193 | -9 94 | -0.184 | -9.78 | -0 071 | -5.09 | -0.067 | -4.80 |
| 2015 | 3188 | 25.4% | -0.223 | -11.34 | -0.198 | -10.22 | -0.190 | -10.57 | -0.192 | -10.67 | -0.188 | -10.72 | -0.157 | -9 06 | -0.151 | -8 90 | -0 048 | -3.78 | -0.044 | -3.54 |
| 2016 | 3165 | 25 0% | -0.235 | -11.41 | -0.217 | -10.60 | -0 219 | -11.47 | -0.224 | -11.74 | -0.219 | -11.67 | -0.190 | -10.29 | -0.178 | -9 98 | -0 062 | -4.81 | -0.058 | -4.54 |
| 2017 | 3143 | 25.1% | -0.271 | -11.20 | -0.252 | -10.48 | -0 250 | -11.01 | -0.258 | -11.46 | -0.255 | -11.47 | -0.224 | -10.22 | -0.206 | -9.78 | -0 062 | -4.23 | -0.059 | -4.05 |
| 2018 | 2952 | 25 5% | -0.279 | -11.32 | -0.263 | -10.72 | -0 251 | -10.80 | -0.259 | -11.18 | -0.256 | -11.19 | -0.227 | -10.05 | -0.213 | -9 88 | -0 063 | -4.32 | -0.060 | -4.08 |

| Table 1(d) | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Gender Differences in Base Pay Rates at Oracle Headquarters by Year, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | Gender Only (1) | | Adds Race/Ethnicity (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Women | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV |
| 2013 | 5198 | 27 3% | -0.140 | -15 83 | -0.131 | -15.14 | -0.132 | -16.07 | -0.132 | -16.13 | -0.127 | -15.83 | -0.102 | -14.76 | -0.086 | -13.70 | -0.039 | -9.03 |
| 2014 | 5155 | 27.4% | -0.142 | -15.73 | -0.134 | -15.01 | -0.131 | -15.38 | -0.131 | -15.43 | -0.126 | -15.13 | -0.098 | -13.75 | -0.080 | -12.38 | -0.036 | -8.17 |
| 2015 | 5169 | 26 8% | -0.141 | -15.61 | -0.134 | -15.01 | -0.133 | -15.59 | -0.133 | -15.72 | -0.127 | -15.29 | -0.096 | -13.43 | -0.079 | -12.18 | -0.035 | -8.23 |
| 2016 | 5111 | 26.7% | -0.134 | -14.49 | -0.128 | -14.03 | -0.128 | -14.71 | -0.129 | -14.89 | -0.124 | -14.55 | -0.094 | -13 01 | -0.078 | -11.87 | -0.036 | -8.30 |
| 2017 | 4969 | 27 0% | -0.134 | -14 34 | -0.129 | -13.97 | -0.123 | -14.09 | -0.125 | -14.32 | -0.121 | -14.12 | -0.092 | -12.61 | -0.078 | -11.72 | -0.032 | -7.32 |
| 2018 | 4691 | 26 9% | -0.150 | -15.14 | -0.146 | -14.86 | -0.137 | -14.61 | -0.139 | -14.86 | -0.133 | -14.57 | -0.104 | -13 04 | -0.088 | -12.11 | -0.036 | -7.52 |

**Table 1(e)**

**2013 through 2018 Gender Differences in Base Pay Rates at Oracle Headquarters by Year, Employees with Recorded Education Characteristics, with Various Characteristics Controlled**

| | | | Controls for ... | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Gender Only (1) | | Adds Race/Ethnicity (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Women | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV |
| 2013 | 1938 | 26.5% | -0.135 | -10.04 | -0.129 | -9.84 | -0.129 | -10.77 | -0.129 | -10 92 | -0.124 | -10.57 | -0.115 | -10.79 | -0.098 | -10.20 | -0.049 | -7 33 |
| 2014 | 2056 | 25.3% | -0.131 | -9.49 | -0.126 | -9.34 | -0.127 | -10.19 | -0.127 | -10 30 | -0.120 | -9.85 | -0.106 | -9.57 | -0.085 | -8.56 | -0.037 | -5 26 |
| 2015 | 2228 | 24.6% | -0.133 | -10.31 | -0.129 | -10.24 | -0.134 | -11.39 | -0.135 | -11.60 | -0.128 | -11.09 | -0.107 | -10.36 | -0.088 | -9.43 | -0.042 | -6.64 |
| 2016 | 2442 | 24.7% | -0.126 | -10.36 | -0.124 | -10.45 | -0.123 | -11.20 | -0.126 | -11.65 | -0.120 | -11.22 | -0.097 | -10.11 | -0.079 | -9.25 | -0.039 | -6.66 |
| 2017 | 2265 | 25.0% | -0.126 | -10.19 | -0.126 | -10.38 | -0.125 | -11.25 | -0.129 | -11.68 | -0.125 | -11.42 | -0.104 | -10.46 | -0.087 | -9.70 | -0.040 | -6 37 |
| 2018 | 1930 | 25.7% | -0.139 | -10.31 | -0.140 | -10.52 | -0.138 | -11.04 | -0.140 | -11 30 | -0.138 | -11.16 | -0.114 | -10.08 | -0.098 | -9.47 | -0.046 | -6.43 |

| Table 1(f) | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Gender Differences in Base Pay Rates at Oracle Headquarters by Year,<br>Employees with Recorded Characteristics of Job Assigned at Hire, with Various Characteristics Considered | | | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | | | |
| | | | Gender Only (1) | | Adds Race/Ethnicity (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Job Descriptor at Hire (6) | | Removes Job Descriptor At Hire and Adds Exempt/Non Exempt and Current Job Descriptor (7) | | Adds Global Career Level (8) | | Adds Job Descriptor at Hire (9) | |
| Year | Number of Workers | % Women | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV |
| 2013 | 3915 | 26 8% | -0.155 | -16.73 | -0.141 | -15.49 | -0.139 | -16 33 | -0.138 | -16 35 | -0.132 | -15 83 | -0.105 | -13.28 | -0.108 | -14.16 | -0.039 | -8 03 | -0.035 | -7.43 |
| 2014 | 3892 | 27 0% | -0.159 | -16.63 | -0.145 | -15.32 | -0.138 | -15.48 | -0.138 | -15 50 | -0.131 | -15 01 | -0.106 | -12.76 | -0.104 | -13.05 | -0.035 | -7.12 | -0.032 | -6 59 |
| 2015 | 3871 | 26 3% | -0.162 | -16.77 | -0.149 | -15.58 | -0.144 | -15 95 | -0.144 | -16 01 | -0.136 | -15 32 | -0.110 | -13.16 | -0.107 | -13.13 | -0.035 | -7 22 | -0.033 | -6 89 |
| 2016 | 3812 | 26 2% | -0.154 | -15.43 | -0.143 | -14.48 | -0.141 | -15.18 | -0.142 | -15 27 | -0.135 | -14.70 | -0.112 | -12.91 | -0.107 | -12.94 | -0.038 | -7.68 | -0.036 | -7 32 |
| 2017 | 3674 | 26.4% | -0.158 | -15.57 | -0.147 | -14.67 | -0.138 | -14.69 | -0.140 | -14 89 | -0.133 | -14 54 | -0.114 | -13.04 | -0.108 | -12.97 | -0.038 | -7.74 | -0.036 | -7.49 |
| 2018 | 3443 | 26.4% | -0.172 | -15.55 | -0.162 | -14.78 | -0.150 | -14.43 | -0.153 | -14.74 | -0.145 | -14 30 | -0.125 | -12.90 | -0.118 | -12.76 | -0.040 | -7 26 | -0.038 | -6 95 |

| Table 1(g) | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2013 through 2018 Gender Differences in Restricted Stock Awards at Oracle Headquarters by Year, with Various Characteristics Controlled** | | | | | | | | | | | | | | | | | | |
| **Controls for ...** | | | | | | | | | | | | | | | | | | |
| | | | **Gender Only (1)** | | **Adds Race/Ethnicity (2)** | | **Adds Age (3)** | | **Adds Education (4)** | | **Adds Time at Oracle (5)** | | **Adds Exempt/Non Exempt and Job Descriptor (6)** | | **Adds Performance Rating (7)** | | **Adds Global Career Level (8)** | |
| **Year** | **Number of Workers** | **% Women** | **Gender Coefficient** | **ST DEV** | **Gender Coefficient** | **ST DEV** | **Gender Coefficient** | **ST DEV** | **Gender Coefficient** | **ST DEV** | **Gender Coefficient** | **ST DEV** | **Gender Coefficient** | **ST DEV** | **Gender Coefficient** | **ST DEV** | **Gender Coefficient** | **ST DEV** |
| 2013 | 4296 | 26.4% | -6231.0 | -8.86 | -6104.2 | -8.68 | -6168.9 | -8.85 | -6213.8 | -8.96 | -6322.1 | -9.21 | -5492 9 | -7.87 | -4505.8 | -6.67 | -1251.5 | -2.42 |
| 2014 | 4279 | 26.4% | -11980.7 | -7.42 | -11538 2 | -7.15 | -11843.3 | -7.35 | -11941.9 | -7.43 | -11881 3 | -7.50 | -7387.1 | -5.90 | -6857.1 | -5.48 | -2240.9 | -1.89 |
| 2015 | 4177 | 26.2% | -10411.2 | -6.66 | -10094 2 | -6.46 | -10039.1 | -6.44 | -10384.2 | -6.67 | -10374.1 | -6.71 | -6516.5 | -5.40 | -5515.0 | -4.53 | -2037.1 | -1.75 |
| 2016 | 4211 | 25.7% | -7954.0 | -6.26 | -7708.5 | -6.07 | -7809.2 | -6.17 | -8201.3 | -6.49 | -8122.4 | -6.48 | -4992 0 | -5.00 | -3704.3 | -3.71 | -1282.3 | -1.38 |
| 2017 | 4241 | 25.8% | -7982.9 | -6.08 | -7792.1 | -5.94 | -7825.9 | -5.98 | -8218.3 | -6.30 | -8349.4 | -6.46 | -4718 3 | -4.76 | -4390.0 | -4.42 | -963.7 | -1.05 |
| 2018 | 4019 | 26.2% | -9676.7 | -2.33 | -9319.6 | -2.25 | -9135.7 | -2.20 | -9902.3 | -2.39 | -8581.8 | -2.08 | -4920 0 | -1.24 | -3639.4 | -0.87 | 1036.3 | 0 25 |

| Table 2(a)<br>2013 through 2018 Asian Differences in Medicare Earnings at Oracle Headquarters by Year, with Various Characteristics Controlled<br>Controls for ... | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | **Asian Only (1)** | | **Adds Gender (2)** | | **Adds Age (3)** | | **Adds Education (4)** | | **Adds Time at Oracle (5)** | | **Adds Exempt/Non Exempt and Job Descriptor (6)** | | **Adds Management Control (7)** | | **Adds Global Career Level (8)** | |
| **Year** | **Number of Workers** | **% Asian** | **Race Coefficient** | **ST DEV** | **Race Coefficient** | **ST DEV** | **Race Coefficient** | **ST DEV** | **Race Coefficient** | **ST DEV** | **Race Coefficient** | **ST DEV** | **Race Coefficient** | **ST DEV** | **Race Coefficient** | **ST DEV** | **Race Coefficient** | **ST DEV** |
| 2013 | 3584 | 72 5% | -0.237 | -12.14 | -0 220 | -11.40 | -0.125 | -6.39 | -0.128 | -6.55 | -0.121 | -6.36 | -0.113 | -6.19 | -0.123 | -7.27 | -0.041 | -3.03 |
| 2014 | 3534 | 73.7% | -0.295 | -13.38 | -0 278 | -12.76 | -0.184 | -8.27 | -0.191 | -8.58 | -0.181 | -8.36 | -0.177 | -8.69 | -0.177 | -9.32 | -0.079 | -5.28 |
| 2015 | 3471 | 74.4% | -0.269 | -13.55 | -0 255 | -12 99 | -0.158 | -8.01 | -0.164 | -8.32 | -0.158 | -8.19 | -0.154 | -8.35 | -0.156 | -9.09 | -0.071 | -5.29 |
| 2016 | 3470 | 75 9% | -0.230 | -10.76 | -0 216 | -10 23 | -0.123 | -5.80 | -0.128 | -6.01 | -0.118 | -5.67 | -0.114 | -5.87 | -0.125 | -6.95 | -0.038 | -2.76 |
| 2017 | 3494 | 76 5% | -0.235 | -9.51 | -0.220 | -9 02 | -0.126 | -5.14 | -0.126 | -5.16 | -0.117 | -4.83 | -0.103 | -4.60 | -0.131 | -6.31 | -0.046 | -2.99 |
| 2018 | 3300 | 77.4% | -0.223 | -8.74 | -0.208 | -8 28 | -0.121 | -4.74 | -0.121 | -4.73 | -0.118 | -4.71 | -0.102 | -4.36 | -0.138 | -6.37 | -0.042 | -2.67 |

| Table 2(b) | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 thorugh 2018 Asian Differences in Medicare Earnings at Oracle Headquarters by Year, Employees with Recorded Educational Characteristics, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | Asian Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Asian | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV |
| 2013 | 1173 | 76.1% | -0.220 | -7.72 | -0.209 | -7.40 | -0.123 | -4.41 | -0.130 | -4.59 | -0.128 | -4.57 | -0.124 | -4.45 | -0.126 | -4 93 | -0.037 | -1.71 |
| 2014 | 1222 | 77 2% | -0.253 | -8 84 | -0.247 | -8.75 | -0.168 | -5 96 | -0.188 | -6.56 | -0.185 | -6.49 | -0.183 | -6.51 | -0.170 | -6.64 | -0.064 | -3.11 |
| 2015 | 1300 | 77 0% | -0.219 | -8 90 | -0.214 | -8.79 | -0.149 | -6.12 | -0.161 | -6.48 | -0.156 | -6.33 | -0.162 | -6.66 | -0.154 | -6 90 | -0.062 | -3 55 |
| 2016 | 1417 | 80 2% | -0.208 | -7.70 | -0.205 | -7.71 | -0.133 | -5.12 | -0.148 | -5.60 | -0.144 | -5.48 | -0.137 | -5.31 | -0.138 | -5 82 | -0.055 | -3 06 |
| 2017 | 1587 | 81 0% | -0.229 | -7.17 | -0.228 | -7 27 | -0.129 | -4 34 | -0.135 | -4.44 | -0.133 | -4.41 | -0.126 | -4.17 | -0.156 | -5 59 | -0.077 | -3.47 |
| 2018 | 1396 | 82 3% | -0.175 | -5.17 | -0.178 | -5 35 | -0.100 | -3 04 | -0.110 | -3.31 | -0.112 | -3.37 | -0 098 | -2.97 | -0.135 | -4.40 | -0.063 | -2.73 |

**Table 2(c)**

**2013 through 2018 Effect of Race on Differences in Medicare Earnings of Asian Employees at Oracle Headquarters by Year, Employees with Recorded Characteristics of Job Assigned at Hire, with Various Characteristics Considered**

| | | | Controls for ... | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Asian Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Job Descriptor at Hire (6) | | Removes Job Descriptor at Hire and Adds Exempt/Non Exempt and Current Job Descriptor (7) | | Adds Global Career Level (8) | | Adds Job Descriptor at Hire (9) | |
| Year | Number of Workers | % Asian | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV |
| 2013 | 2913 | 77.8% | -0.247 | -11.16 | -0.218 | -9.95 | -0.122 | -5.66 | -0.122 | -5.64 | -0.143 | -6.72 | -0.115 | -5.45 | -0.117 | -5.70 | -0.046 | -2.98 | -0.045 | -2.88 |
| 2014 | 2870 | 79.0% | -0.295 | -11.72 | -0.265 | -10.61 | -0.172 | -6.90 | -0.175 | -7.03 | -0.199 | -8.15 | -0.177 | -7.35 | -0.173 | -7.46 | -0.080 | -4.66 | -0.082 | -4.80 |
| 2015 | 2824 | 79.3% | -0.273 | -11.97 | -0.247 | -10.92 | -0.154 | -6.93 | -0.157 | -7.05 | -0.179 | -8.21 | -0.159 | -7.38 | -0.165 | -7.88 | -0.084 | -5.44 | -0.084 | -5.42 |
| 2016 | 2793 | 80.5% | -0.225 | -9.21 | -0.197 | -8.16 | -0.114 | -4.77 | -0.116 | -4.86 | -0.135 | -5.74 | -0.114 | -4.90 | -0.123 | -5.47 | -0.053 | -3.30 | -0.052 | -3.24 |
| 2017 | 2802 | 80.7% | -0.237 | -8.28 | -0.204 | -7.22 | -0.123 | -4.36 | -0.121 | -4.29 | -0.138 | -4.96 | -0.115 | -4.17 | -0.112 | -4.28 | -0.062 | -3.41 | -0.063 | -3.49 |
| 2018 | 2620 | 81.5% | -0.233 | -7.73 | -0.198 | -6.68 | -0.122 | -4.09 | -0.120 | -4.03 | -0.145 | -4.89 | -0.122 | -4.15 | -0.108 | -3.87 | -0.038 | -2.04 | -0.038 | -2.05 |

| Table 2(d) | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Asian Differences in Base Pay Rate at Oracle Headquarters by Year, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | Asian Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Asian | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV |
| 2013 | 4297 | 73.3% | -0.147 | -15.75 | -0.136 | -14.84 | -0.075 | -8.09 | -0 078 | -8.36 | -0 069 | -7 57 | -0.071 | -8.31 | -0.072 | -9.49 | -0.027 | -5.16 |
| 2014 | 4256 | 74.1% | -0.141 | -14.52 | -0.128 | -13.50 | -0.076 | -7.89 | -0 080 | -8.27 | -0 071 | -7.48 | -0.073 | -8.27 | -0.072 | -9.19 | -0.025 | -4.67 |
| 2015 | 4233 | 75.5% | -0.142 | -14.48 | -0.129 | -13.46 | -0.078 | -8.03 | -0 082 | -8.36 | -0 074 | -7.68 | -0.072 | -8.10 | -0.074 | -9.32 | -0.028 | -5 24 |
| 2016 | 4171 | 76.7% | -0.130 | -12.85 | -0.119 | -12.04 | -0.069 | -6.89 | -0 074 | -7.26 | -0 066 | -6.61 | -0.062 | -6.77 | -0.072 | -8.73 | -0.024 | -4.40 |
| 2017 | 4069 | 77.4% | -0.129 | -12.51 | -0.119 | -11.84 | -0.068 | -6.78 | -0 070 | -6.92 | -0 062 | -6 25 | -0.055 | -6.04 | -0.067 | -8.14 | -0.028 | -5.16 |
| 2018 | 3854 | 77.5% | -0.111 | -9.87 | -0.099 | -9.11 | -0.064 | -5.85 | -0 064 | -5.85 | -0 056 | -5.17 | -0.047 | -4.60 | -0.063 | -6.90 | -0.024 | -3 92 |

| Table 2(e) | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Asian Differences in Base Pay Rate at Oracle Headquarters by Year, Employees with Recorded Education Characteristics, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | Asian Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Asian | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV |
| 2013 | 1555 | 75 9% | -0.161 | -10.81 | -0.151 | -10.43 | -0.087 | -6.21 | -0.097 | -6.81 | -0.090 | -6.36 | -0 086 | -6.38 | -0.080 | -6.72 | -0.029 | -3.48 |
| 2014 | 1652 | 76 0% | -0.140 | -9.35 | -0.131 | -8.99 | -0.083 | -5.87 | -0.094 | -6.52 | -0.085 | -5.94 | -0 085 | -6.21 | -0.077 | -6.36 | -0.023 | -2 57 |
| 2015 | 1749 | 78 3% | -0.134 | -9.37 | -0.124 | -8.96 | -0.081 | -5.94 | -0.090 | -6.50 | -0.084 | -6.19 | -0 082 | -6.24 | -0.079 | -6.81 | -0.032 | -4 02 |
| 2016 | 1947 | 80.7% | -0.131 | -9.30 | -0.126 | -9.21 | -0.068 | -5.13 | -0.078 | -5.81 | -0.074 | -5.62 | -0 068 | -5.33 | -0.077 | -6.85 | -0.032 | -4 28 |
| 2017 | 1819 | 81 8% | -0.121 | -8.25 | -0.119 | -8.35 | -0.062 | -4.56 | -0.068 | -4.92 | -0.066 | -4.80 | -0 057 | -4.25 | -0.072 | -6.05 | -0.032 | -3 91 |
| 2018 | 1548 | 81 9% | -0.094 | -5.67 | -0.094 | -5.86 | -0.053 | -3.36 | -0.057 | -3.60 | -0.055 | -3.47 | -0 045 | -2.93 | -0.065 | -4.67 | -0.031 | -3 27 |

**Table 2(f)**

**2013 through 2018 Asian Differences in Base Pay Rate at Oracle Headquarters by Year,**
**Employees with Recorded Characteristics of Job Assigned at Hire, with Various Characteristics Considered**

| | | | Controls for ... | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Asian Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Job Descriptor at Hire (6) | | Removes Job Descriptor At Hire and Adds Exempt/NonExempt and Current Job Descriptor (7) | | Adds Global Career Level (8) | | Adds Job Descriptor at Hire (9) | |
| Year | Number of Workers | % Asian | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV |
| 2013 | 3481 | 78.8% | -0.164 | -15.62 | -0.144 | -14.12 | -0.086 | -8.47 | -0.087 | -8.60 | -0.092 | -9.15 | -0.074 | -7.62 | -0.079 | -8.33 | -0.033 | -5.57 | -0.032 | -5.41 |
| 2014 | 3461 | 79.2% | -0.153 | -13.92 | -0.131 | -12.25 | -0.081 | -7.64 | -0.083 | -7.81 | -0.086 | -8.17 | -0.071 | -6.94 | -0.073 | -7.40 | -0.029 | -4.75 | -0.029 | -4.69 |
| 2015 | 3426 | 80.4% | -0.150 | -13.20 | -0.128 | -11.58 | -0.079 | -7.16 | -0.081 | -7.29 | -0.086 | -7.82 | -0.073 | -6.94 | -0.075 | -7.30 | -0.032 | -5.20 | -0.031 | -5.08 |
| 2016 | 3362 | 81.3% | -0.135 | -11.35 | -0.116 | -9.92 | -0.067 | -5.74 | -0.070 | -6.01 | -0.073 | -6.34 | -0.060 | -5.36 | -0.063 | -5.81 | -0.026 | -4.05 | -0.025 | -4.02 |
| 2017 | 3259 | 81.6% | -0.139 | -11.45 | -0.120 | -10.09 | -0.073 | -6.22 | -0.075 | -6.34 | -0.077 | -6.70 | -0.063 | -5.64 | -0.061 | -5.70 | -0.032 | -5.15 | -0.032 | -5.08 |
| 2018 | 3054 | 81.4% | -0.127 | -9.58 | -0.106 | -8.19 | -0.073 | -5.63 | -0.073 | -5.63 | -0.074 | -5.77 | -0.059 | -4.70 | -0.054 | -4.49 | -0.025 | -3.59 | -0.024 | -3.50 |

| Table 2(g) | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Asian Differences in Restricted Stock Awards at Oracle Headquarters by Year, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | Asian Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Performance Rating (7) | | Adds Global Career Level* (8) | |
| Year | Number of Workers | % Asian | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV |
| 2013 | 3584 | 72.5% | -5767.3 | -4 51 | -5116 9 | -4.01 | -4863.9 | -3.58 | -5217.0 | -3.83 | -4889.5 | -3.62 | -3021.0 | -2.72 | -2874.3 | -2.61 | -60.4 | -0.06 |
| 2014 | 3534 | 73.7% | -6841.5 | -5.19 | -6209 8 | -4.73 | -6422.9 | -4.58 | -6740.0 | -4.78 | -6261.9 | -4.50 | -4133.1 | -3.85 | -4192.3 | -3.98 | -605 0 | -0.64 |
| 2015 | 3425 | 74.4% | -5141.3 | -3.71 | -4584 3 | -3.31 | -5298.5 | -3.56 | -5710.3 | -3.82 | -5345.1 | -3.58 | -3484.1 | -2.94 | -3794.9 | -3.21 | -387 8 | -0.35 |
| 2016 | 3418 | 76.0% | -3264.0 | -3.19 | -2859 9 | -2.81 | -3201.3 | -2.93 | -3257.3 | -2.98 | -2996.5 | -2.76 | -1772.9 | -2.14 | -1807.3 | -2.24 | 555.3 | 0.80 |
| 2017 | 3494 | 76.5% | -2459.1 | -2.15 | -2140 0 | -1.88 | -2713.7 | -2.23 | -2845.2 | -2.34 | -2550.3 | -2.11 | -1073.5 | -1.20 | -902.4 | -1.02 | 734.5 | 0.96 |
| 2018 | 3300 | 77.4% | -7240.1 | -1 53 | -6806.6 | -1.44 | -11890.4 | -2.34 | -11925.2 | -2.35 | -10672.5 | -2.10 | -7036 0 | -1.47 | -5904.7 | -1.17 | -3219.5 | -0.64 |

*The Tobit regression for the populations included in columns 1 through 7 does not converge for 2013 or 2014 estimations. As a result, the race coefficients listed in this column for 2013 and 2014 were computed, but no t scroes were computed. The t scores reported here were from an estimation that excluded a handful of employees who were in job classification that received no stock awards. The race coefficents for that model were identical to those computed for the model that did not converge.

| Table 3(a) | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 African American Differences in Medicare Earnings at Oracle Headquarters by Year, with Various Characteristics Considered | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | African American Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % African American | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV |
| 2013 | 1008 | 2.3% | -0.229 | -1.84 | -0.219 | -1.78 | -0.148 | -1.25 | -0.159 | -1.34 | -0.139 | -1.21 | -0.096 | -0.95 | -0.007 | -0.08 | 0.027 | 0.04 |
| 2014 | 954 | 2.4% | -0.490 | -3.43 | -0.459 | -3.24 | -0.391 | -2.83 | -0.416 | -3.03 | -0.383 | -2.91 | -0.314 | -2.77 | -0.194 | -1.86 | -0.089 | -1.12 |
| 2015 | 916 | 2.8% | -0.431 | -3.73 | -0.412 | -3.58 | -0.335 | -2.99 | -0.362 | -3.24 | -0.336 | -3.09 | -0.298 | -3.09 | -0.221 | -2.49 | -0.082 | -1.20 |
| 2016 | 867 | 3.5% | -0.501 | -4.46 | -0.479 | -4.27 | -0.343 | -3.15 | -0.352 | -3.24 | -0.336 | -3.17 | -0.273 | -3.00 | -0.203 | -2.42 | -0.075 | -1.19 |
| 2017 | 848 | 3.3% | -0.538 | -4.19 | -0.508 | -3.97 | -0.446 | -3.53 | -0.440 | -3.50 | -0.413 | -3.36 | -0.320 | -2.97 | -0.255 | -2.58 | 0.123 | -1.74 |
| 2018 | 772 | 3.5% | -0.514 | -3.88 | -0.495 | -3.75 | -0.410 | -3.15 | -0.394 | -3.06 | -0.367 | -2.92 | -0.222 | -2.03 | -0.202 | -2.02 | -0.074 | -1.07 |

**Table 3(b)**

**2013 through 2018 African American Differences in Base Pay Rates at Oracle Headquarters by Year, with Various Characteristics Considered**

**Controls for ...**

| | | | African American Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | Number of Workers | % African American | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV |
| 2013 | 1178 | 2.6% | -0.244 | -4.21 | -0 233 | -4.10 | -0.167 | -3.08 | -0.172 | -3.17 | -0.172 | -3.23 | -0.144 | -3.19 | -0.099 | -2.45 | -0.042 | -1.58 |
| 2014 | 1133 | 2.7% | -0.270 | -4.47 | -0 259 | -4 34 | -0.173 | -3.03 | -0.179 | -3.13 | -0.172 | -3.08 | -0.154 | -3.22 | -0.099 | -2.28 | -0.039 | -1.32 |
| 2015 | 1072 | 3.2% | -0.260 | -4.70 | -0 246 | -4.49 | -0.167 | -3.18 | -0.169 | -3.23 | -0.163 | -3.18 | -0.140 | -3.22 | -0.099 | -2.53 | -0.017 | -0.68 |
| 2016 | 1007 | 3.4% | -0.289 | -5.26 | -0 277 | -5 09 | -0.196 | -3.73 | -0.195 | -3.71 | -0.188 | -3.65 | -0.163 | -3.67 | -0.126 | -3.15 | -0.048 | -1.87 |
| 2017 | 951 | 3.3% | -0.288 | -5.08 | -0 273 | -4 87 | -0.217 | -4.00 | -0.214 | -3.94 | -0.209 | -3.92 | -0.165 | -3.57 | -0.133 | -3.18 | -0.073 | -2.75 |
| 2018 | 903 | 3.8% | -0.314 | -5.49 | -0 301 | -5 32 | -0.226 | -4.11 | -0.220 | -4.02 | -0.213 | -3.98 | -0.155 | -3.32 | -0.136 | -3.21 | -0.063 | -2.24 |

**Table 3(c)**

**2013 through 2018 African American Differences in Restricted Stock Awards at Oracle Headquarters by Year, with Various Characteristics Controlled**

**Controls for ...**

| | | | African American Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Performance Rating (7) | | Adds Global Career Level* (8) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | Number of Workers | % African American | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV | Race Coefficient | ST DEV |
| 2013 | 1008 | 2.3% | -25823.1 | -2.00 | -25888.9 | -2.07 | -25197.2 | -2.00 | -26647.8 | -2.12 | -24550.4 | -2.01 | -18642.7 | -1.91 | -14649.3 | -1.46 | -7986.2 | -0.82 |
| 2014 | 954 | 2.4% | -33392.2 | -2.60 | -32412.9 | -2.52 | -29576.3 | -2.32 | -30831.4 | -2.42 | -28742.4 | -2.32 | -21501.6 | -2.22 | -20443.2 | -2.12 | -8705.5 | -0.99 |
| 2015 | 903 | 2.9% | -30649.7 | -2.25 | -29688.1 | -2.18 | -25177.0 | -1.86 | -26223.4 | -1.94 | -24743.0 | -1.84 | -18777.1 | -1.80 | -16908.6 | -1.56 | -3055.4 | -0.29 |
| 2016 | 848 | 3.4% | -14932.2 | -2.32 | -14145.9 | -2.19 | -12114.6 | -1.86 | -12379.4 | -1.91 | -11904.8 | -1.86 | -7266.6 | -1.80 | -6169.4 | -1.54 | -1107.6 | -0.33 |
| 2017 | 848 | 3.3% | -15117.7 | -2.16 | -14823.8 | -2.11 | -14193.3 | -2.01 | -13507.8 | -1.93 | -12245.9 | -1.78 | -6561.2 | -1.53 | -5759.9 | -1.35 | -752.0 | -0.21 |
| 2018 | 772 | 3.5% | -12760.4 | -0.29 | -13435.0 | -0.31 | -14885.2 | -0.34 | -11671.9 | -0.27 | -15291.0 | -0.35 | -3819.6 | -0.10 | -11609.2 | -0.27 | -15897.3 | -0.36 |

*The Tobit regression for the populations included in columns 1 through 7 does not converge. As a result, the race coefficients listed in this column were computed, but no t scroes were computed. The t scores reported here were from an estimation that excluded a handful of employees who were in job classification that received no stock awards. The race coefficents for that model were identical to those computed for the model that did not converge.

| Table 4 | | | | | |
|---|---|---|---|---|---|
| **2013 through 2018 Gender and Race Differences in Starting, Prior and Current Base Pay at Oracle, Employees with Recorded Prior Base Pay and Base Pay at Hire** | | | | | |
| | **All Employees in Class Period Jobs** | **Employees in Class Period Jobs with Prior Pay Data** | | | **All Employees in Class Period Jobs** |
| | **Starting Pay** | **Starting Pay** | **Prior Pay** | **Starting Pay Minus Prior Pay** | **Current Base Pay during Class Period*** |
| **Controlling for gender, (race), age, education, and hire year** | 1 | 2 | 3 | 4 | 5 |
| **Women** | | | | | |
| **Coefficient** | -0.087 | -0.120 | -0.123 | 0.003 | -0.135 |
| **Standard Deviations** | -11.36 | -9.06 | -6.15 | 0.21 | -9.11 |
| **Number** | 3632 | 1258 | 1258 | 1258 | 4384 |
| **Asian Employees** | | | | | |
| **Coefficient** | -0.037 | -0.078 | -0.078 | 0.024 | -0.100 |
| **Standard Deviations** | -3.92 | -4.94 | -2.91 | 1.31 | -4.85 |
| **Number** | 3176 | 1080 | 1080 | 1080 | 3808 |
| **African American Employees** | | | | | |
| **Coefficient** | -0.067 | -0.152 | -0.043 | -0.035 | -0.108 |
| **Standard Deviations** | -1.21 | -1.47 | -0.027 | -0.36 | -1.14 |
| **Number** | 634 | 245 | 245 | 245 | 795 |
| **Controlling for above plus starting job descriptor**** | | | | | |
| **Women** | | | | | |
| **Coefficient** | -0.060 | -0.097 | -0.096 | 0.000 | -0.104 |
| **Standard Deviations** | -8.7 | -7.7 | -4.82 | -0.01 | -7.34 |
| **Number** | 3632 | 1258 | 1258 | 1258 | 4384 |
| **Asian Employees** | | | | | |
| **Coefficient** | -0.034 | -0.069 | -0.068 | 0.025 | -0.101 |
| **Standard Deviations** | -3.91 | -4.62 | -2.56 | 1.37 | -4.88 |
| **Number** | 3176 | 1080 | 1080 | 1080 | 3808 |
| **African American Employees** | | | | | |
| **Coefficient** | -0.052 | -0.126 | 0.047 | -0.082 | -0.115 |
| **Standard Deviations** | -1.09 | -1.20 | 0.28 | -0.78 | -1.20 |
| **Number** | 634 | 245 | 245 | 245 | 795 |
| **Controlling for above plus starting global career level**** | | | | | |
| **Women** | | | | | |
| **Coefficient** | -0.019 | -0.027 | -0.019 | -0.009 | -0.030 |
| **Standard Deviations** | -4.35 | -4.01 | -1.12 | -0.57 | -4.48 |
| **Number** | 3632 | 1258 | 1258 | 1258 | 4384 |
| **Asian Employees** | | | | | |
| **Coefficient** | -0.002 | -0.009 | -0.011 | 0.027 | -0.026 |
| **Standard Deviations** | -0.37 | -1.15 | -0.46 | 1.42 | -2.72 |
| **Number** | 3176 | 1080 | 1080 | 1080 | 3808 |
| **African American Employees** | | | | | |
| **Coefficient** | 0.015 | -0.087 | 0.071 | -0.056 | -0.041 |
| **Standard Deviations** | 0.53 | -1.65 | 0.53 | -0.53 | -0.65 |
| **Number** | 634 | 245 | 245 | 245 | 795 |

* Base Pay Regressions do not include the dummy for hire year. The number listed is the number of unique hires in the regressions, not total observations.
** Base pay regression controls for time in company

| Table 5(a) | | | | | | |
|---|---|---|---|---|---|---|
| 2013 through 2018 Gender Differences in Medicare Earnings at Oracle, by Year<br>Employees with Recorded Characteristics of Job Assignments | | | | | | |
| Controls for Race, Ethnicity, Age, Education, Time at Oracle, Job at Hire and Global Career Level at Hire (1) | | | Adds Exempt/Nonexempt, Current Job Descriptor (2) | | Adds Current Global Career Level (3) | |
| Year | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score |
| 2013 | -0.110 | -7.04 | -0.100 | -6.62 | -0.043 | -3.45 |
| 2014 | -0.130 | -7.43 | -0.114 | -6.69 | -0.058 | -4.20 |
| 2015 | -0.099 | -6.30 | -0.086 | -5.61 | -0.040 | -3.23 |
| 2016 | -0.129 | -7.62 | -0.115 | -7.04 | -0.054 | -4.27 |
| 2017 | -0.157 | -7.90 | -0.137 | -7.17 | -0.052 | -3.54 |
| 2018 | -0.160 | -7.70 | -0.139 | -7.01 | -0.053 | -3.64 |

| Table 5(b) | | | | | | |
|---|---|---|---|---|---|---|
| 2013 through 2018 Gender Differences in Base Pay at Oracle, by Year<br>Employees with Recorded Characteristics of Job Assignments | | | | | | |
| Controls for Race, Ethnicity, Age, Education, Time at Oracle, Job at Hire and Global Career Level at Hire (1) | | | Adds Exempt/Nonexempt, Current Job Descriptor (2) | | Adds Current Global Career Level (3) | |
| Year | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score |
| 2013 | -0.071 | -10.81 | -0.067 | -10.71 | -0.034 | -7.28 |
| 2014 | -0.070 | -9.96 | -0.062 | -9.25 | -0.031 | -6.33 |
| 2015 | -0.075 | -10.38 | -0.066 | -9.47 | -0.031 | -6.63 |
| 2016 | -0.079 | -10.56 | -0.071 | -9.99 | -0.035 | -7.30 |
| 2017 | -0.083 | -11.01 | -0.073 | -10.22 | -0.034 | -7.16 |
| 2018 | -0.089 | -10.51 | -0.077 | -9.58 | -0.036 | -6.63 |

| Table 6(a) | | | | | | |
|---|---|---|---|---|---|---|
| 2013 through 2018 Asian Differences in Medicare Earnings at Oracle, By Year<br>Employees with Recorded Characteristics of Job Assignments | | | | | | |
| Controls for Gender, Age, Education, Time at Oracle, Job at Hire and Global Career Level at Hire (1) | | | Adds Exempt/Nonexempt, Current Job Descriptor (2) | | Adds Current Global Career Level (3) | |
| Year | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score |
| 2013 | -0.053 | -2.80 | -0.046 | -2.50 | -0.040 | -2.62 |
| 2014 | -0.098 | -4.41 | -0.092 | -4.30 | -0.082 | -4.74 |
| 2015 | -0.083 | -4.18 | -0.083 | -4.30 | -0.079 | -5.05 |
| 2016 | -0.052 | -2.40 | -0.058 | -2.79 | -0.054 | -3.34 |
| 2017 | -0.062 | -2.44 | -0.058 | -2.40 | -0.070 | -3.81 |
| 2018 | -0.058 | -2.15 | -0.050 | -1.92 | -0.041 | -2.14 |

| Table 6(b) | | | | | | |
|---|---|---|---|---|---|---|
| 2013 through 2018 Asian Differences in Base Pay at Oracle<br>Employees with Recorded Characteristics of Job Assignments | | | | | | |
| Controls for Gender, Age, Education, Time at Oracle, Job at Hire and Global Career Level at Hire (1) | | | Adds Exempt/Nonexempt, Current Job Descriptor (2) | | Adds Current Global Career Level (3) | |
| Year | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score |
| 2013 | -0.029 | -3.54 | -0.030 | -3.81 | -0.028 | -4.84 |
| 2014 | -0.025 | -2.87 | -0.026 | -3.00 | -0.027 | -4.46 |
| 2015 | -0.031 | -3.35 | -0.032 | -3.54 | -0.031 | -5.11 |
| 2016 | -0.026 | -2.69 | -0.028 | -3.00 | -0.025 | -3.99 |
| 2017 | -0.032 | -3.24 | -0.029 | -3.14 | -0.031 | -5.00 |
| 2018 | -0.027 | -2.43 | -0.023 | -2.17 | -0.026 | -3.72 |

| Table 7(a) | | | | | | |
|---|---|---|---|---|---|---|
| **2013 through 2018 African American Differences in Medicare Earnings at Oracle, by Year<br>Employees with Recorded Characteristics of Job Assignments** | | | | | | |
| **Controls for Gender, Age, Education, Time at Oracle, Job at Hire and Global Career Level at Hire (1)** | | | **Adds Exempt/Nonexempt, Current Job Descriptor (2)** | | **Adds Current Global Career Level (3)** | |
| **Year** | **Race Coefficient** | **t score** | **Race Coefficient** | **t score** | **Race Coefficient** | **t score** |
| 2013 | -0.002 | -0.01 | 0.041 | 0.40 | 0.068 | 0.84 |
| 2014 | -0.168 | -1.28 | -0.145 | -1.21 | -0.072 | -0.73 |
| 2015 | -0.202 | -1.91 | -0.190 | -1.91 | -0.077 | -0.97 |
| 2016 | -0.217 | -2.18 | -0.196 | -2.05 | -0.107 | -1.47 |
| 2017 | -0.274 | -2.19 | -0.235 | -1.97 | -0.118 | -1.38 |
| 2018 | -0.198 | -1.51 | -0.121 | -0.98 | -0.028 | -0.32 |

| Table 7(b) | | | | | | |
|---|---|---|---|---|---|---|
| **2013 through 2018 African American Differences in Base Pay at Oracle, by Year<br>Employees with Recorded Characteristics of Job Assignments** | | | | | | |
| **Controls for Gender, Age, Education, Time at Oracle, Job at Hire and Global Career Level at Hire (1)** | | | **Adds Exempt/Nonexempt, Current Job Descriptor (2)** | | **Adds Current Global Career Level (3)** | |
| **Year** | **Race Coefficient** | **t score** | **Race Coefficient** | **t score** | **Race Coefficient** | **t score** |
| 2013 | -0.104 | -2.30 | -0.092 | -2.14 | -0.064 | -2.09 |
| 2014 | -0.112 | -2.20 | -0.104 | -2.16 | -0.060 | -1.71 |
| 2015 | -0.092 | -2.00 | -0.081 | -1.88 | -0.027 | -0.93 |
| 2016 | -0.119 | -2.50 | -0.109 | -2.42 | -0.063 | -2.02 |
| 2017 | -0.170 | -3.34 | -0.147 | -3.06 | -0.086 | -2.70 |
| 2018 | -0.038 | -2.53 | -0.110 | -2.15 | -0.068 | -2.01 |

**Table 8**

**Lost Compensation Damages for Women at Oracle, 2013-2018**

| | Damages Based on Men and Women of the Same Race, Ethnicity, Age, Education and Time at Oracle (Column 5 of Table 1a) | | | | Damages Based on Men and Women of the Same Race, Ethnicity, Age, Education, Time at Oracle, Exempt Status and Job Descriptor (Column 6 of Table 1a) | | | | Damages Based on Men and Women of the Same Race, Ethnicity, Age, Education, Time at Oracle, Exempt Status, Job Descriptor and Global Career Level (Column 8 of Table 1a) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | Lost Earnings (1) | Lost Fringes (2) | Interest (3) | Total Lost Compensation Plus Interest (4) | Lost Earnings (1) | Lost Fringes (2) | Interest (3) | Total Lost Compensation Plus Interest (4) | Lost Earnings (1) | Lost Fringes (2) | Interest (3) | Total Lost Compensation Plus Interest (4) |
| 2013 | $ 32,328,524 | $ 969,856 | $ 8,186,056 | $ 41,484,435 | $ 26,407,492 | $ 792,225 | $ 6,686,764 | $ 33,886,481 | $ 10,179,053 | $ 305,372 | $ 2,577,485 | $ 13,061,910 |
| 2014 | $ 38,694,889 | $ 1,160,847 | $ 8,351,884 | $ 48,207,620 | $ 30,514,966 | $ 915,449 | $ 6,586,334 | $ 38,016,749 | $ 12,632,970 | $ 378,989 | $ 2,726,693 | $ 15,738,652 |
| 2015 | $ 30,415,515 | $ 912,465 | $ 5,461,193 | $ 36,789,173 | $ 23,699,181 | $ 710,975 | $ 4,255,256 | $ 28,665,413 | $ 8,970,702 | $ 269,121 | $ 1,610,715 | $ 10,850,538 |
| 2016 | $ 35,347,787 | $ 1,060,434 | $ 4,951,379 | $ 41,359,599 | $ 27,685,070 | $ 830,552 | $ 3,878,015 | $ 32,393,637 | $ 10,493,174 | $ 314,795 | $ 1,469,842 | $ 12,277,812 |
| 2017 | $ 47,969,855 | $ 1,439,096 | $ 4,625,865 | $ 54,034,816 | $ 37,601,905 | $ 1,128,057 | $ 3,626,055 | $ 42,356,017 | $ 13,632,709 | $ 408,981 | $ 1,314,640 | $ 15,356,329 |
| 2018 | $ 49,369,006 | $ 1,481,070 | $ 2,756,305 | $ 53,606,380 | $ 40,252,956 | $ 1,207,589 | $ 2,247,350 | $ 43,707,895 | $ 14,034,038 | $ 421,021 | $ 783,530 | $ 15,238,589 |
| 2013-2018 | $ 234,125,575 | $ 7,023,767 | $ 34,332,681 | $ 275,482,024 | $ 186,161,571 | $ 5,584,847 | $ 27,279,774 | $ 219,026,192 | $ 69,942,645 | $ 2,098,279 | $ 10,482,906 | $ 82,523,830 |

| Table 9 | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Lost Compensation Damages for Asian Employees at Oracle, 2013-2018 | | | | | | | | | | | | |
| | Damages Based on Asian and White Employees of the Same Gender, Age, Education and Time at Oracle (Column 5 of Table 2a) | | | | Damages Based on Asian and White Employees of the Same Gender, Age, Education, Time at Oracle, Exempt Status and Job Descriptor (Column 6 of Table 2a) | | | | Damages Based on Asian and White Employees of the Same Gender, Age, Education, Time at Oracle, Exempt Status, Job Descriptor and Global Career Level (Column 8 of Table 2a) | | | |
| Year | Lost Earnings (1) | Lost Fringes (2) | Interest (3) | Total Lost Compensation Plus Interest (4) | Lost Earnings (1) | Lost Fringes (2) | Interest (3) | Total Lost Compensation Plus Interest (4) | Lost Earnings (1) | Lost Fringes (2) | Interest (3) | Total Lost Compensation Plus Interest (4) |
| 2013 | $ 54,709,776 | $ 1,641,293 | $ 13,853,317 | $ 70,204,386 | $ 51,104,194 | $ 1,533,126 | $ 12,940,331 | $ 65,577,651 | $ 19,834,821 | $ 595,045 | $ 5,022,467 | $ 25,452,333 |
| 2014 | $ 88,495,396 | $ 2,654,862 | $ 19,100,799 | $ 110,251,057 | $ 86,985,772 | $ 2,609,573 | $ 18,774,963 | $ 108,370,308 | $ 42,095,309 | $ 1,262,859 | $ 9,085,829 | $ 52,443,997 |
| 2015 | $ 72,801,369 | $ 2,184,041 | $ 13,071,695 | $ 88,057,106 | $ 71,204,253 | $ 2,136,128 | $ 12,784,929 | $ 86,125,309 | $ 35,372,023 | $ 1,061,161 | $ 6,351,149 | $ 42,784,332 |
| 2016 | $ 61,417,290 | $ 1,842,519 | $ 8,603,092 | $ 71,862,900 | $ 59,507,711 | $ 1,785,231 | $ 8,335,605 | $ 69,628,548 | $ 21,292,453 | $ 638,774 | $ 2,982,563 | $ 24,913,790 |
| 2017 | $ 77,386,803 | $ 2,321,604 | $ 7,462,622 | $ 87,171,029 | $ 69,520,003 | $ 2,085,600 | $ 6,704,005 | $ 78,309,608 | $ 32,665,745 | $ 979,972 | $ 3,150,047 | $ 36,795,765 |
| 2018 | $ 79,803,599 | $ 2,394,108 | $ 4,455,489 | $ 86,653,195 | $ 70,159,283 | $ 2,104,778 | $ 3,917,040 | $ 76,181,101 | $ 30,409,020 | $ 912,271 | $ 1,697,756 | $ 33,019,047 |
| 2013-2018 | $ 434,614,233 | $ 13,038,427 | $ 66,547,013 | $ 514,199,673 | $ 408,481,217 | $ 12,254,437 | $ 63,456,872 | $ 484,192,525 | $ 181,669,371 | $ 5,450,081 | $ 28,289,811 | $ 215,409,263 |

**Table 10**

**Lost Compensation Damages for African American Employees at Oracle, 2013-2018**

| | Damages Based on African American and White Employees of the Same Gender, Age, Education, and Time at Oracle (Column 5 of Table 3a) | | | | Damages Based on African American and White Employees of the Same Gender, Age, Education, Time at Oracle, Exempt Status, and Job Descriptor (Column 6 of Table 3a) | | | | Damages Based on African American and White Employees of the Same Gender, Age, Education, Time at Oracle, Exempt Status, Job Descriptor and Global Career Level (Column 8 of Table 3a) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | Lost Earnings (1) | Lost Fringes (2) | Interest (3) | Total Lost Compensation (4) | Lost Earnings (1) | Lost Fringes (2) | Interest (3) | Total Lost Compensation (4) | Lost Earnings* (1) | Lost Fringes (2) | Interest (3) | Total Lost Compensation (4) |
| 2013 | $ 639,752 | $ 19,193 | $ 161,995 | $ 820,939 | $ 459,586 | $ 13,788 | $ 116,374 | $ 589,747 | $ - | $ - | $ - | $ - |
| 2014 | $ 1,443,675 | $ 43,310 | $ 311,602 | $ 1,798,587 | $ 1,246,506 | $ 37,395 | $ 269,045 | $ 1,552,946 | $ 424,486 | $ 12,735 | $ 91,621 | $ 528,841 |
| 2015 | $ 1,007,216 | $ 30,216 | $ 180,848 | $ 1,218,281 | $ 918,222 | $ 27,547 | $ 164,869 | $ 1,110,639 | $ 304,496 | $ 9,135 | $ 54,673 | $ 368,304 |
| 2016 | $ 1,144,194 | $ 34,326 | $ 160,274 | $ 1,338,794 | $ 973,999 | $ 29,220 | $ 136,434 | $ 1,139,653 | $ 315,408 | $ 9,462 | $ 44,181 | $ 369,052 |
| 2017 | $ 1,441,700 | $ 43,251 | $ 139,027 | $ 1,623,978 | $ 1,195,452 | $ 35,864 | $ 115,281 | $ 1,346,596 | $ - | $ - | $ - | $ - |
| 2018 | $ 1,429,188 | $ 42,876 | $ 79,793 | $ 1,551,856 | $ 968,826 | $ 29,065 | $ 54,090 | $ 1,051,981 | $ 364,821 | $ 10,945 | $ 20,368 | $ 396,134 |
| 2013-2018 | $ 7,105,724 | $ 213,172 | $ 1,033,539 | $ 8,352,435 | $ 5,762,591 | $ 172,878 | $ 856,093 | $ 6,791,562 | $ 1,409,211 | $ 42,276 | $ 210,843 | $ 1,662,331 |

*When total losses for the 2013-2018 period are calculated by summing up losses in each year, an entry of zero losses is included for those years and analyses where there was no loss of earnings.

**APPENDICES**

# Appendix A: Job Descriptors

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| ACCOUNT SALES REPRESENTATIVE | Account Sales Representative I |
| ACCOUNTANT | ACCOUNTANT 1 |
| ACCOUNTANT-FIN | Accountant 3-Fin |
| ACCOUNTING SUPPORT -FIN | Accounting Support A3-Fin |
| ACCOUNTING SUPPORT-FIN | Accounting Support A2-Fin |
| ACCOUNTING-FIN | Accounting Supervisor-Fin |
| ACCOUNTING-FIN | Accounting Manager-Fin |
| ACCOUNTING-FIN | Accounting Snr Manager-Fin |
| ADMIN ASSISTANT | Administrative Assistant A2 |
| ADMIN ASSISTANT | Senior Administrative Assistant |
| ADMIN ASSISTANT | ADMINISTRATIVE ASSISTANT 1 |
| ADMIN ASSISTANT | Administrative Assistant A3 |
| ADMIN ASSISTANT | Executive Assistant to the Executive Office |
| ADMIN ASSISTANT | Executive Assistant |
| ALLIANCES | Alliances Senior SC |
| ALLIANCES | Alliances Principal SC |
| ALLIANCES | Alliances Consultant 2 |
| ALLIANCES | Alliances Consultant 4 |
| ALLIANCES | Alliances Consultant 5 |
| ALLIANCES | Alliances Consultant 1 |
| ALLIANCES | Alliances Program Senior Director |
| ALLIANCES | Alliances Vice President |
| ALLIANCES | Alliances Consultant 3 |
| ALLIANCES | Alliances Senior Partner Manager I |
| ALLIANCES | Alliances Senior Manager |
| ALLIANCES | Alliances Senior Director |
| ALLIANCES | Alliances Manager III |
| ALLIANCES | Alliances Manager |
| ALLIANCES | Alliances Director |
| ALLIANCES MARKETING | Alliances Marketing Manager |
| ALLIANCES MARKETING | Alliances Senior Marketing Director |
| ALLIANCES SALES | Alliances Global Account Manager (CGAM) |
| ALLIANCES SALES | Alliances HQ Sales Representative |
| APPS. DEVELOPER | APPS. DEVELOPER 1 |
| APPS. DEVELOPER | APPS. DEVELOPER 2 |
| APPS. DEVELOPER | APPS. DEVELOPER 3 |
| APPS. DEVELOPER | APPS. DEVELOPER 4 |
| APPS. DEVELOPER | APPS. DEVELOPER 5 |
| APPS. DEVELOPER | Applications Developer 1 |
| APPS. DEVELOPER | Applications Developer 2 |
| APPS. DEVELOPER | Applications Developer 3 |
| APPS. DEVELOPER | Applications Developer 4 |
| APPS. DEVELOPER | Applications Developer 5 |
| APPS. DEVELOPER | Applications Developer - Architect |
| BAD | Bad |
| BUDGET/FINANCE | Budget/Finance Manager |
| BUDGET/FINANCE | Budget/Finance Snr Mgr |
| BUDGET/FINANCE | Budget/Finance VP |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| BUSINESS ANALYST -OPS | Business Analyst A4-Ops |
| BUSINESS ANALYST-OPS | Business Analyst 1-Ops |
| BUSINESS ANALYST-OPS | Business Analyst 2-Ops |
| BUSINESS ANALYST-OPS | Business Analyst 3-Ops |
| BUSINESS ANALYST-OPS | Business Analyst 4-Ops |
| BUSINESS ANALYST-OPS | Business Analyst 5-Ops |
| BUSINESS DEVELOPMENT REPRESENTATIVE | Business Development Representative I |
| BUSINESS DEVELOPMENT REPRESENTATIVE | Business Development Representative II |
| BUSINESS DEVELOPMENT REPRESENTATIVE | Business Development Representative III |
| BUSINESS DEVELOPMENT REPRESENTATIVE | Business Development Representative IV |
| BUSINESS DEVELOPMENT REPRESENTATIVE | Business Development Representative V |
| BUSINESS DEVELOPMENT-CORP PLAN | Business Development Snr Manager - Corp Plan |
| BUSINESS DEVELOPMENT-CORP PLAN | Business Development Director - Corp Plan |
| BUSINESS DEVELOPMENT-CORP PLAN | Business Development Snr Director - Corp Plan |
| BUSINESS DEVELOPMENT-CORP PLAN | Business Development Consultant 1-Corp Plan |
| BUSINESS DEVELOPMENT-CORP PLAN | Business Development Consultant 2-Corp Plan |
| BUSINESS DEVELOPMENT-CORP PLAN | Business Development Consultant 3-Corp Plan |
| BUSINESS DEVELOPMENT-CORP PLAN | Business Development Consultant 4-Corp Plan |
| BUSINESS DEVELOPMENT-CORP PLAN | Business Development Consultant 5-Corp Plan |
| BUSINESS DEVELOPMENT-SALES | Business Development Director - Sales |
| BUSINESS DEVELOPMENT-SALES | Business Development Snr Director - Sales |
| BUSINESS DEVELOPMENT-SALES | Business Development VP - Sales |
| BUSINESS PLANNING-OPS | Business Planning Snr Manager-Ops |
| BUSINESS PLANNING-OPS | Business Planning Director-Ops |
| BUSINESS PLANNING-OPS | Business Planning Snr Director-Ops |
| BUSINESS PLANNING-OPS | Business Planning VP-Ops |
| BUSINESS PROCESS | Business Process Analyst 3 |
| BUSINESS PROCESS | Business Process Analyst 4 |
| BUSINESS PROCESS | Business Process Analyst 5 |
| BUSINESS PROCESS | Business Process Director |
| BUSINESS PROCESS | Business Process Snr Director |
| BUSINESS SERVICES-SUPPORT | Business Services Representative 4-Support |
| BUSINESS SERVICES-SUPPORT | Business Services Representative 5-Support |
| BUSINESS SERVICES-SUPPORT | Business Services Snr Manager-Support |
| BUSINESS SERVICES-SUPPORT | Business Services Director-Support |
| BUSINESS SERVICES-SUPPORT | Business Services Snr Director-Support |
| BUYER-FIN | Buyer 1-Fin |
| BUYER-FIN | Buyer 2-Fin |
| BUYER-FIN | Buyer 3-Fin |
| BUYER-FIN | Buyer 4-Fin |
| CHANNEL MARKETING | Channel Marketing Manager 6 |
| CHANNEL MARKETING | Channel Marketing Specialist 4 |
| CLIENT SOLUTIONS | Client Solutions II, Director-Cons |
| CLIENT SUCCESS | Client Success Specialist I |
| CLIENT SUCCESS | Client Success Specialist IV |
| CLIENT SUCCESS | Client Success Specialist V |
| CLIENT SUCCESS | Client Success Snr Director |
| CLIENT SUCCESS | Client Success VP |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| COMPUTER OPER | COMP OPER MGMT 1 |
| COMPUTER OPER | COMPUTER OPER 1 |
| COMPUTER OPER | COMPUTER OPER 2 |
| COMPUTER OPER | Computer Operations Manager 1 |
| COMPUTER TAPE LIBRARIAN | Computer Tape Librarian |
| CONSULTING | Change Mgmt Senior Consultant |
| CONSULTING | SENIOR CONSULTANT |
| CONSULTING | Change Mgmt Principal Consultant |
| CONSULTING | ASSOCIATE CONSULTANT |
| CONSULTING | Associate Consultant Other |
| CONSULTING | Associate Consultant |
| CONSULTING | Senior Consultant Other |
| CONSULTING | Senior Consultant |
| CONSULTING | REGIONAL CONSULTING MANAGER |
| CONSULTING | Consulting GVP |
| CONSULTING | Consulting RVP |
| CONSULTING | Senior Practice Director Other |
| CONSULTING | Consulting Senior Practice Director |
| CONSULTING PROJECT | Consulting Project Snr Principal Consultant |
| CONSULTING PROJECT | Consulting Project Manager |
| CONSULTING PROJECT | Consulting Project Director |
| CONSULTING PROJECT | Consulting Project Technical Manager |
| CONSULTING SALES | Consulting Sales Snr Manager |
| CONSULTING SALES | Consulting Sales VP |
| CONSULTING SALES | Consulting Sales Rep 3 |
| CONSULTING SOLUTION | Consulting Solution Manager |
| CONSULTING SOLUTION | Consulting Solution Director |
| CONSULTING SOLUTION | Consulting Solution Lead |
| CONSULTING SOLUTION | Consulting Solution Senior Director |
| CONSULTING STAFF | Consulting Staff Principal |
| CONSULTING STAFF | Consulting Staff Snr Principal |
| CONSULTING STAFF | Consulting Staff Technical Manager |
| CONSULTING STAFF | Consulting Staff Technical Director |
| CONSULTING STAFF | Consulting Staff Practice Manager |
| CONSULTING STAFF | Consulting Staff Practice Director |
| CONSULTING STAFF | Consulting Staff Senior Practice Director |
| CONSULTING TECHNICAL | Technical Manager Other |
| CONSULTING TECHNICAL | Consulting Technical Manager |
| CONSULTING TECHNICAL | Technical Director Other |
| CONSULTING TECHNICAL | Consulting Technical Director |
| CONSULTING TECHNICAL | Consulting Technical Snr Director |
| CONSULTING TECHNICAL | Consulting Technical Mgmt Manager |
| CONSULTING TECHNICAL | Consulting Technical Mgmt Director |
| CONSULTING TECHNICAL | Consulting Technical Mgmt Snr Director |
| CONSULTING TECHNICAL | Consulting Technical Lead Director |
| CONSULTING, PROGRAM MANAGEMENT | Consultant, Program Management |
| CONTRACT DEVELOPMENT SPECIALIST-OPS | Contract Development Specialist 5-Ops |
| CONTRACT SUPPORT -FIN | Contract Support A2-Fin |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| CONTRACT SUPPORT -FIN | Contract Support A3-Fin |
| CONTRACT SUPPORT -FIN | Contract Support A4-Fin |
| CONTRACTS ADMINISTRATOR-FIN | Contracts Administrator 1-Fin |
| CONTRACTS ADMINISTRATOR-FIN | Contracts Administrator 2-Fin |
| CONTRACTS ADMINISTRATOR-FIN | Contracts Administrator 3-Fin |
| CONTROLLER-FIN | Controller Director-Fin |
| CORPORATE DEVELOPMENT-OPS | Corporate Development Director-Ops |
| CORPORATE DEVELOPMENT-OPS | Corporate Development Snr Director-Ops |
| CORPORATE TRAINER-HR | Corporate Trainer 2-HR |
| CORPORATE-OPS | Corporate SVP-Ops |
| COURSE/CURRICULUM DEV-TRAINING | Course/Curriculum Dev 1-Training |
| COURSE/CURRICULUM DEV-TRAINING | Course/Curriculum Dev 2-Training |
| COURSE/CURRICULUM DEV-TRAINING | Course/Curriculum Dev 3-Training |
| COURSE/CURRICULUM DEV-TRAINING | Course/Curriculum Dev 4-Training |
| COURSE/CURRICULUM DEV-TRAINING | Course/Curriculum Dev 5-Training |
| COURSE/CURRICULUM DEV-TRAINING | Course/Curriculum Dev Mgr - Training |
| COURSE/CURRICULUM DEV-TRAINING | Course/Curriculum Dev Snr Mgr - Training |
| COURSE/CURRICULUM DEV-TRAINING | Course/Curriculum Dev Director - Training |
| COURSE/CURRICULUM DEV-TRAINING | Course/Curriculum Dev Snr Director - Training |
| CREDIT & COLLECTIONS-FIN | Credit & Collections Supervisor-Fin |
| CREDIT & COLLECTIONS-FIN | Credit & Collections Manager-Fin |
| CREDIT AND SYNDICATIONS-FIN | Credit and Syndications Manager-Fin |
| CREDIT AND SYNDICATIONS-FIN | Credit and Syndications Snr Manager-Fin |
| CREDIT AND SYNDICATIONS-FIN | Credit and Syndications Director-Fin |
| CREDIT MGMT | CREDIT MGMT 1 |
| CURRICULUM | Curriculum Manager |
| CURRICULUM | Curriculum Manager 2 |
| CUSTOMER ADVOCATE-SALES | Customer Advocate Director-Sales |
| CUSTOMER SERVICE ACCOUNT MANAGEMENT CONSULTAN | Customer Service Account Management Consultant 3-Support |
| CUSTOMER SERVICE EXPEDITER-MFG&DIST | Customer Service Expediter 3-Mfg&Dist |
| CUSTOMER SERVICE REPRESENTATIVE | Customer Service Representative 2 |
| CUSTOMER SERVICE REPRESENTATIVE | Customer Service Representative 3 |
| CUSTOMER SERVICE REPRESENTATIVE-OPS | Customer Service Representative 2-Ops |
| CUSTOMER SERVICE STAFF | CUSTOMER SERVICE STAFF |
| CUSTOMER SERVICE-SUPPORT | Customer Service Administrative Support 2 |
| CUSTOMER SERVICE-SUPPORT | Customer Service Administrative Support 3 |
| CUSTOMER SERVICE-SUPPORT | Customer Service Admin Support A4 |
| CUSTOMER SERVICE-SUPPORT | Customer Service Analyst 1-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service Analyst 2-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service Analyst 3-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service Analyst 4-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service Analyst 5-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service Consultant |
| CUSTOMER SERVICE-SUPPORT | Customer Service Account Management Consultant 4-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service Account Management Consultant 5-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service Acct Mgmt Cons 5- Support (Outside CA) |
| CUSTOMER SERVICE-SUPPORT | Adv Customer Service Support Manager |
| CUSTOMER SERVICE-SUPPORT | Adv Customer Service Support Snr Manager |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| CUSTOMER SERVICE-SUPPORT | Adv Customer Service Support Director |
| CUSTOMER SERVICE-SUPPORT | Adv Customer Service Support Snr Director |
| CUSTOMER SERVICE-SUPPORT | Customer Service Manager-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service Snr Manager-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service Director-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service Snr Director-Support |
| CUSTOMER SERVICE-SUPPORT | Customer Service VP-Support |
| DATA SCIENTIST | Data Scientist 4 |
| DATA SERVICES SUPPORT -IT | Data Services Support A3-IT |
| DATA SERVICES SUPPORT -IT | Data Services Support A4-IT |
| DATA SERVICES SUPPORT-IT | Data Services Support A1-IT |
| DATA SERVICES SUPPORT-IT | Data Services Support A2-IT |
| DATABASE ADMIN | DATABASE ADMIN 2 |
| DATABASE ADMIN | DATABASE ADMIN 3 |
| DATABASE ADMIN | DATABASE ADMIN 4 |
| DATABASE ADMIN | Database Administrator 1-IT |
| DATABASE ADMIN | Database Administrator 2-IT |
| DATABASE ADMIN | Database Administrator 3-IT |
| DATABASE ADMIN | Database Administrator 4-IT |
| DATABASE ADMIN | Database Administrator 5-IT |
| DEVELOPMENT SYSTEMS ADMINISTRATOR | Development Systems Administrator 4 |
| DEVELOPMENT SYSTEMS ADMINISTRATOR | Development Systems Administrator 5 |
| DIGITAL CONTENT SPECIALIST | Digital Content Specialist 3 |
| DIRECTOR-WWCS | Director - WWCS |
| DMD CONTRACT SUPPORT SPECIALIST | DMD Contract Support Specialist I |
| DMD SALES CONSULTING | DMD Sales Consulting Manager |
| DMS | DMS Director |
| EDUCATION | Education Director |
| EDUCATION | Education Account Manager 4 |
| EDUCATION | Education Manager Other |
| EDUCATION | Education Manager Applications |
| EDUCATION | Education Project Manager 2 |
| EVENT SPECIALIST | Event Specialist 2 |
| EXECUTIVE VICE PRESIDENT-OPS | Executive Vice President-Ops |
| FACILITIES MGMT | FACILITIES MGMT 1 |
| FACILITIES SPECIALIST | Facilities Specialist 1 |
| FACILITIES SPECIALIST | Facilities Specialist 2 |
| FACILITIES SPECIALIST | Facilities Specialist 3 |
| FACILITIES SPECIALIST | Facilities Specialist 4 |
| FIELD MARKETING SPECIALIST | Field Marketing Specialist 5 |
| FIELD SUPPORT SPECIALIST | Field Support Specialist 3 |
| FIELD TECHNICAL SPECIALIST APPLICATIONS | Field Technical Specialist Applications |
| FINANCE STAFF | FINANCE STAFF |
| FINANCIAL ANALYST | Financial Analyst 1 |
| FINANCIAL ANALYST | Financial Analyst 2 |
| FINANCIAL ANALYST | Financial Analyst 4 |
| GENERIC ADMINISTRATIVE SUPPORT | Generic Administrative Support 3 |
| GOLD SUPPORT ACCOUNT | Gold Support Account Manager 2 |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| GOLD SUPPORT ACCOUNT | Gold Support Account Manager 3 |
| GOVERNMENT CONTRACTS ADMINISTRATOR | Government Contracts Administrator 2 |
| GRAPHICS DESIGNER-MKT | Graphics Designer 2-Mkt |
| GRAPHICS DESIGNER-MKT | Graphics Designer 3-Mkt |
| HARDWARE DEVELOPMENT | Hardware Developer 1 |
| HARDWARE DEVELOPMENT | Hardware Developer 2 |
| HARDWARE DEVELOPMENT | Hardware Developer 3 |
| HARDWARE DEVELOPMENT | Hardware Developer 4 |
| HARDWARE DEVELOPMENT | Hardware Developer 5 |
| HARDWARE DEVELOPMENT | Hardware Developer 6 |
| HARDWARE DEVELOPMENT | Hardware Development Snr Manager |
| HARDWARE DEVELOPMENT | Hardware Development Director |
| HARDWARE DEVELOPMENT | Hardware Development Snr Director |
| HARDWARE DEVELOPMENT | Hardware Development VP |
| HARDWARE SALES REPRESENTATIVE | Hardware Sales Representative I |
| HELPDESK ENGINEER | Helpdesk Engineer 4 |
| HR | HR Director |
| HR | HR Consultant 2 |
| HR SUPPORT | HR Support A2 |
| HR SUPPORT | HR Support A3 |
| HR SUPPORT | HR Support A4 |
| HRIS | HRIS Analyst 3 |
| HW DEVELOPMENT TECHNICIAN | HW Development Technician 3 |
| IBM GLOBAL ALLIANCE | Director, IBM Global Alliance |
| IC NON-TECH | IC 2 NON-TECH |
| IC TECH | IC 3 TECH |
| IC TECH | IC 4 TECH |
| INCENTIVE PLANNING-FIN | Incentive Planning Supervisor-Fin |
| INDUSTRY BDM | Industry BDM V |
| INDUSTRY DIRECTOR | INDUSTRY DIRECTOR |
| INFO SYS MGMT | INFO SYS MGMT 2 |
| INSTRUCTOR | Senior Instructor Other |
| INSTRUCTOR | Senior Instructor-Training |
| INSTRUCTOR | Principal Instructor Other |
| INSTRUCTOR | Principal Instructor-Training |
| INSTRUCTOR | Instructor Other |
| INSTRUCTOR | Associate Instructor-Training |
| INSTRUCTOR | Staff Instructor Other |
| INTERNAL APPLICATION ENGINEER | Internal Application Engineer 1 |
| INTERNAL APPLICATIONS ENGINEER | Internal Applications Engineer 2 |
| INTERNAL APPLICATIONS ENGINEER | Internal Applications Engineer 3 |
| INTERNAL APPLICATIONS ENGINEER | Internal Applications Engineer 4 |
| INTERNAL APPLICATIONS ENGINEER | Internal Applications Engineer 5 |
| INTERNAL AUDITOR-FIN | Internal Auditor 3-Fin |
| INTERNAL AUDITOR-FIN | Internal Auditor 4-Fin |
| INTERNAL CUSTOMER TECH SUPPORT -IT | Internal Customer Tech Support A3-IT |
| INTERNAL CUSTOMER TECH SUPPORT -IT | Internal Customer Tech Support A4-IT |
| INTERNAL CUSTOMER TECH SUPPORT-IT | Internal Customer Tech Support 1-IT |

**Appendix A**

**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| INTERNAL CUSTOMER TECH SUPPORT-IT | Internal Customer Tech Support 2-IT |
| INTERNAL CUSTOMER TECH SUPPORT-IT | Internal Customer Tech Support 3-IT |
| INTERNAL CUSTOMER TECH SUPPORT-IT | Internal Customer Tech Support 4-IT |
| INTERNET SALES CONSULTANT | Associate Sales Representative OD Prime |
| INTERNET SALES CONSULTANT | Associate Technical Publications Specialist |
| INTERNET SALES CONSULTING | Associate Internet Sales Representative |
| INTERNET SALES CONSULTING | Associate Sales Consultant |
| INTERNET SALES CONSULTING | Associate Technical Analyst Tools |
| INTERNET SALES CONSULTING | Associate Internet Sales Consultant |
| INTERNET SALES CONSULTING | Staff Internet Sales Consultant |
| INTERNET SALES CONSULTING | Senior Internet Sales Consultant |
| INTERNET SALES CONSULTING | TL Internet Sales Consultant |
| INTERNET SALES CONSULTING | Master Principal Internet Sales Consultant |
| INTERNET SALES CONSULTING | Internet Sales Consulting Snr Manager |
| INTERNET SALES REPRESENTATIVE | Internet Sales Representative I |
| INTERNET SALES REPRESENTATIVE | Internet Sales Representative III |
| IT | IT Supervisor |
| IT | IT Manager |
| IT | IT Snr Manager |
| IT | IT Director |
| IT | IT Snr Director |
| IT | IT VP |
| IT | IT SVP |
| IT BUSINESS IMPLEMENTATION ANALYST | IT Business Implementation Analyst 1 |
| IT BUSINESS IMPLEMENTATION ANALYST | IT Business Implementation Analyst 2 |
| IT BUSINESS IMPLEMENTATION ANALYST | IT Business Implementation Analyst 3 |
| IT BUSINESS IMPLEMENTATION ANALYST | IT Business Implementation Analyst 4 |
| IT BUSINESS IMPLEMENTATION ANALYST | IT Business Implementation Analyst 5 |
| IT SECURITY ANALYST | IT Security Analyst 2 |
| IT SECURITY ANALYST | IT Security Analyst 3 |
| IT SECURITY ANALYST | IT Security Analyst 4 |
| IT SECURITY ANALYST | IT Security Analyst 5 |
| KNOWLEDGE ANALYST-SUPPORT | Knowledge Analyst 2-Support |
| KNOWLEDGE ANALYST-SUPPORT | Knowledge Analyst 3-Support |
| KNOWLEDGE ANALYST-SUPPORT | Knowledge Analyst 4-Support |
| LEGAL COUNSEL | Legal Counsel 3 |
| LEGAL COUNSEL | Legal Counsel 4 |
| LEGAL COUNSEL | Legal Counsel 5 |
| LEGAL SUPPORT | Legal Support A4 |
| LICENSE MANAGEMENT ANALYST-FIN | License Management Analyst 4-Fin |
| LICENSE MANAGEMENT ANALYST-FIN | License Management Analyst 5-Fin |
| M&D LOGISTICS | M&D Logistics Manager I |
| MANAGING PRINCIPAL | MANAGING PRINCIPAL |
| MANAGING PRINCIPAL | Managing Principal Other |
| MANAGING PRINCIPAL | Managing Principal Consultant |
| MANUFACTURING TEST | Manufacturing Test Snr Manager |
| MARKET ANALYST | Market Analyst 1 |
| MARKET ANALYST | Market Analyst 2 |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| MARKET RESEARCH ANALYST | Market Research Analyst 2 |
| MARKET RESEARCH ANALYST | Market Research Analyst 3 |
| MARKET RESEARCH ANALYST | Market Research Analyst 4 |
| MARKETING COMM / PR | Marketing Comm / PR Manager |
| MARKETING COMM / PR | Marketing Comm / PR Snr Manager |
| MARKETING COMM / PR | Marketing Comm / PR Director |
| MARKETING COMM / PR | Marketing Comm / PR Snr Director |
| MARKETING COMM / PR | Marketing Comm / PR VP |
| MARKETING COMM / PR | Marketing Comm / PR Specialist 2 |
| MARKETING COMM / PR | Marketing Comm / PR Specialist 3 |
| MARKETING COMM / PR | Marketing Comm / PR Specialist 4 |
| MARKETING COMM / PR | Marketing Comm / PR Specialist 5 |
| MARKETING COORDINATOR | Marketing Coordinator A1 |
| MARKETING RESEARCH | Marketing Research Supervisor |
| MARKETING RESEARCH | Marketing Research Snr Manager |
| MARKETING RESEARCH | Marketing Research Director |
| MARKETING RESEARCH | Marketing Research Snr Director |
| MARKETING RESEARCH | Marketing Research VP |
| MARKETING RESEARCH | Market Research Analyst 5 |
| MASTER SCHEDULER | Master Scheduler 1 |
| MASTER SCHEDULER | Master Scheduler 2 |
| MASTER SCHEDULER | Master Scheduler 3 |
| MASTER SCHEDULER | Master Scheduler 4 |
| MATERIALS ADMINISTRATIVE SUPPORT | Materials Administrative Support 1 |
| MATERIALS HANDLER-MFG&DIST | Materials Handler A1-Mfg&Dist |
| MATERIALS PLANNER-MFG&DIST | Materials Planner 2-Mfg&Dist |
| MFG & DISTRIBUTION | Mfg & Distribution Manager |
| MFG & DISTRIBUTION | Mfg & Distribution Snr Manager |
| MG TECH | MG 2 TECH |
| MKT RESEARCH | MKT RESEARCH MGMT 3 |
| N | N |
| NETWORK ENGINEER | Network Engineer 2 |
| NETWORK ENGINEER | Network Engineer 3 |
| NETWORK SYSTEM ADMINISTRATOR | Network System Administrator 1 |
| NETWORK SYSTEM ADMINISTRATOR | Network System Administrator 2 |
| NETWORK SYSTEM ADMINISTRATOR | Network System Administrator 3 |
| NETWORK/TELECOM SYSTEMS -IT | Network/Telecom Systems Analyst 1-IT |
| NETWORK/TELECOM SYSTEMS -IT | Network/Telecom Systems Analyst 2-IT |
| NETWORK/TELECOM SYSTEMS -IT | Network/Telecom Systems Analyst 3-IT |
| NETWORK/TELECOM SYSTEMS -IT | Network/Telecom Systems Analyst 4-IT |
| NETWORK/TELECOM SYSTEMS -IT | Network/Telecom Systems Analyst 5-IT |
| NETWORK/TELECOM SYSTEMS -IT | Network/Telecom Systems Technician A1-IT |
| NETWORK/TELECOM SYSTEMS -IT | Network/Telecom Systems Technician A2-IT |
| NETWORK/TELECOM SYSTEMS -IT | Network/Telecom Systems Technician A3-IT |
| NETWORK/TELECOM SYSTEMS -IT | Network/Telecom Systems Technician A4-IT |
| NETWORK/TELECOM SYSTEMS -IT | Telecommunications Technician 5 |
| NM-COLLECTIONS ANALYST | NM-COLLECTIONS ANALYST |
| NM-COMP TAPE LIBRARIAN | NM-COMP TAPE LIBRARIAN |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| NM-CONTRACT SPEC | NM-CONTRACT SPEC 1 |
| NM-CONTRACTS MGR | NM-CONTRACTS MGR 1 |
| NM-MEDIA COORDINATOR | NM-MEDIA COORDINATOR |
| NM-OEM ROYALTIES MGR | NM-OEM ROYALTIES MGR |
| NM-TECHNICAL IC | NM-TECHNICAL IC 4 |
| NON-TECHNICAL IC | Non-Technical IC 1 |
| NON-TECHNICAL IC | Non-Technical IC 2 |
| NT BROAD MKT STRATEGY | NT Sr Director Broad Mkt Strategy |
| OEM ROYALTY | OEM Royalty Manager |
| OFFICE SERVICE-FAC | Office Service Manager-Fac |
| OFFICE SERVICES SUPPORT | Office Services Support A1 |
| OFFICE SERVICES SUPPORT | Office Services Support A2 |
| OFFICE SERVICES SUPPORT | Office Services Support A3 |
| ORDER PROCESS | Order Process Manager 1 |
| ORDER PROCESS | Order Process Manager 2 |
| ORDER PROCESS MGMT | ORDER PROCESS MGMT 1 |
| ORDER PROCESS SUPPORT | ORDER PROCESS SUPPORT 2 |
| PARALEGAL | Paralegal 1 |
| PAYROLL ANALYST-FIN | Payroll Analyst 2-Fin |
| PAYROLL ANALYST-FIN | Payroll Analyst 3-Fin |
| POST UNIVERSITY STUDENT | Post University Student |
| PRACTICE MGMT | CONSULTING MANAGER |
| PRACTICE MGMT | GROUP MANAGER |
| PRACTICE MGMT | Practice Manager Other |
| PRACTICE MGMT | Consulting Practice Manager |
| PRACTICE MGMT | Practice Director Other |
| PRACTICE MGMT | Consulting Practice Director |
| PRINCIPAL CONSULTANT | PRINCIPAL CONSULTANT |
| PRINCIPAL CONSULTANT | SR PRINCIPAL CONSULTANT |
| PRINCIPAL CONSULTANT | Principal Consultant Other |
| PRINCIPAL CONSULTANT | Principal Consultant |
| PRINCIPAL CONSULTANT | Senior Principal Consultant Other |
| PRINCIPAL CONSULTANT | Senior Principal Consultant |
| PRINCIPAL INSTRUCTOR OTHER | Senior Principal Instructor Other |
| PRINCIPAL INSTRUCTOR-TRAINING | Snr Principal Instructor-Training |
| PRINCIPAL SALES CONSULTANT | Principal Sales Consultant |
| PRINCIPAL SALES CONSULTANT | Principal Sales Consultant - Apps Server |
| PRINCIPAL SALES CONSULTANT | Principal Sales Consultant - Manufacturing |
| PRINCIPAL SALES CONSULTANT | Principal Sales Consultant - Financial |
| PRINCIPAL SALES CONSULTANT | PRINCIPAL SALES CONSULTANT |
| PRINCIPAL SALES CONSULTANT | Principal Sales Consultant Tools |
| PRINCIPAL SALES CONSULTANT | DMS Principal Sales Consultant |
| PRINCIPAL SALES CONSULTANT | Principal Sales Consultant Applications |
| PROD MKTG | PROD MKTG MGMT 2 |
| PROD MKTG | PROD MKTG MGMT 3 |
| PROD MKTG | PROD MKTG MGMT 4 |
| PROD MKTG | PROD MKTG ANALYST 1 |
| PROD MKTG | PROD MKTG ANALYST 2 |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| PROD MKTG | PROD MKTG ANALYST 3 |
| PROD MKTG | Product Marketing Analyst 1 |
| PROD MKTG | Product Marketing Analyst 2 |
| PROD MKTG | Product Marketing Analyst 3 |
| PROD MKTG | Product Marketing Analyst 4 |
| PROD MKTG | Product Marketing Analyst 5 |
| PROD PLANNER/SCHEDULER | PROD PLANNER/SCHEDULER 1 |
| PROD PLANNER/SCHEDULER | PROD PLANNER/SCHEDULER 2 |
| PROD PLANNER/SCHEDULER | PROD PLANNER/SCHEDULER 4 |
| PRODUCT MGMT | Product Manager II |
| PRODUCT MGMT | Product Manager III |
| PRODUCT MGMT | Product Manager V |
| PRODUCT DEVELOPMENT | Product Development SVP |
| PRODUCT DEVELOPMENT | Product Development EVP |
| PRODUCT ENGINEER | Product Engineer II |
| PRODUCT ENGINEER | Product Engineer IV |
| PRODUCT ENGINEER | Product Engineer V |
| PRODUCT ENGINEER | Product Engineer III |
| PRODUCT MARKETING | Product Marketing Manager |
| PRODUCT MARKETING | Product Marketing Snr Manager |
| PRODUCT MARKETING | Product Marketing Director |
| PRODUCT MARKETING | Product Marketing Snr Director |
| PRODUCT MARKETING | Product Marketing VP |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Manager/Strategy 1-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Manager/Strategy 2-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Manager/Strategy 3-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Manager/Strategy 4-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Manager/Strategy 5-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Manager/Strategy 6-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Mgmt/Strategy Manager-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Mgmt/Strategy Snr Manager-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Mgmt/Strategy Director-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Mgmt/Strategy Snr Director-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Mgmt/Strategy VP-ProdDev |
| PRODUCT MGMT/STRATEGY-PRODDEV | Product Mgmt/Strategy SVP-ProdDev |
| PRODUCT PROJECT LEADER | PRODUCT PROJECT LEADER 2 |
| PRODUCT SUPPORT | Product Support Manager |
| PRODUCT SUPPORT | Product Support Sr. Manager |
| PRODUCT SUPPORT | Product Support Director |
| PRODUCT SUPPORT | Product Support Sr. Director |
| PRODUCT SUPPORT | Product Support VP |
| PRODUCT SUPPORT ENGINEER | Product Support Engineer 2 |
| PRODUCT SUPPORT ENGINEER | Product Support Engineer 3 |
| PRODUCT TECHNOLOGIST-SALES | Product Technologist Manager II-Sales |
| PRODUCT TRAINING | Product Training Manager |
| PRODUCT TRAINING | Product Training Snr Manager |
| PRODUCT TRAINING | Product Training Director |
| PRODUCT TRAINING | Product Training Snr Director |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| PRODUCTION PLANNER | Production Planner 2-Mfg&Dist |
| PRODUCTION SERVICES SYSTEM ADMINISTRATOR | Production Service Systems Administrator 4 |
| PRODUCTION SERVICES SYSTEM ADMINISTRATOR | Production Service Systems Administrator 5 |
| PROGRAM MANAGER | Program Manager |
| PROGRAM MANAGER | Senior Program Manager |
| PROGRAM MGMT-PRODDEV | Program Mgmt VP-ProdDev |
| PROGRAM MGMT-PRODDEV | Program Manager 1-ProdDev |
| PROGRAM MGMT-PRODDEV | Program Manager 2-ProdDev |
| PROGRAM MGMT-PRODDEV | Program Manager 3-ProdDev |
| PROGRAM MGMT-PRODDEV | Program Manager 4-ProdDev |
| PROGRAM MGMT-PRODDEV | Program Manager 5-ProdDev |
| PROGRAM MGMT-PRODDEV | Program Mgmt Manager-ProdDev |
| PROGRAM MGMT-PRODDEV | Program Mgmt Sr Manager-ProdDev |
| PROGRAM MGMT-PRODDEV | Program Mgmt Director-ProdDev |
| PROGRAM MGMT-PRODDEV | Program Mgmt Sr Director-ProdDev |
| PROGRAM MGMT-PRODDEV | Program Manager 6-ProdDev |
| PROGRAMMER ANALYST | PROGRAMMER ANALYST 3 |
| PROGRAMMER ANALYST-IT | Programmer Analyst 1-IT |
| PROGRAMMER ANALYST-IT | Programmer Analyst 2-IT |
| PROGRAMMER ANALYST-IT | Programmer Analyst 3-IT |
| PROGRAMMER ANALYST-IT | Programmer Analyst 4-IT |
| PROGRAMMER ANALYST-IT | Programmer Analyst 5-IT |
| PROJECT MANAGER | Senior Project Manager |
| PROJECT MANAGER | Project Coordinator |
| PROJECT MANAGER | Project Manager |
| PROJECT MANAGER | Project Manager 1 |
| PROJECT MANAGER | Project Manager 2 |
| PROJECT MANAGER | Project Manager 3 |
| PROJECT MANAGER | Project Manager 4 |
| PROJECT MANAGER | Project Manager 5 |
| PROJECT MANAGER | Project Mgmt Manager |
| PROJECT MANAGER | Project Mgmt Snr Manager |
| PROJECT MANAGER | Project Mgmt Director |
| PROJECT MANAGER | Project Manager 2 - Ops |
| PROJECT MANAGER | Project Manager 3 - Ops |
| PROJECT MANAGER | Project Manager 4 - Ops |
| PROJECT MANAGER | Project Manager 5 - Ops |
| PROJECT MANAGER | Project Mgmt Snr Manager-Ops |
| PROJECT MANAGER | Project Mgmt Director-Ops |
| PROJECT MANAGER | Project Mgmt Snr Director |
| PUBLIC RELATIONS | Public Relations Manager 3 |
| PURCHASING-FIN | Purchasing Manager-Fin |
| QA ENGINEER | QA ENGINEER 1 |
| QA ENGINEER | QA ENGINEER 3 |
| QA-PRODDEV | QA Analyst 1-ProdDev |
| QA-PRODDEV | QA Analyst 2-ProdDev |
| QA-PRODDEV | QA Analyst 3-ProdDev |
| QA-PRODDEV | QA Analyst 4-ProdDev |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| QA-PRODDEV | QA Analyst 5-ProdDev |
| QA-PRODDEV | QA Manager-ProdDev |
| QA-PRODDEV | QA Snr Manager-ProdDev |
| QA-PRODDEV | QA Director-ProdDev |
| QA-PRODDEV | QA Snr Director-ProdDev |
| QA-PRODDEV | QA VP-ProdDev |
| REGULATORY COMPLIANCE SPECIALIST | Regulatory Compliance Specialist 4 |
| RELEASE DEVELOPER | Release Developer 2 |
| RELEASE DEVELOPER | Release Developer 3 |
| RELEASE DEVELOPER | Release Developer 4 |
| RELEASE DEVELOPER | Release Developer 5 |
| RESOURCE OPS | Resource Analyst 1-Ops |
| RESOURCE OPS | Resource Manager-Ops |
| RESOURCE OPS | Resource Director-Ops |
| ROYALTY AUDITOR | Royalty Auditor |
| SALES | Sales VP |
| SALES & BUSINESS DEVELOPMENT REPRESENTATIVE | Sales & Business Development Representative |
| SALES COMMISSION ANALYST | Sales Commission Analyst 2 |
| SALES COMMISSION ANALYST | Sales Commission Analyst 3 |
| SALES CONSULTANT | ASSOCIATE SALES CONSULTANT |
| SALES CONSULTANT | Associate Sales Consultant Tools |
| SALES CONSULTANT | DMS Associate Sales Consultant |
| SALES CONSULTANT | Associate Sales Consultant Applications |
| SALES CONSULTANT | Senior SC-Applied Technology |
| SALES CONSULTING | SENIOR SALES CONSULTANT |
| SALES CONSULTING | Senior Sales Consultant Tools |
| SALES CONSULTING | DMS Senior Sales Consultant |
| SALES CONSULTING | Senior Sales Consultant Financial |
| SALES CONSULTING | Senior Sales Consultant Applications |
| SALES CONSULTING | Senior Sales Consultant |
| SALES CONSULTING | Senior Sales Consultant - Apps |
| SALES CONSULTING | Principle Sales Consultant - Apps |
| SALES CONSULTING | Senior Sales Consultant - Apps Server |
| SALES CONSULTING | Senior Sales Consultant - Financial |
| SALES CONSULTING | Senior Sales Consultant - SA |
| SALES CONSULTING | Sales Consulting Manager I |
| SALES CONSULTING | DMS Consulting Manager I |
| SALES CONSULTING | Sales Consulting Manager II |
| SALES CONSULTING | DMS Consulting Manager II |
| SALES CONSULTING | Master Principal Sales Consultant |
| SALES CONSULTING | Sales Consulting Mgr I - Fin |
| SALES CONSULTING | Sales Consulting Manager |
| SALES CONSULTING | Sales Consulting Mgr II - Technology |
| SALES CONSULTING | Sales Consulting Mgr II - Fin |
| SALES CONSULTING | Sales Consulting Snr Manager |
| SALES CONSULTING | Sales Consulting Director |
| SALES CONSULTING | Sales Consulting Snr Director |
| SALES CONSULTING | Sales Consulting Vice President |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| SALES CONSULTING TECHNICAL | Sales Consulting Technical Team Leader |
| SALES PERFORMANCE DESIGNER | Sales Performance Designer 4 |
| SALES REPRESENTATIVE OD PRIME | Sales Representative OD Prime I |
| SALES SUPPORT STAFF TOOLS | Sales Support Staff Tools |
| SCHEDULER-EDUCATION | Scheduler-Education |
| SECURITY-FAC | Security Specialist 3-Fac |
| SECURITY-FAC | Security Supervisor-Fac |
| SERVICE DELIVERY MANAGEMENT CONSULTANT- SUPPORT | Service Delivery Management Consultant 1- Support |
| SERVICE DELIVERY MANAGEMENT CONSULTANT- SUPPORT | Service Delivery Management Consultant 3- Support |
| SERVICE DELIVERY MANAGEMENT CONSULTANT- SUPPORT | Service Delivery Management Consultant 4- Support |
| SERVICE DELIVERY MANAGEMENT CONSULTANT- SUPPORT | Service Delivery Management Consultant 5- Support |
| SERVICES SALES | Services Sales SVP |
| SERVICES SALES REPRESENTATIVE | Services Sales Representative III |
| SERVICES SALES REPRESENTATIVE | Services Sales Representative V |
| SITE RELIABILITY DEVELOPER | Site Reliability Developer 5 |
| SITE RELIABILITY DEVELOPER | Site Reliability Developer 6 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVT MGMT 2 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVT MGMT. 3 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVT MGMT 4 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVT MGMT. 5 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVT MGMT 6 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVELOPER 1 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVELOPER 2 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVELOPER 3 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVELOPER 4 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVELOPER 5 |
| SOFTWARE DEVELOPMENT | SOFTWARE DEVELOPER 6 |
| SOFTWARE DEVELOPMENT | Software Development Manager |
| SOFTWARE DEVELOPMENT | Software Development Snr Manager |
| SOFTWARE DEVELOPMENT | Software Development Director |
| SOFTWARE DEVELOPMENT | Software Development Snr Director |
| SOFTWARE DEVELOPMENT | Software Development VP |
| SOFTWARE DEVELOPMENT | Software Developer 1 |
| SOFTWARE DEVELOPMENT | Software Developer 2 |
| SOFTWARE DEVELOPMENT | Software Developer 3 |
| SOFTWARE DEVELOPMENT | Software Developer 4 |
| SOFTWARE DEVELOPMENT | Software Developer 5 |
| SOFTWARE DEVELOPMENT | Software Developer - Architect |
| SOFTWARE DEVELOPMENT | Software Developer - Architect (Derry Kabcenell Only) |
| SOLUTIONS | Solutions Analyst |
| SOLUTIONS | Solutions Specialist |
| SOLUTIONS | Solutions Sr Specialist |
| SOLUTIONS | Solution Specialist II |
| SOLUTIONS | Solution Specialist III |
| SOLUTIONS | Solution Specialist IV |
| SOLUTIONS | Solution Specialist V |
| SOLUTIONS | Solution Specialist Snr Manager |
| SOLUTIONS | Solution Specialist Director |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| SOLUTIONS | Solution Specialist Snr Director |
| SOLUTIONS | Solution Specialist Vice President |
| STAFF CONSULTANT | STAFF CONSULTANT |
| STAFF CONSULTANT | Staff Consultant Other |
| STAFF CONSULTANT | Staff Consultant |
| STAFF SALES CONSULTANT | Staff Sales Consultant |
| STAFF SALES CONSULTANT | Staff Sales Consultant - Apps Server |
| STAFF SALES CONSULTANT | Staff Sales Consultant - Financials |
| STAFF SALES CONSULTANT | Staff Sales Consultant - Energy |
| STAFF SALES CONSULTANT | Staff SC-Applied Technology |
| STAFF SALES CONSULTANT | STAFF SALES CONSULTANT |
| STAFF SALES CONSULTANT | Staff Sales Consultant Tools |
| STAFF SALES CONSULTANT | DMS Staff Sales Consultant |
| STAFF SALES CONSULTANT | Staff Sales Consultant Applications |
| STUDENT | Student / Intern |
| STUDENT | Professional Student |
| SUPPLIER SOURCING PROGRAM | Supplier Sourcing Program Manager 3 |
| SUPPLIER SOURCING PROGRAM | Supplier Sourcing Program Manager 4 |
| SUPPLY CHAIN | Supply Chain Analyst 1 |
| SUPPLY CHAIN | Supply Chain Analyst 2 |
| SUPPLY CHAIN | Supply Chain Analyst 3 |
| SUPPLY CHAIN | Supply Chain Manager |
| SUPPLY CHAIN | Supply Chain Snr Manager |
| SUPPORT | Support SVP |
| SYSTEM ADMIN | SYSTEM ADMIN 2 |
| SYSTEM ADMIN | SYSTEM ADMIN 3 |
| SYSTEM ADMIN | System Administrator 1-IT |
| SYSTEM ADMIN | System Administrator 2-IT |
| SYSTEM ADMIN | System Administrator 3-IT |
| SYSTEM ADMIN | System Administrator 4-IT |
| SYSTEM ADMIN | System Administrator 5-IT |
| SYSTEM ANALYST | SYSTEM ANALYST 2 |
| SYSTEM ANALYST | Systems Analyst 1-IT |
| SYSTEM ANALYST | Systems Analyst 2-IT |
| SYSTEM ANALYST | Systems Analyst 3-IT |
| SYSTEM ANALYST | Systems Analyst 4-IT |
| SYSTEM ANALYST | Systems Analyst 5-IT |
| SYSTEM ENGINEER | SYSTEM ENGINEER 3 |
| SYSTEMS ANALYST-SUPPORT | Systems Analyst 2-Support |
| SYSTEMS ANALYST-SUPPORT | Systems Analyst 3-Support |
| SYSTEMS ANALYST-SUPPORT | Systems Analyst 5-Support |
| SYSTEMS ENGINEERING SPECIALIST-SUPPORT | Senior Systems Engineering Specialist-Support |
| SYSTEMS ENGINEER-IT | Systems Engineer 2-IT |
| SYSTEMS ENGINEER-IT | Systems Engineer 3-IT |
| SYSTEMS ENGINEER-IT | Systems Engineer 4-IT |
| SYSTEMS PROGRAMMING | SYSTEMS PROGRAMMER 2 |
| SYSTEMS PROGRAMMING | Systems Programming Manager 3 |
| SYSTEMS PROGRAMMING | Systems Programmer 2 |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| **Job Descriptor** | **Oracle Job Title** |
|---|---|
| SYSTEMS PROGRAMMING | Systems Programmer 4 |
| SYSTEMS PROGRAMMING | Systems Programmer 5 |
| TAM | Technical Account Representative (TAM) 2 |
| TAM | Technical Account Representative (TAM) 3 |
| TAM | Technical Account Representative (TAM) 4 |
| TAM | Technical Account Representative (TAM) 5 |
| TAM | TAM Manager |
| TECH SUPPORT | TECH SUPPORT MGMT 3 |
| TECH SUPPORT | TECH SUPPORT ANALYST 1 |
| TECH SUPPORT | TECH SUPPORT ANALYST 2 |
| TECH SUPPORT | TECH SUPPORT ANALYST 3 |
| TECH SUPPORT | TECH SUPPORT ANALYST 4 |
| TECH SUPPORT | TECH SUPPORT ANALYST 5 |
| TECH SUPPORT | Technical Support Analyst 1 - Helpdesk |
| TECH SUPPORT | Technical Support Analyst 1 |
| TECH SUPPORT | Technical Support Analyst 2 |
| TECH SUPPORT | Technical Support Analyst 3 |
| TECH SUPPORT | Technical Support Analyst 4 |
| TECH SUPPORT | TECH SUPPORT MGMT 2 |
| TECH WRITING | TECH WRITING MGMT 3 |
| TECH WRITING | TECH WRITING MGMT 5 |
| TECH WRITING | TECH WRITER 1 |
| TECH WRITING | TECH WRITER 2 |
| TECH WRITING | TECH WRITER 3 |
| TECH WRITING | TECH WRITING MGMT 2 |
| TECH WRITING | Technical Writer 6 |
| TECH WRITING | Technical Writer Manager-ProdDev |
| TECH WRITING | Technical Writer Snr Manager-ProdDev |
| TECH WRITING | Technical Writer Director-ProdDev |
| TECH WRITING | Technical Writer Snr Director-ProdDev |
| TECH WRITING | Technical Writer VP-ProdDev |
| TECH WRITING | Technical Writer 1-ProdDev |
| TECH WRITING | Technical Writer 2-ProdDev |
| TECH WRITING | Technical Writer 3-ProdDev |
| TECH WRITING | Technical Writer 4-ProdDev |
| TECH WRITING | Technical Writer 5-ProdDev |
| TECHNICAL ANALYST | Technical Specialist Tools |
| TECHNICAL ANALYST | Senior Technical Specialist Tools |
| TECHNICAL ANALYST | Technical Specialist-Support |
| TECHNICAL ANALYST | Technical Analyst 4-Support |
| TECHNICAL ANALYST | Technical Analyst A4-Support |
| TECHNICAL ANALYST | Technical Analyst Tools |
| TECHNICAL ANALYST | Senior Technical Analyst Tools |
| TECHNICAL ANALYST | Technical Analyst 1-Support |
| TECHNICAL ANALYST | Technical Analyst 2-Support |
| TECHNICAL ANALYST | Technical Analyst 3-Support |
| TECHNICAL ANALYST | Gold Support Account Manager 1 |
| TECHNICAL ANALYST | Technical Analyst 6-Support |

**Appendix A**
**Table linking Oracle Job Titles to Job Descriptors Used in Analyses**

| Job Descriptor | Oracle Job Title |
|---|---|
| TECHNICAL ANALYST | Consulting Technical Specialist Tools |
| TECHNICAL ANALYST | Technical Analyst 5-Support |
| TECHNICAL APPLICATION | Technical Application Analyst 3 |
| TECHNICAL APPLICATION | Technical Application Analyst 4 (outside of CA) |
| TECHNICAL APPLICATION | Technical Application Analyst 5 |
| TECHNICAL ARCHITECT | Technical Architect 4 |
| TECHNICAL ARCHITECT | Technical Architect 5 |
| TECHNICAL EDITOR | Technical Editor I |
| TECHNICAL MANAGER | Technical Manager 2 |
| TECHNICAL MANAGER | Technical Manager 3 |
| TECHNICAL MANAGER | Technical Manager 4 |
| TECHNICAL SPECIALIST | Staff Technical Specialist |
| TECHNICAL SPECIALIST | Senior Technical Specialist |
| TECHNICAL SPECIALIST | Principal Technical Specialist |
| TECHNICAL SUPPORT | Senior Field Technical Specialist Applications |
| TECHNICAL SUPPORT | Systems Analyst 4-Support |
| TECHNICAL SUPPORT | Technical Support Manager 3 Applications |
| TECHNICAL SUPPORT | Technical Support Manager 4 Applications |
| TECHNICAL SUPPORT | Technical Support Manager 5 Applications |
| TECHNICAL SUPPORT | Technical Support Manager 6 Applications |
| TELECOMM TECH | TELECOM TECH 2 |
| TELECOMM TECH | TELECOMM TECH 5 |
| TELECOMMUNICATIONS | Telecommunications Manager 3 |
| TELEPHONE/RECEPTIONIST | Telephone/Receptionist A1 |
| TELESALES BUSINESS DEVELOPMENT | Associate Telesales Business Development Representative |
| TELESALES REPRESENTATIVE | Telesales Representative II |
| TELESALES REPRESENTATIVE | Telesales Representative III |
| TELESALES/INTERNET SALES | Telesales/Internet Sales Manager |
| TL SALES CONSULTANT | TL Sales Consultant |
| TRAINING COORDINATOR | Training Coordinator-A4 |
| TRANSITION ANALYST | Translation Analyst 4 |
| TTL SALES CONSULTANT-FINANCIAL | TTL Sales Consultant - Financial |
| TV PRODUCTION-MKT | TV Production 4-Mkt |
| USER ASSISTANCE | User Assistance Developer 3 |
| USER ASSISTANCE | User Assistance Developer 4 |
| USER ASSISTANCE | User Assistance Developer 5 |
| USER ASSISTANCE | User Assistance Snr Manager |
| USER ASSISTANCE | User Assistance Director |
| USER ASSISTANCE | User Assistance Snr Director |
| USER EXPERIENCE DEVELOPER-PRODDEV | User Experience Developer 1-ProdDev |
| USER EXPERIENCE DEVELOPER-PRODDEV | User Experience Developer 2-ProdDev |
| USER EXPERIENCE DEVELOPER-PRODDEV | User Experience Developer 3-ProdDev |
| USER EXPERIENCE DEVELOPER-PRODDEV | User Experience Developer 4-ProdDev |
| USER EXPERIENCE DEVELOPER-PRODDEV | User Experience Developer 5-ProdDev |
| USER EXPERIENCE DEVELOPER-PRODDEV | User Experience Developer 6-ProdDev |
| WEB TECHNOLOGIST | Web Technologist 3 |
| WWCS ACCOUNT APPLICATIONS | WWCS Account Manager Applications |

## Appendix B: Table

Regression Analyses of Movement from IC3 and IC4 by Gender

| Appendix B : Regression Analysis | | | | | |
|---|---|---|---|---|---|
| Gender Differences in Probability of Moving from Global Career Levels IC3 and IC4 | | | | | |
| Controlling for Race, Ethnicity, Age, Education, Time at Oracle, Time in Grade and Year, 2013-2018 | | | | | |
| IC3 | | | IC4 | | |
| Gender Coefficient | Standard Deviation | N | Gender Coefficient | Standard Deviation | N |
| -0.193 | -3.08 | 3,433 | -0.156 | -2.87 | 6,823 |

# Appendix C: Glossary

## Appendix C
## Glossary

*Coefficient* -- A number that measures the effect of one independent variable, such as race or gender on the dependent variable, such as compensation or stock units, after all other independent variables are "controlled" or held to a constant value. Both ordinary least squares regression analysis and tobit regression analysis compute coefficients for each independent variable.

*Controls* – Variables or characteristics used to define the comparator groups. In a regression analysis, the controls are the independent variables, that is, the explanatory characteristics included in the regression.

*Dependent variable* -- A variable to be explained, such as compensation or stock units, by independent variables, such as race or gender. Both ordinary least squares regression analysis and tobit regression analysis have a dependent variable and several independent variables.

*Independent variable* – A variable, such as race or gender, that is being analyzed to evaluate whether it explains or determines, in part, a dependent variable, such as compensation or stock units. Both ordinary least squares regression analysis and tobit regression analysis have a dependent variable and several independent variables.

*Logarithm* – A mathematical transformation of a number commonly used for variables such as compensation to improve the "fit" or the ability of statistical model to track the pattern of observations.

*Power* – The probability that a statistical test will correctly reject a false hypothesis. The power of a test increases as there are more observations and decreases as there are more controls or independent variables included in the analysis. In the context of litigation, the power of the test is usually the probability that the test will conclude that there has been discrimination when discrimination has, in fact, occurred. Other things being equal, one wants the power of a test to be as high as possible.

*Probability* – The likelihood that an event will occur in the long run with numerous replications using the same, or constant, system. Probability is expressed as a value between 0 and 1.

*Productivity* –An economics term-of-art. Productivity is the value of the output obtained from a unit of input. For example, if an employee in one hour produces 2 units of product that can be sold for $10 each with no other inputs, then the employee's productivity is $20 per hour.

*Random variation* – Erratic fluctuations caused by unknown factors resulting in a distribution of outcomes around the average outcome that are due to chance and not due to specific cause.

*Tobit regression analysis* – A statistical technique that measures the simultaneous effects of several independent variables, such as race, education, and experience, on a dependent variable that is limited in some way. For example, stock units have a positive value in any year for many employees, but many receive none, or a value of zero. .

*Ordinary least squares (linear) regression analysis* -- A statistical technique that measures the simultaneous effects of several independent variables, such as race, education, and experience, on a dependent variable that has a continuous set of values, such as salary which can take any of value from zero into the millions.

*Standard deviation* -- A measure of the likelihood that an observed difference (for example, compensation for white employees minus compensation for Asian employees) could have occurred purely by chance when the true difference is zero. As the number of standard deviations increases, the likelihood that the difference could have occurred purely by chance decreases. Equivalently, as the number of standard deviations increases, the level of statistical significance decreases.

*Statistical significance* – The probability that a null hypothesis will be rejected when it is, in fact, true. The courts have generally chosen the level of statistical significance as 0.05. In the context of litigation, statistical significance is usually the probability that the test will conclude that there has been discrimination when discrimination has not, in fact, occurred.

# ATTACHMENTS

# Attachment A: Janice Madden Curriculum Vitae

ATTACHMENT A
CURRICULUM VITAE OF DR. JANICE F. MADDEN

June 2019

# JANICE FANNING MADDEN


**ADDRESS:** Department of Sociology
University of Pennsylvania
3718 Locust Walk
Philadelphia, PA 19104-6299

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| | |
|---|---|
| Office | (215) 898-6739 |
| Home | (215) 546-5144 |
| Fax | (215) 898-2124 |
| Email | madden@upenn.edu |


**PERSONAL:** U.S. Citizen

**EDUCATION:** Duke University, Durham, North Carolina
M.A., Economics, 1971
Ph.D., Economics, 1972

University of Denver, Colorado
B.A., *cum laude*, Economics, 1969

**EMPLOYMENT:**

University of Pennsylvania, Philadelphia, PA:

Professor, Department of Sociology, 1994 to present; Department of Regional Science, 1988 to 1994; Associate Professor, 1979-88; Assistant Professor, 1972-78. Professor, Department of Real Estate, The Wharton School, 1990 to 2016.

President-elect, Penn Association for Senior and Emeritus Faculty, 2019-2020.

Associate Chair, Department of Sociology, 2009-11.

Chair, Graduate Group in Demography, 2007-8.

Director of Alice Paul Research Center and the Women's Studies Program, chair, Women's Studies Undergraduate Major, University of Pennsylvania, 1988-1991; 2002-2004.

Interim Director (1998-99); Director of the Masters of Government Administration Program (2000-2002), Fels Institute of Government.

Vice Provost for Graduate Education, 1991 to 1999.

Undergraduate Chair, Department of Regional Science, 1979-91.

Member of the Graduate Groups in Regional Science, in Demography, in Sociology, and in City and Regional Planning.

Research Associate, Population Studies Center.

Professor, Fels Center of Government, 1999 to 2016.

Co-Director, Penn-Temple Philadelphia Economic Monitoring Project, 1987-91.

Visiting Scholar, Research Division, Federal Reserve Bank of Philadelphia, 1999-2000 and 2005.

Visiting Scholar, Indonesia Second University Development Project, University of Indonesia, Jakarta, 1991.Member and Consultant, Scientific Advisory Committee, U.S. Army Family Research Program, 1987-92.

Consultant, HCR, Washington, D.C. 1983-85.

Faculty, Federal Judicial Center, Washington, D.C. 1983-84.

Board of Directors (1980-2002) and Consultant (1980-present), Econsult Corp., Philadelphia, PA.

Consultant, U.S. Equal Employment Opportunity Commission, 1979-1991.

Consultant, U.S. Department of Justice, 1984-1988.

Consultant, Abt Associates, Cambridge, Mass., 1979-81.

Staff Economist, National Commission on Employment and Unemployment Statistics Washington, D.C., 1978.

Instructor, Department of Economics, Duke University, Durham, NC, 1971-72.

Consultant, Low Income Housing Corporation, Durham, NC, 1971.

Economist, Federal Power Commission, Washington, D.C., 1970.

AIESEC intern, Computer Programmer, Ladapoulos Paper Mill, Patras Greece, 1968.

**HONORS AND AWARDS:**

Boettcher Scholar, 1965-69
Phi Beta Kappa, 1969
AAUW Outstanding Senior Woman, 1969
James B. Duke Fellow, 1969-72

Manpower Development and Training Act Dissertation Fellow, 1972
Robert C. Daniels Foundation Term Chair in Urban Studies, 1990-2000
Academic Excellence Award, Trustees' Council of Penn Women, 1997
Leadership Alliance Award, 1999
Woman of Distinction, 2000, *Philadelphia Business Journal*
Fritz Pollard Alliance (NFL) Game Ball Award, 2004
Faculty Award, Friars Senior Society of the University of Pennsylvania, 2004
Ballard Scholar, University of Pennsylvania Real Estate Center, 2005
Penn Women's Center 2007 Leadership Award
Fellow, Regional Science Association International, elected 2009
Faculty Fellow, Penn Urban Research Institute, 2009
Chair, North American Regional Science Council, 2010
David E. Boyce Award, North American Regional Science Council, 2010
Chair of the Board, American Academy for Political and Social Sciences, 2011-2017.
President, North American Regional Science, 2014
Trustee's Council of Penn Women/Provost Award for Promoting Gender Equality, 2017

**PUBLICATIONS:**

**Books**:

*The Economics of Sex Discrimination* (Lexington, Mass.: D.C. Heath and Company, 1973). Second Printing, 1975.

*Post-Industrial Philadelphia: Structural Changes in the Metropolitan Economy* with William Stull (Philadelphia: University of Pennsylvania Press, 1990).

*Work, Wages, and Poverty: Income Distribution in Post-Industrial Philadelphia* with William Stull (Philadelphia: University of Pennsylvania Press, 1991).

*Changes in Income Inequality within U.S. Metropolitan Areas* (Kalamazoo, MI: Upjohn Institute for Employment Research, 2000).

*Mommies and Daddies on the Fast Track: Success of Parents in Demanding Professions* with Jerry A. Jacobs (ed.) *The Annals of the American Academy of Political and Social Sciences,* (November 2004)

**Articles**:

"The Paradox of Expanding Ghettoes and Declining Racial Segregation in Large U.S. Metropolitan Areas," with Matthew Ruther, *Journal of Housing Economics,* Vol. 40, June 2018, pp. 117-128.

"Performance Pay, Performance-Support Bias, and Racial Pay Gaps among Stock Brokers," with Alexander Vekker, *Industrial Relations*, Vol. 56, no. 4, October 2017, pp. 662-687.

"Foreign Born Population Concentration and Neighborhood Growth and Development within U.S. Metropolitan Areas," with Matthew Ruther and Rebbeca Tesfai, *Urban Studies,* Vol. 55(4), March 2018, pp. 826-843.

"Gayborhoods: The Economics and Demographics of the Concentration of Gays within Large American Cities," with Matthew Ruther, in *Regional Science Matters –Studies Dedicated to Walter Isard* edited by Adam Rose, Peter Nijkamp, and Karima Kourtit. (Berlin: Springer Verlag, 2014)

"Changing Racial and Poverty Segregation in Large U.S. Metropolitan Areas, 1970-2009," *International Regional Science Review,* Vol. 37, no. 3, January 2014, pp. 9-35. Lead article.

"Limitations on Diversity in Basic Science Departments," with Phoebe Leboy, *DNA and Cell Biology,* Vol. 31, no. 8, August 2012, pp. 1365-1371.

"Performance-Support Bias and the Gender Pay Gap among Stockbrokers," *Gender & Society*, Vol. 26, no. 3, June 2012, pp. 488-518.

"Have the NFL's Rooney Rule Efforts 'Leveled the Field' for African American Head Coach Candidates?" with Matthew Ruther, *Journal of Sports Economics* Vol. 12, no. 4, April 2011, pp. 127-142. Lead article.

"Reply to: Differences in the Success of NFL Coaches by Race: A Different Perspective," with Matthew Ruther, *Journal of Sports Economics* Vol. 10, no. 5, 2009, pp. 543-550.

"Practitioners' Roles and Practicum Courses in the Degree Program," with Robert Garris and William M. Rodgers III, *Journal of Policy Analysis and Management*, Vol. 27, no. 4, Autumn 2008, pp. 992-1003.

"Population Changes and the Economy," *Wharton Real Estate Review*, Vol. IX, no. 1, Spring 2005, pp. 41-61.

"Differences in the Success of NFL Coaches by Race, 1990-2002: Evidence of Last Hire, First Fire" *Journal of Sports Economics,* Vol. 5, no. 1, February 2004, 6-19. Lead article.

"Has the Concentration of Income and Poverty Among Suburbs of Large U.S. Metropolitan Areas Changed Over Time? *Papers in Regional Science,* Vol. 82, no.2, April 2003, 249-75.

"The Changing Spatial Concentration of Income and Poverty among Suburbs of Large U.S. Metropolitan Areas" *Urban Studies*, Vol. 40, no. 3, March 2003, 481-503.

"Measuring Changes in the Spatial Concentration of Income and Poverty among Suburbs of Large U.S. Metropolitan Areas." In *Uddevalla Symposium 2001: Regional Economies in Transition*, (Uddevalla, Sweden: University of Trollhättan/Uddevalla, 2001), pp. 327-348.

"Do Racial Composition and Segregation Affect Economic Outcomes in Metropolitan Areas?" in E. Anderson and D. Massey (ed.) *Problem of the Century: Racial Stratification in the United States at Century's End* (New York: Russell Sage, 2001), pp. 290-316.

"Creating Jobs, Keeping Jobs, and Losing Jobs: Cities and Suburbs in the Global Economy" *The Annals of the American Academy of Political and Social Science,* Vol. 572, November 2000, pp.78-90.

"Have Economic Changes Made Metropolitan Government More Attractive to Suburbs?" *State and Local Government* Vol. 1, Spring 2000, pp. 28-39.

"The Challenges That Success Has Generated for the Research University," in W. Xin and M. Wanhua (ed.) *The University of the 21st Century: Proceedings of the Forum of Higher Education in Conjunction with the Centennial of Peking University* (Beijing: Peking University Press, 1998), pp. 127-130.

"Changes in the Distribution of Poverty across and within U.S. Metropolitan Areas: 1979-89," *Urban Studies,* vol. 33, no. 9, November 1996, pp. 1581-1600.

"Regional Science: A Call for Multi-Disciplinary Integration," *International Regional Science Review*, Vol. 17 no. 3, 1994, pp. 351-3.

"Problems Solved and Problems Unaddressed by the Civil Rights Act of 1991," *Forum for Social Economics* (Fall 1992), pp. 60-70.

"The Wage Effects of Residential Location and Commuting Constraints on Employed Married Women" with Lee-in Chen Chiu, *Urban Studies*, (June 1990), pp. 353-369.

"Residential Segregation and the Economic Status of Black Workers: New Evidence for an Old Debate" with Mark Hughes, *Journal of Urban Economics*, Vol. 29 (1991), pp. 28-49.

"The Distribution of Economic Losses Among Displaced Workers: Measurement Methods Matter," *Journal of Human Resources*, (Winter 1988), pp. 93-107.

"Gender Differences in the Cost of Displacement: An Empirical Test of Discrimination in the Labor Market," *American Economic Review* (May 1987), pp. 246-251.

"The Year of the Tenure Decision: Strategies for Survival," *Newsletter* of the American Economic Association Committee on the Status of Women in the Economics Profession (Spring/Summer 1987), pp. 8-13.

"Shifts among the Counties in Job and Resident Workers, 1960-1980" with Mark Hughes, in A.A. Summers and T.F. Luce (eds.), *Economic Development within the Philadelphia Metropolitan Area* (Philadelphia: University of Pennsylvania Press, 1987), pp. 24-34 and 165-170.

"Achieving Title VII Objectives at Minimum Social Costs: Optimal Remedies and Awards" with Jennifer Wissink, *Rutgers Law Review* (Spring 1985), pp. 997-1017.

"The Persistence of Pay Differentials: The Economics of Sex Discrimination," *Women and Work: An Annual Review* (Beverly Hills: Sage Publications, 1985), pp. 76-114.

"Urban Wage Gradients: Empirical Evidence," *Journal of Urban Economics* (1985), pp. 291-301.

"The Measurement of Employment Discrimination: Reduced Forms, Reverse Regression, Comparable Worth and the Definition of Labor Markets" *Proceedings of the American Statistical Association, Social Statistics Section*, 1982, pp. 162-8.

"Interstate Sales and Employment Effects in the Wholesale and Retail Trade Industries of Changes in the Federal Minimum Wage Legislation, 1958-1977" with Joyce Cooper, *Report of the Minimum Wage Study Commission* (Washington, D.C.: Government Printing Office, 1981), pp. 273-296.

"Why Women Work Closer to Home" *Urban Studies* 18 (1981), pp. 181- 194.

"Spatial Implications of Increases in the Female Labor Force: A Theoretical and Empirical Synthesis" with Michelle White, *Land Economics* (November 1980), pp. 432-446.

"Urban Land Use and the Growth in Two Earner Households" *American Economic Review* 70 (May 1980), pp. 191-197.

"Economic Rationale for Sex Differences in Education" *Southern Economic Journal* 44 (April 1978), pp. 778-797.

"Women's Work Trips: An Empirical and Theoretical Overview" with Michelle White, *Women's Travel Issues: Research Needs and Priorities*, U.S. Department of Transportation, (Washington, D.C.: Government Printing Office, 1979), pp. 201-242.

"A Spatial Theory of Sex Discrimination" *Journal of Regional Science* 17 (December 1977), pp. 151-171.

"An Empirical Analysis of the Spatial Elasticity of Labor Supply" *Papers, Regional Science Association* 39 (1977), pp. 151-171.

"Discrimination--A Manifestation of Male Market Power? in C.B. Lloyd (ed.), *Sex, Discrimination and the Division of Labor* (New York: Columbia University Press, 1975), pp. 146-174.

"The Development of Economic Thought on the 'Women Problem'" *The Review of Radical Political Economics* 4 (July 1972), pp. 21-33.

**Comments and Reviews**:

"Gender Pay Gap*" Encyclopedia of Social Theory,* Sage Publications, forthcoming 2015.

"Comment: Job Decentralization and Postwar Suburbanization: Evidence from State Capitals," in *Brookings-Wharton Papers on Urban Affairs 2009* (Washington, DC: The Brookings Institution, 2009), pp. 24-29

Book Review: *Urban America: Growth, Crisis and Rebirth* by John F. McDonald in *Journal of Regional Science* (August 2009), pp. 574-7.

Book Review: *The Face of Discrimination: How Race and Gender Impact Work and Home Lives* by Vincent J. Roscigno in *Social Forces*, Vol. 87(4), (June 2009), pp. 2218-2220.

"Preface." *Mommies and Daddies on the Fast Rack: Success of Parents in Demanding Professions* with Jerry A. Jacobs (ed.) *The Annals of the American Academy of Political and Social Sciences,* (November 2004)

Review: *The Boston Renaissance* (by Bluestone and Stevenson), *Detroit Divided* (by Farley, Danziger, and Holzer) and *The Atlanta Paradox* (edited by Sjoquist) in *Urban Studies* (Jan. 2002) Vol. 39, No. 1, pp 163-7.

Book Review, *The New Urban Frontier: Gentrification and the Revanchist City* in *Journal of Regional Science* (February 1998), 179-81.

"Comment: Work Norms and Professional Labor Markets" in Francine Blau and Ronald Ehrenberg (ed.) *Gender, Family, and the Workplace* (New York: Sage Publications, 1997), pp. 206-209.

Book Review, *Forbidden Grounds: The Case Against Employment Discrimination Laws* in *Journal Policy Analysis and Management* (1993).

"Discussion: Empirical Consequences of Comparable Worth" in M.A. Hill and M.R. Killingsworth (ed.) *Comparable Worth: Analyses and Evidence* (Ithaca, NY: ILR Press, 1989), pp. 107-111.

Book Review, *Regional Labor Markets*, in *Journal of Regional Science* (February 1989).

"Comparable Worth" *Journal of Policy Analysis and Management*, (Fall 1987), Vol. 7, No. 1, pp. 147-150.

"Review of Recent Research on Women and Work" *Signs: A Journal of Women in Culture and Society*, (Spring 1985), pp. 589-593.

"Availability Analyses for Affirmative Action Plans" in *Restructuring Availability Analysis for Affirmative Action Planning* (Abt Associates, Inc., 1981), pp. 181-191.

"Discussion: Has Occupational Licensing Reduced Geographic Mobility and Raised Earnings?" in S. Rottenberg (ed.) *Occupational Licensure and Regulation* (Washington, D.C.: American Enterprise Institute, 1980, pp. 337-339).

"Comments on Career Decisions" in E. Andrews, C. Gilroy, and C.B. Lloyd (ed.), *Women in the Labor Market*, (New York: Columbia University Press, 1979), pp. 158-167.

"Discussion: The Implications of Changing Family Patterns and Behavior for Labor Force and Hardship Measurement" in *Concepts and Data Needs*, National Commission on Employment and "Comments on Impacts of Transportation Control Plans" Proceedings of Conference on the Regional and Urban Impacts of Government Policy, State University of New York, Buffalo, NY, May 1978.

"The Patterns of Sex Discrimination" *Monthly Labor Review* 98 (November 1975).

Book Review, *Equal Employment Opportunity and the AT&T Case*, in *Journal of Human Resources*, (Winter 1977).

Book Review, *Time of Transition*, in *Signs: A Journal of Women in Culture and Society* (Summer 1978).

Book Review, *Women, Minorities and Employment Discrimination*, in *Industrial and Labor Relations Review*, (October 1978).

"Women and the New Reserve Army of the Unemployed: Comment III. " *Signs: A Journal of Women in Culture and Society* (Spring 1976).

**Working Papers:**

"Are Gender Differences in the Gay Pay Gap Due to Unmeasured Gender-Linked Characteristics, Household Division of Labor, or Greater Bias Against Gay Men?" with Pearl Kyei, May 2013.

**Academic Conference and Invited Presentations** (last five years):

"The Anatomy of Declining Racial Segregation: Large US Metropolitan Areas, 1970-2013," North American Regional Science, Portland, OR, November 14, 2015.

"Foreign Born Population Concentration and Neighborhood Growth and Development within U.S. Metropolitan Areas," with Matt Ruther and Rebbeca Tesfai, Urban Affairs Association, Miami, FL April 10, 2015.

"The Anatomy of Declining Racial Segregation: Large US Metropolitan Areas, 1970-2009," Western Regional Science Association, Phoenix, AZ, February 16, 2015.

"Labor, Economics, and Discrimination," University of Houston, Department of Africana Studies, February 6, 2015.

"The Demography of Commuting: How Population Groups Create and Respond to Cities," North American Regional Science Association, Washington, DC, Presidential Lecture, November 2014.

"The Anatomy of Declining Racial Segregation: Large US Metropolitan Areas, 1970-2009," Southern Regional Science Association, San Antonio., TX, March 28, 2014.

"The Anatomy of Declining Racial Segregation: Large US Metropolitan Areas, 1970-2009," USC Lusk Center Rena Sivitranidou Annual Research Symposium, Los Angeles, CA, March 7, 2014.

"Gayborhoods: The Economics and Demographics of the Concentration of Gays within Large American Metropolitan Areas," Association for Real Estate and Urban Economics, Philadelphia, PA, January 2014.

"Gayborhoods: The Economics and Demographics of the Concentration of Gays within Large American Metropolitan Areas," Association for Public Policy and Management, Washington, DC, November 2013.

"Gender Differences in the Gay Pay Gap: Unmeasured Gender-Linked Characteristics, Household Division of Labor, or Greater Bias against Gay Men?" with Pearl Kyei, Association for Public Policy and Management, Washington, DC, November 2013.

**Reports**:

"Statement of Janice Fanning Madden on HB 1890," Labor and Industry Committee Public Hearing, Commonwealth of Pennsylvania, Harrisburg PA, September 18, 2014

"The Demographic and Income Dynamics of Shifts within Large Metropolitan Areas, 1970-2000: Explaining Variations in Racial and Poverty Segregation across Large Metropolitan Areas" Office of Policy Development and Research, U.S. Department of Housing and Urban Development Grant H-21443RG (June 2006)

"Are the Suburbs Really Changing? Examining Changes in the Distribution of Income and Poverty Among Suburban Municipalities of Large Metropolitan Areas" Center on Urban and Metropolitan Policy, The Brookings Institution (January 2001)

"Interstate Sales and Employment Effects in the Wholesale Trade and Retail Trade Industries of Changes in the Federal Minimum Wage Legislation, 1958-77" Contract No. J-9-M-0-0072, Minimum Wage Study Commission (March 1981).

"The Effects of Employment Location and Scheduling of Work Shifts on Women's Employment Opportunities" Grant No. 91-42-78-31, Department of Labor (January 1981).

"The Geographic Targeting of Job Programs" Contract No. 99-0-2698-50-24, National Commission for Employment Policy, (October 1980).

"Report on House Bill 2044: Consequences for the General Assistance Population (joint with others), Senate, Commonwealth of Pennsylvania (May 1980).

"Effects of Changing Household Structure on Cities" Grant No. R01-H-31400-01, National Institute on Mental Health, (June 1980).

"Evaluating the Returns to the Education of Women: Economic Rationale for Sex Differences in Education" Grant No. NIG-G-74-0094, National Institute of Education, (January 1977).

"Evaluating the Returns to the Education of Women" Spencer Foundation, (January 1975).

"The Economics of Sex Discrimination" Grant No. 91-37-72-26 Manpower Administration, U.S. Department of Labor, (July 1972).

**FELLOWSHIPS AND GRANTS:**

Wharton Sports Business Initiative, "Differences in the Success of NFL Coaches by Race, 2003-2008: Is There Still Evidence of Last Hire, First Fire?" July 2008-June 2009

Penn Urban Research Institute, "Faculty Forum: Cities around the World: Networks, Form, Function" January 2006-July 2007 co-investigators: Richard Estes and Don Kettl.

U.S. Department of Housing and Urban Development, "The Demographic and Income Dynamics of Shifts across Suburban Municipalities within Large Metropolitan Areas: 1970-2000." June 2004-September 2005.

Alfred P. Sloan Foundation, "Parents on the Fast Track in Demanding Professions." (with Jerry Jacobs) September 2003-April 2004.

Ronald McNair Grant to support undergraduate students to prepare for Ph.D. education, 2000-5, $1 million.

Brookings Foundation, "The Changing Demographics of Suburbs: Implications for City-Suburban Cooperation**,**" May 1998-May 2000.

National Science Foundation "Analysis of Variation in the Intrametropolitan Distribution of Income and Earnings," February 1993-March 1995. REU June-August 1993.

W.E. Upjohn Institute for Employment Research, "Changes in Income Inequality within U.S. Metropolitan Areas," January 1993- December 1995.

Patricia Roberts Harris Grant to support doctoral students at Penn, 1993-8, $1.7 million.

William Penn Foundation joint with Ben Franklin Partnership, "Temple-Penn Philadelphia Economic Monitoring Project" July 1988-June 1991.

Faculty Grant, Mellon Foundation Program on Assessing and Revitalizing the Social Sciences, "Industrial Transitions, Work Schedule Changes and the Welfare of American Workers" May 1987 - December 1987.Faculty Grant, Mellon Foundation Program on Assessing and Revitalizing the Social Sciences, "City Residences and the Employment of Black Women Who Head Households" August 1986 - February 1987.

Public Policy Initiatives Fund, "The Economic Significance of Displacement for Workers: An Empirical Investigation of Gender Differences," July 1985 - June 1986.

Faculty Grant, Mellon Foundation Program on Assessing and Revitalizing the Social Sciences, "Racial Wage Gradients in the Philadelphia, New York, and Washington, D.C. Labor Markets: An Examination of the Gilded Ghetto Debate" May 1985 - December 1985.

National Commission on Employment Policy, "Geographic Boundaries of Labor Markets" June 1980 - October 1980.

Minimum Wage Study Commission, U.S. Department of Labor, "Interstate Employment Effects of the Federal Minimum Wage Law," March 1980 - February 1981.

U.S. Department of Labor, "The Effects of Employment Location and Scheduling of Work Shifts on Women's Employment Opportunities," September 1978 - May 1980.

National Institute of Mental Health, R01-MH-31400-01 "Effects of Changing Household Structure on Cities," July 1978 – July 1980.

National Institute of Education, "Evaluating the Returns to the Education of Women," September 1974 - May 1976.

Spencer Foundation, "Evaluating the Returns to the Education of Women," January 1974 - December 1974.

University of Pennsylvania Faculty Fellowship, "Deriving a Spatial Labor Supply Curve," June 1974 - September 1974.

**OTHER PROFESSIONAL ACTIVITIES:**

North American Regional Science Council:

Elected President for 2014;
Elected Council Chair, 2010;
Elected by membership to council, 1992-95 and 2008-11;
Member, Benjamin R. Stevens Dissertation Fellowship Committee, 2005-8, Chair, 2006;
Chair and Organizer, North American Regional Science Meetings, Philadelphia, PA, November 20-22, 2003.

Association for Public Policy Analysis and Management (APPAM):

Elected Secretary, 2012-2014;
Elected member of Policy Council (representative of the Institutional Representatives), 2008-2012;
Chair, Doctoral Dissertation Prize Committee, 2007;
Elected Secretary, Association Institutional Representatives Committee, 2007-9.

Member, American Academy of Political and Social Sciences Board, 2001-7; 2010-2018; member of Finance Committee, 2003-present; chair of the board, 2011-2018.

Member, National Academies Committee on National Statistics' Panel on Measuring and Collecting Pay Information from U.S. Employers by Gender, Race, and National Origin, 2011 to present. Published report: *Collecting Compensation Data from Employers* (Washington, DC: National Academy Press, 2013).

Chair, National Research Council Committee on Assessing the Portfolio of the Science Resources Studies Division of the National Science Foundation, 1998-2000. Published report: *Measuring the Science and Engineering Enterprise: Priorities for the Division of Science Resources Studies* (Washington, DC: National Academy Press, 2000).

Association of Graduate Schools (AGS):

President, 1996-97;
Elected member of Steering Committee, AAU/AGS Project for Research on Doctoral Education, 1993-00.
Elected to Executive Committee, 1994-8.

Association of American Universities (AAU) Committee on Graduate Education, 1996-98.

Elected to Board, Council of Graduate Schools, 1996-1999.

Graduate Record Examination Board (AGS representative) 1994-8; Research Committee.

Editorial Boards:

*International Economic Review*, 1978-1993
*Economic Geography*, 1991-1995
*Women and Work*, 1984-2000
*Urban Studies,* 1996-2012;
U.S. editor, 1997-2001
*Journal of Regional Science,* 2012-present

Advisory Board, The H. John Heinz III School of Public Policy and Management, Carnegie Mellon University, 1992-1998.

Advisory Committee, Graduate School of Arts and Sciences, Emory University, 1999

External Review Committees, The Sanford Institute of Public Policy, Duke University, 1995; graduate education at the University of Virginia, 1997, Graduate School of Arts and Science, Washington University at St. Louis, 2005.

Review Committee, Ontario Council on Graduate Studies, Canada, December 1998-March 1999.

Oversight Committee, Career Planning Center for Beginning Scientists and Engineers, National Academy of Sciences, 1996-1999.

Member, Committee on Vocational Education and Economic Development in Depressed Areas, National Research Council, National Academy of Sciences, 1982-83; prepared *Education for Tomorrow's Jobs* (Washington, D.C.: National Academy Press, 1983).

Review Panel, NSF Faculty Awards for Women, Social and Economic Science, 1991.

American Economic Association Committee on the Status of Women in the Economics Profession, 1975-78.

Advisory Council, Office of Employment and Training, City of Philadelphia, 1981-84; Budget Committee; Executive Committee; Chair, Long Range Planning Committee.

Friends Select School:

Member, Board of Trustees, member, 1991-2000, 2002-2011;
Vice-Chairman, Board of Trustees, 1993-6;
Chair of Finance Committee, 1998-2000; member 1991-present.
Chair of Financial Aid Committee, 2009-2011.

Board of Directors, Lombard Swim Club, 2010-present.

Chair of Audit Committee, 2013
Chair of Finance Committee, 2013-14
Treasurer, 2014-present.

1920 Chestnut Condo Association, 2019-present, Board member and treasurer

Advisory Board, Philadelphia Child Support Project, 1987-1990.

Board of Directors, Creative Alternatives for Women, Jenkintown, Pa., 1979-82.

Board of Commissioners, Fellowship Commission, 1981-82.

Referee: American Economic Review; Journal of Political Economy; American Sociological Review; Economics of Education Review; Journal of Business and Economics; International Economic Review; Journal of Human Resources; Land Economics; Journal of Regional Science; Urban Studies; Regional Science and Urban Economics; International Regional Science Review; Regional Studies; Journal of Urban Affairs; Regional Science and Urban Economics; Journal of Public Policy and Management; Economic Development and Cultural Change; Growth and Change; Journal of Sports Economics; Journal of Peace Science; Policy Analysis; Signs: A Journal of Women in Culture and Society; Environment and Planning; Urban Studies; Geographic Analysis; The Professional Geographer; Industrial Relations; Industrial and Labor Relations Review; Journal of Economic Behavior and Organization; Social Science Research; Cityscape; Social Forces; Sociological Quarterly; Annals of Regional Science; Survey Research Center - Institute for Social Research, University of Michigan; National Council on Employment Policy, Washington, D.C.; American Academy, Berlin Germany.

Research Proposal Reviewer: National Institute of Education, U.S. Department of Health, Education and Welfare; National Science Foundation--Economics, Geography and Regional Science, Social Indicators, Sociology, and Public Policy and Regulation Sections.

**COURSES TAUGHT:**

Undergraduate: Quantitative Methods of Urban and Regional Analysis, Economics of Discrimination, Sociology of Discrimination, Location Theory, Principles of Economics, Principles of Regional Science, Urban Economics.

Graduate: Microeconomic Theory, Regional Development and Human Capital Investment, Workshop in Labor Economics, Location Theory and Regional Analysis, Regional Labor Market Issues, Gender and the Labor Market, Research in Demography, Economic Demography; Research Methods in Demography, Economics and the Public Sector.

**FACULTY COMMITTEES AT PENN:**

Head, Regional Science Department Graduate Admissions Committee, 1973-77
Member, Regional Science Department Dissertation Proposals Committee, 1973-77
Member, SAS Women's Advisory Committee, 1975-77, 1979-85, 2009-12.
Member, SAS Women's Studies Governing Board, 1974-76
Member, SAS Distributional Requirements Subcommittee, 1975-77
Member, SAS Women's Studies Evaluation Committee, 1976-77
Member, University Benefits Committee, 1976-77
Member, SAS Regional Science Chairman Search Committee, 1976-77
Chair, Faculty Senate Nominating Committee, 2008 (member 1978, 1980)
Hearing List, University Grievance Panel, 1979-82
Member, Search Committee for Executive Vice President, 1981
Member, SAS Undergraduate Statistics Education Committee, 1982
Chair, Faculty Senate Committee on the Faculty, 1981-82 (Member 1980-81, 2000-2004)
Member, President's Affirmative Action Council, 1982-1988 and 1991-1999.
Vice President, Women for Equal Opportunity at the University of Pennsylvania, 1981-82
Chair, Faculty Senate Committee on the Economic Status of the Faculty, 1984-85 (Member 1982-84); (Member 2000-2003); (Member 2011-present).
Member, Urban Studies Committee, 1982-85.
Chair, SAS Committee on Academic Freedom and Responsibility, 1986-1987 (Member 1987-1988).
Member, SAS Social Sciences Division Planning Committee, 1986-1988
Member, University Academic Planning and Budgeting Committee, 1987-90.
Member, Advisory Council, Women's Center, 1987-present.
Member, Provost's Committee for Planning the Academic Information Environment, 1988-1990.
Chair, SAS Committee on Committees, 1990-91 (Member 1989-90).
Faculty Affirmative Action Officer for the Social Sciences, SAS 1990-91.
Member, IRMC Education Subcommittee (use of computers in education), 1990-91.
Member, Provost's Staff Council, 1991-99.
Member, Minority Permanence Committee, 1992-99.
Member, Task Force on Revision of Just Cause and Other Personnel Procedures, 1992-93.
Member, Provost's Committee on Urban/Regional Programs, 1994-95.
Member, Search Committee for Associate Provost, 1995.
Member, Penn World Wide Web Steering and Advisory Committees, 1995-99.
Member, Executive Committee, Martin Luther King Holiday Activities, chair, external relations sub-committee, 1995-99.
Member, Council on Advice, University Chaplain's Office, 1995-96.
Member, Department of Sociology Undergraduate Curriculum Committee, 1995-97.
Member, Student Services Re-engineering Committee, 1996-97.
Member, Department of Sociology Executive Committee, 1997-98, 2001-2002, 2006, 2007-8.
Member, Personnel Committee, Department of Real Estate, 1996-98.
Member, Program, Executive, and Curriculum Committees, Fels Center of Government, 1997-2002.
Member, Personnel Committee, Department of Sociology, 1997-98, 2003-4, 2005-6 (chair), 2007-2009, 2009-2011(chair), 2013-14 (chair).
Chair, Student Health Insurance Committee, 1997-98, member, 1998-99.
Member, Distance Learning Committee, 1997-98.
Co-Chair, Ph.D. Funding Committee, 1997-99.
Chair, President's Committee on Asian American Students, 1998.
Member, SAS Saul Steinberg Lecture Committee, 1998.

Chair, Gender Equity in Athletics, 1999-2002.
Member, Deputy Provost Search Committee, 1999.
Member, Search Committee for Director of Fels Program, 1998-99, 2008.
Member, SAS Personnel Committee, 2000-2002.
Member, Gender Equity Task Force, 2000-2002.
President, Penn Chapter of Phi Beta Kappa, 2001-2002; Vice-President 2000-2001.
Member, Provost's National Research Council Study of Graduate Programs Committee, 2001-4.
Member, University Committee on Graduate Prizes, 2002.
Chair, University Planning Committee on Organizations, Institutions, and Leadership, 2001-02.
Member, University Committee on School of Social Work, 2001.
Member, Dean Search Committee, School of Social Work, 2002-2003.
Member, Penn Middle States Committee on Graduate Education; chair of student support subcommittee, 2002-2004.
Member, Spatial Data Analysis Graduate Planning Committee, 2004-2006.
Chair, University TA Teaching Prize Committee, 2004.
Member, Executive Committee, Penn Institute for Urban Research, 2004-present.
Member, Masters of Urban Spatial Analytics Faculty Committee, 2004-present.
Member, University Minority Equity Committee, 2004-5.
Member, Faculty Senate Executive Committee, 2007-11.
Chair, Extraordinary Recruitment Committee, Department of Sociology, 2008-9.
Member, University Review Committee for Penn Institute for Urban Research, 2009.
Member, Women's Faculty Forum, 2009-present.
Chair, Faculty Committee for Fels, 2009-2012; member 2000-present.
Chair, Faculty Senate Faculty Climate Survey Review Committee, 2011-2013.
Member, Board of Penn Senior and Emeritus Faculty, 2011-2014.
Member, Advisory Committee Gender, Sexuality and Women's Studies, 2010-2014.
Chair, Penn Urban Research Institute Review Committee, 2014.
Faculty Panelist, Sexual Misconduct Hearing Committee, 2015-16.

## Attachment B:  Janice Madden Testifying History

ATTACHMENT B

EXPERT TESTIMONY OF DR. JANICE F. MADDEN
Since June 2015

1. *U.S. Equal Employment Opportunity Commission v. DOLGENCORP, LLC d/b/a. Dollar General,* United States District Court for the Northern District of Illinois, Eastern Division, Case No.: 13 Cv 4307 (May 2019)

2. *David McCollum v. Ray H. LaHood, Department of Transportation (FAA),* Equal Employment Opportunity Commission (EEOC), Dallas District Office, EEOC Docket No. 310-2004-00322X, Agency No. 5-04-5026. (March 2015 and November 2018)

3. *Office of Federal Contract Compliance Programs, United States Department of Labor v. Enterprise RAC Company of Baltimore, LLC.,* United States Department of Labor, Office of Administrative Judges, Case No.: 2016-OFC-00006 (May 2018, June 2018)

4. *Office of Federal Contract Compliance Programs, United States Department of Labor v. WMS Solutions, LLC.,* United States Department of Labor, Office of Administrative Judges, Case No. 2015-OFC-00009 (July 2016)

5. *United States of America v. Commonwealth of Pennsylvania and Pennsylvania State Police,* United States District Court for the Middle District of Pennsylvania, Harrisburg Division, Civil Action No. 1:14-cv-01474-SHR (July 2016).

# Attachment C: Janice Madden Fees

ATTACHMENT C

STATEMENT REGARDING COMPENSATION OF JANICE FANNING MADDEN

*OFCCP v. Oracle America, Inc.,* U.S. Department of Labor,
Administrative Law Judges, OALJ, Case No. No. 2017-OFC-00006, OFCCP No. R00192699

The services of Dr. Janice Fanning Madden are offered through Econsult Corporation. Dr. Madden's services are currently charged at the hourly rate of $690.00.

# Attachment D:  Material Considered for the Report

ATTACHMENT D
MATERIAL CONSIDERED FOR REPORT

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Application - Education.xlsx
Application - Experience.xlsx
Application - History.xlsx
Application - Source.xlsx
Application Data.xlsx
Application-Education.xls
Candidate - Demographics.xlsx
Candidate - GovtClearance.xlsx
Candidate - Languages.xlsx
Candidate - Referrals.xlsx
Candidate Preferences - Job Field.xlsx
Candidate Preferences - Location.xlsx
Candidate Preferences - Organization.xlsx
CC Data Dictionary.xlsx
Cover letter re: 25th production (2019.04.12 Mantoan Ltr to Bremer…)
Cover letter re: 28th Production (2019.05.24 Mantoan Ltr to Bremer…)
Cover letter re: 30th Production (2019.05.30 [Oracle] Mantoan Ltr to [OFCCP] Bremer…)
Cover letter re: 31st Production (2019.05.31 Mantoan Ltr to Bremer…)
Cover letter re: 32nd Production (2019.06.07 [Oracle] Pitcher Ltr to [OFCCP] Bremer…)
December 18, 2017 letter from Jinnifer Pitcher to Marc Pilotin
December 5, 2017 letter from Marc Pilotin to Erin Connell and Jinnifer Pitcher
December 8, 2017 letter from Jinnifer Pitcher to Marc Pilotin
Decl and Report of Labor Economist Neumark re Motion for Class Cert
Deposition of Kate Waggoner, taken by OFCCP
Dodson Miranda Decl
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DOL000034179-34181
DOL000038077-38266
DOL000039913

ATTACHMENT D
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DOL000039928
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FY13 Last Name M-Z Text Fields.xlsx
FY14 Last Name A-L Text Fields.xlsx
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FY18 Text Fields.xlsx
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gsi cwb detail
gsi_comp_history.xlsx
hcm wfc detail.xls
HQCA IREC DATA.xls
July 13, 2018 letter from Jinnifer Pitcher to Laura Bremer
July 6, 2018 letter from Laura Bremer to Jinnifer Pitcher
June 29, 2018 letter from Jinnifer Pitcher to Laura Bremer
June 8, 2018 letter from Laura Bremer to Erin Connell re: data questions
Merged Assignment History, Medicare and Sal Admin.xls
OFCCP Privilege Log 2019-04-26.pdf
OFCCP's Motion for Leave to File a Second Amended Complaint
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ORACLE_HQCA_0000381036
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ORACLE_HQCA_0000416489-499
ORACLE_HQCA_0000547858-867
PT1_HQCA_IREC_MAIN.xlsx
Requisition - Collaborators Data.xlsx
Requisition - Description and Qualification Data.xlsx
Requisition - Other Locations.xlsx
Requisition Data.xlsx
Saad Expert Rebuttal regarding Neumark
Waggoner Declaration - Evidence Compendium in Support of Motion for Summary Judgement

# DECLARATION OF RIDDELL ISO MOTION TO SEAL

# EXHIBIT B

**EXHIBIT D**

**EXHIBIT D**

**Expert Rebuttal Report**

**Response to Dr. Ali Saad's Expert Report on Gender and Racial Differences in Compensation at Oracle USA**

**Janice Fanning Madden, PhD**
**Econsult Corporation**

**August 16, 2019**

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## INTRODUCTION

In this report, I respond to the comments and analyses of Dr. Ali Saad that are included in his expert report, submitted on July 19, 2019. Dr. Saad's report responds to data and approaches that the Office of Federal Contract Compliance Programs (OFCCP) included in their Second Amended Complaint (SAC). The data and approaches in the SAC differ in numerous ways from those used in my July 19, 2019 report, "Analysis of Gender and Racial Differences in Compensation at Oracle, 2013-2018." Some of the data and approaches, however, are similar to those that I used in my report. I discuss here only those parts of Dr. Saad's report that are relevant to the data and approaches used in my report. To the extent that the data and approaches Dr. Saad reviews are not relevant to my analyses, I do not respond.

I focus on the principal issues raised in Dr. Saad's report: how to measure and analyze whether there are patterns of gender and racial differences in compensation-related outcomes for Oracle employees, and which are the appropriate employee characteristics or controls to include in analyses of gender and racial differences in such outcomes.[1] The question I analyze is whether there is evidence that women, Asian, or African American employees who come to Oracle with equivalent credentials to men or white employees have systematically different compensation outcomes, including

[1] Dr. Saad objects to the use of Medicare earnings in his report. He implies, incorrectly, that Medicare earnings do not reflect current year earnings accurately because they are decreased by varying choices of contributions to retirement plans. Dr. Saad is incorrect. Contributions to pension plans are included in Medicare earnings He also objects to Medicare earnings because they sometimes reflect earnings based on decisions made in other years, such as exercising bonus stock options. While his point is empirically accurate, and potentially an issue for measuring individual earnings, it is not an issue for measuring group differences. If we want to get average earnings for a group, the exercising of stock options would "average out" for the group by combining employees who are awarded such options but do not yet cash them with those who are cashing in from past compensation. On average, they should "even out" for the group to reflect their overall experience at getting such compensation.

whether there are gender and racial differences in Oracle's initial job assignments and promotions or subsequent assignments that contribute to the differences in current compensation. Any differences in outcomes by gender or race evident in the statistical analyses must come from one or a combination of the following reasons: (1) gender or racial differences in treatment when setting compensation; (2) systematic differences by gender or race in job assignments, or (3) systematic differences by gender or race in unmeasured characteristics *after controlling for any gender or race differences in measured characteristics*. The first two are forms of gender or racial discrimination, while the last reason ascribes gender and racial differences to a systematic inferiority in qualifications that are observed by Oracle management (but that are not recorded in the database) for women, Asian, and African American employees with the same database-recorded qualifications as men and white employees.

The principal opinions discussed in more detail below are:

- Statistical analyses of whether there is gender and racial discrimination in compensation by an employer are required to use only exogenous characteristics of employees. Exogenous characteristics are those that the employee, and not the employer, control.
- Dr. Saad's report presents no statistical analyses of gender and racial compensation discrimination using only exogenous characteristics. He does not control for the obvious exogenous characteristic of education. Rather, most of his control variables, such as job title and organizational name, reflect Oracle's decisions. These are the very decisions whose gender and racial neutrality are to be determined by the statistical analysis, and not assumed.

- Exogenous characteristics include the skills that employees have as they come to the employer, such as educational attainment and prior experience, and time at the current employer. The analyses in my prior report control for these characteristics in the estimation of gender and racial compensation disparities. Dr. Saad's report identified another potentially exogenous control variable, patent production. When I add this characteristic (which is likely to be endogenous, that is affected by Oracle assignments) to the exogenous characteristics I previously included, the estimated gender and racial compensation disparities decrease by about fifteen percent and remain large and highly statistically significant.
- Dr. Saad's use of cumulative years of leave of absence as a control effectively justifies compensation discrimination against mothers, biasing the measurement of gender compensation differences. Leaves of absence decrease experience. Adjustment of experience for the leave of absence is the correct approach to the consideration of the compensation effects of taking a leave of absence.
- While endogenous characteristics, such as Oracle's job assignments, may be used to assess the sources of gender and racial compensation disparities, they cannot be used as measures of discrimination. Dr. Saad's use of controls for time in job and organizational name of job are clearly endogenous variables. Organizational name of job is a problematic control because Oracle indicated it does not measure the product produced, labor economics theory indicates it should not affect compensation, almost all employees move between these

organizational names, and the control adds hundreds of variables to the analyses resulting in insufficient data to precisely estimate the effects of any control variables, including gender and racial disparities.

- Dr. Saad's clustering of word descriptions of jobs also creates endogenous variables, as Oracle creates the job descriptions and assigns employees to them. The sorting of one job for 500 employees into 24 word clusters is descriptive, but does not appear to meet scientific standards for explanation. The example he gives for one job title is limited in scope. The example shows that clusters are not connected to the racial disparity in compensation and have a fractional effect on the gender disparity in compensation for this one job.
- Dr. Saad's study of global career level at hire for experienced hires does not refute my findings of gender and racial differences in initial assignments.
    - His analyses include less than a fifth of employees in the compensation analyses.
    - His analyses do not control for the global career levels of the job requisitions. When global career levels of the job applied for are controlled, there are significant gender and racial disparities in assignments.
- Dr. Saad's study of starting salary for experienced hires does not refute my findings of gender and racial differences in initial assignments.
    - His analyses include less than a fifth of employees in the compensation analyses.

    - His analyses include detailed controls for job assignment at hire, which is the outcome of interest. He gets his results by including endogenous variables and not including any control for education, an exogenous variable.
- Dr. Saad's study of pay growth effectively removes the two most important sources of pay growth, job title and global career level changes, and does not control for prior pay. When all sources of pay growth are included and initial pay is controlled, women experience significantly less pay growth.

I present the bases for these conclusions in the next three sections. The first section examines the criterion for including specific characteristics or control variables in order to determine whether gender and racial compensation disparities exist. The subsequent section compares the approaches taken by Dr. Saad and me, both conceptually and empirically. The next two sections examine the role of initial job assignments and pay, and of job assignments and pay decisions subsequent to hire, on gender and racial compensation disparities.

## EMPLOYEE CHARACTERISTICS INCLUDED IN THE ANALYSIS

In my July 19, 2019 report, I present a series of statistical analyses estimating compensation differences by gender and race, for each year between 2013 and 2018. After discussing the differences between a compensation analysis that explains individual differences and one that explains group differences, I report my analyses showing the effects on measured gender and racial differences of adding characteristics or controls. Specifically, I compare the gender or racial coefficients across the compensation regression analyses. Tables 1 through 3 in my report, presented in several panels, show the effects on the measured gender or racial disparity of adding controls for various characteristics. The columns of each panel for each table show the gender or racial coefficients as I add various controls to the regression analyses. The individual panels differ in the dependent variable used (Medicare compensation versus base pay versus restricted stock units), and in the employee observations included (all employees versus those with education data versus employees with records of job at hire).

My analyses establish that the compensation differences by gender and by race are not the result of differences in exogenous characteristics. Exogenous characteristics are the characteristics of Oracle employees when they arrive at Oracle (education and prior experience) and the tenure or quantity of company experience they accrue after arrival. Exogenous characteristics are characteristics that Oracle does not control, but that employees themselves control.

Table 1 of my July 19, 2019 report presents clear evidence that the measure of compensation disparities for women is not affected by experience or education controls, showing that women are comparable to men with respect to these characteristics, at least in terms of the effects of the characteristics on compensation. When I add job descriptors (for example, column 6 of Table 1(a)), the measured gender disparity falls by about a quarter, implying that women are in different job areas or fields. To the extent that this variable accurately (and only) reflects gender differences in areas of prior experience and education, it is an appropriate control. The disparities in compensation by gender, after adding the job descriptors control, remain highly statistically significant and are generally over ten percent. If the job descriptors -- based on decisions made by Oracle -- are biased in any way, then the estimated gender disparities controlling for job descriptor are understated.

Table 2 of my report presents clear evidence that the measure of compensation disparities for Asian employees is not affected by education or tenure controls, showing that Asian employees are comparable to white employees in these characteristics at least in terms of their effects on compensation. When I add age (for example, column 3 of Table 2(a)), the measured Asian disparity falls by about ten percentage points, implying that Asian employees are younger and therefore have less experience than white employees. The disparities in compensation for Asian employees, after adding the age control, remain highly statistically significant and are generally over ten percent. In contrast to the gender disparity, the racial disparity for Asian employees does not change when job descriptors are added to the analyses. Asian employees are comparable to white employees of the same experience and education in their areas of specialization. The measured Asian disparity, after controlling for the exogenous characteristics of education, experience, and area of specialization, is between 10 and 18 percent and highly statistically significant in every year between 2013 and 2018.

Table 3 of my report indicates that compensation disparities for African American employees are not affected by education or tenure controls, showing that African American employees are comparable to white employees in these characteristics, at least as weighted by the effects of the characteristics on compensation. As for Asian employees, however, the addition of age (for example, column 3 of Table 3(a)) results in a drop in the measured African American disparity of about a third, implying that African American employees are also younger and therefore have less experience than white employees. As with women, the addition of job descriptors decreases the estimated racial disparity. The measured racial disparity for African American employees, after controlling for the exogenous characteristics of education, experience, and area of specialization, is between 22 and 32 percent and statistically significant in every year between 2014 and 2018. The disparity in 2013 is not statistically significant. As explained in my July 19, 2019 report, there are simply too few African American employees at Oracle to permit precision in statistical analyses of compensation disparities between African American and white employees.

The main reasons for the differences in the estimated effects of gender and race on compensation between my report and Dr. Saad's report are differences in the employee characteristics or controls. Dr. Saad decreases the statistical power of his analyses by adding hundreds of control variables and by dividing employees into separate, smaller groupings. Specifically, Dr. Saad includes several hundred control variables for Oracle's assignment of employees to organizations and job titles (endogenous variables), but includes no controls for education (exogenous variables). Dr. Saad's studies answer a different question from the question I address in my report. Dr. Saad studies gender and racial compensation differences within a job, and does not evaluate compensation differences arising from gender or racial differences in Oracle's promotion or initial assignment decisions. The gender and racial compensation effects of job assignments cannot be analyzed with a statistical analysis that controls for job assignments (effectively assuming from the start that no such gender and racial differences exist). Dr. Saad shows that most of the gender and racial differentials in compensation are due to gender and racial differences in job assignments. I concur with this finding, as shown in my July 19, 2019 report. He assumes without any scientific testing, however, that *all* of these differences in jobs (at the level of organizational names and standard job titles) are due to the unobserved systematic productivity inferiority of women, Asians and African American employees who are otherwise identical in age, tenure, education, and job descriptors to their male or white counterparts.

I discuss endogenous and exogenous characteristics or controls in greater detail below. The next section reviews the concepts of endogeneity and exogeneity. The subsequent section reviews the reasons why endogenous controls cannot be included in any analyses, including analyses of race and gender discrimination. In the following section I discuss the endogenous and exogenous characteristics or controls used by Dr. Saad and by me and present some additional analyses that clarify the roles of these characteristics in determining gender and racial disparities.

## The Concepts of Endogeneity and Exogeneity

A characteristic is considered to be "endogenous" (i.e., determined "inside") if its value is determined, at least in part, by the process (or the behavior) the statistical analysis is describing. Alternatively, a characteristic is considered to be "exogenous" (i.e., determined "outside") if its value is determined outside the process (or the behavior) the statistical analysis is describing. For example, the educational attainment of an employee is not determined by an employer's decision, so educational attainment is an exogenous attribute, determined outside of Oracle. The job title of an employee is assigned by the employer. Current job title is the accumulation of the employer's initial job title assignment and the employer's subsequent job assignments of promotion decisions. So, job title is an endogenous attribute, determined, at least in part, by Oracle's employment processes.[2]

**Endogenous Characteristics Cannot Be Included**

Both Dr. Saad and I want to compare women, Asian, African American, men and white employees who are "similarly situated." For these comparisons, Dr. Saad defines similarly situated persons as those whom Oracle has defined as similarly situated (endogenously), that is, as those whom Oracle has assigned to the same job and same tasks (or clusters). He does not use the clearly exogenous (to Oracle's decision-making) characteristic of education (a characteristic which employees, and not Oracle, control) to define "similarly situated."

Dr. Saad's approach to deciding which employee characteristics should be included in his analysis is circular because his approach requires the assumption that Oracle does not discriminate in job assignments, as a condition or premise for his test of whether Oracle discriminates in compensation. If there were discrimination at Oracle, then that discrimination would quite likely affect how women, Asian, African American, men, and white employees were assigned to jobs; that is, discrimination would affect how they were promoted and assigned to jobs and tasks at hire. If there were discrimination, women, Asian, African American, men, and white employees with the same relevant

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2 The standard approach to these issues in the economics of discrimination literature is discussed in David E. Bloom and Mark R. Killingsworth, "Pay Discrimination Research and Litigation: The Use of Regression," *Industrial Relations*, 21:3, (Fall 1982). They explain that only "pre-hire" characteristics of employees are "not affected by practices of the present employer…[and] not subject to the kinds of difficulties that arise in the context of analyses… which in effect control for at-hire or post-hire variables denoting job level or job type at one's present employer." (p. 326). Later, at p. 329, "The essential point is that both pay and [having a particular current job placement] are outcomes that depend on decision of the employer, i.e., they are 'endogenous.'"

skills would be assigned to different jobs and tasks. An analysis of discrimination that assumes from the start that such work assignments are nondiscriminatory (or exogenous and not endogenous) begs the question. Dr. Saad's inclusion of endogenous attributes means that his analyses are biased toward finding no discrimination when discrimination truly exists.

My approach to the inclusion of employee characteristics is fundamentally different. I make no assumption, one way or the other, about whether Oracle discriminates. I use exogenous employee attributes *that are not the result of Oracle's decisions*, but are the result of employee's decisions, to define similarly situated individuals. Women, Asian, African American, men, and white employees are similarly situated when they come to Oracle with equivalent education and work experience, characteristics that are not the result of Oracle's decisions. Although some of my analyses control for Oracle's endogenous job assignments, I perform them only to parse out the specific sources or practices that yield differential compensation by gender or race, such as compensation differences within-job versus compensation differences arising from promotion versus compensation differences arising from the initial job assignment.[3] Full and complete analyses of gender and racial differences in compensation require that there be no assumption that Oracle does not discriminate; full and complete analyses of differences in outcomes require that the statistical analysis use exogenous characteristics and not be biased by including endogenous characteristics of employees (those characteristics that are the result of decisions by the employer). There

[3] I also use some of Oracle's broader assignments of job (job descriptors) as measures of the field or area of education and prior experience. Implicitly, I then assume for the sake of argument that there is no discrimination in this level of assignment of employees at Oracle. If these assignments were to be affected by gender or race, then I have underestimated the compensation differentials by gender or race.

can be no prejudicial assumptions that Oracle does not discriminate in fair and accurate statistical analyses, or tests, of whether they discriminate.

As described above, an endogenous characteristic is one affected by the process under investigation, regardless of the direction of the effect. If the endogenous attribute at issue is also "tainted"—that is, the direction of the effect is clearly adverse to women or Asian or African American employees—then including that effect results in biased underestimates of the extent of the true gender and racial differences.

**Identifying Exogenous Characteristics**

So how do these issues affect the list of characteristics that should be included in an analysis of gender and racial disparities in compensation and initial job assignments? Because I examine whether there are unexplained gender and racial disparities that are consistent with discrimination among employees who are "otherwise the same," I require data capable of identifying which employees are "otherwise the same" that are *exogenous* or *not potentially tainted by Oracle's gender or race discrimination*.

In the next subsection, I describe the most obvious exogenous characteristics as used in my analyses included in my report of July 19, 2019. The second subsection discusses the characteristics that Dr. Saad used in his analyses included in his report of July 19, 2019 and that I did not.

*Education, Age, and Tenure*

I use educational attainment and years of experience prior to coming to Oracle,[4] as well as time at Oracle,[5] as metrics, which are unlikely to be affected by any potential discrimination by Oracle, to identify similarly situated employees. I am not using educational attainment or years of non-Oracle experience primarily as measures of productivity differentials among employees in the same job. While there is evidence that education and work experience acquired with other employers affect productivity levels within a job,[6] that is not how I use them in my analyses. I use education and non-Oracle experience along with other characteristics, including time at Oracle and job descriptors (not as job controls, but as measures of the field or area in which education and prior work experience occurred) as independent or exogenous measures of employee attributes that Oracle does not control. These measures, which are not affected by the very discriminatory behavior that we are trying to detect, define similarly situated, or "otherwise the same," employees of different races and genders at Oracle. The

[4] I use age (and age squared) along with controls for highest degree attained and for Oracle tenure as a proxy for experience before coming to Oracle.

[5] Dr. Saad criticizes the OFCCP analyses supporting SAC for not considering leave of absence time in calculating the amount of tenure at Oracle. My computation of time at Oracle, as used in my July 19, 2019 report, did remove leave time in calculating time at Oracle. I discuss below the reasons why Dr. Saad's techniques for measuring tenure at Oracle are flawed.

[6] Dr. Saad's discussion of the correlation between age and compensation within a job and global career level (Software Developer IC4) at pp. 106-108 of his report is misleading because it is based on the well-known "ecological inference fallacy." As software developers (or workers within any skill category) age, the more successful ones move to higher global career levels and the less successful ones stay at lower levels. Similarly, the youngest software developers who are more talented are more likely than the less talented to have attained global career level 4. As a result, the naïve correlation of age with compensation *within* the software developer 4 job ignores the larger ecology of how movement in and out of the particular job and global career level interacts with age and compensation. The youngest software developers within a global career level are the most talented (and therefore more highly compensated) of their age group and the oldest are the least talented (and therefore less compensated) of their age group. As a result, the observation of a flatter age-compensation curve reflects the selection into and out of the job, and not the relationship of age, other things being equal, to compensation or productivity.

education measures are statistically significant, with the expected effects, in my analyses of gender and racial disparities in compensation. Table R1, for example, shows the estimated effects of various educational attainments on compensation in 2018, in the Information Technology, Product Development, and Support job functions for men and women and in Product Development job function for Asian and white employees. The coefficients are of magnitudes entirely consistent with the expectations of labor economics.[7]

*Variables Included in Dr. Saad's Compensation Analyses*

Dr. Saad adds four variables that I did not include in any column of my Tables 1, 2, and 3. These include data on patents, cumulative leaves of absence, time in current job, and organizational names of job assignment. Time in current job and the organizational name of current job are both clearly endogenous variables set by Oracle. They are characteristics determined by Oracle's decision-making. As endogenous variables, they cannot be used to measure the gender and racial disparities in compensation. I will discuss these two variables in more detail below as endogenous variables.

*Patents.* Dr. Saad uses the data on whether an employee has ever received a bonus from Oracle for receiving a patent as a control variable in his compensation analyses. As employees who develop patents are more productive than those who, given the same assignments, do not, and the innovativeness represented by patent attainment is arguably an exogenous variable to Oracle, patents, especially patents awarded before hire at

[7] Table R1 provides the education estimates for the results reported in Column 4 of my Tables 1b and 2b from my July 19, 2019 report. Please note that the estimation technique measures the effects of these degrees relative to a bachelor's degree.

Oracle, may be reasonably included in an analysis of gender and racial compensation disparities. It does not appear, however, that data on prior patents awarded were considered. Rather, Dr. Saad uses compensation data indicating whether an employee has ever received a bonus for receiving a patent as an Oracle employee. If there were no evidence of racial or gender differences in assignments to project teams, in whether members of a project team are included on a patent, and if all patent holders receive a bonus,[8] then receiving a bonus for a patent is an exogenous and therefore appropriate variable to include. If Oracle were to differentially assign women, Asian, or African American employees to project teams developing patents, then the patent bonus variable should not be included as a control in analyses of gender and racial compensation disparities. Another way to say this is, if Oracle were to assign women, Asian, or African American employees to teams responsible for cutting edge products and services at a different rate than were men and white employees, then the patent bonus variable is endogenous and should not be included. If women, Asian, or African American employees were less likely to be included in patent applications by their project teams, then the patent bonus variable should not be included as a control in analyses of gender and racial compensation disparities. If there were gender or racial differences in whether Oracle employees listed on patents are awarded a bonus, then the patent bonus variable should not be included as a control in analyses of gender and racial compensation disparities. I have produced extensive evidence of differential assignments by gender and race among Oracle employees. I cannot accept the fact that an employee at some time

[8] Oracle states that these awards are at the discretion of the Oracle patent department (see ORACLE_HQCA_0000414169-70.pdf, ORACLE_HQCA_0000414368-71.pdf, and ORACLE_HQCA_0000414372.ppts for example). I have not seen any data that allows me to determine how frequently such discretion is used.

received a patent bonus as endogenous (unaffected by Oracle's decisions) in the absence of evidence that the above standards have been met. I also note that Dr. Saad could have obtained data on patents prior to Oracle employment, a clearly exogeneous variable, from the applications materials. He did not do so.

I add this patent variable to the analyses presented in the 7th column of Tables 1(a) and 2(a) of my July 19, 2019 report. The effects of including patents on the measurement of gender and racial disparities within jobs appear on Tables R2 and R3.

Adding a control for having received a patent bonus decreases the gender disparity. To determine this, I compare the gender coefficients of column 2 (which adds a control for having received a patent bonus) with column 1 (which has the same controls with the exception of the patent bonus) of Table R2. The gender disparity decreases by about two percentage points, or by about 15 percent. The gender compensation disparity, after controlling for patents, is between 9 and 13 percent and 6 to 8 standard deviations.

Adding a control for having received a patent bonus also decreases the Asian compensation disparity. As with gender, I compare the race coefficients of column 2 (which adds a control for having received a patent bonus) with column 1 (which has the same controls with the exception of the patent bonus) of Table R3. The racial disparity decreases by between two and two and a half percentage points or by about 15 percent. The Asian compensation disparity, after controlling for patents, is between 10 and 16 percent and 5 to 8 standard deviations.

*Cumulative leaves of absence.* In my July 19, 2019 report, I controlled for cumulative leaves of absence by reducing the time employed at Oracle by the cumulative leave time. Time at Oracle quantifies the experience within the firm that each employee has. This experience within the firm allows employees to get more on-the-job training and therefore become more productive. Taking a leave of absence, while keeping the employee in touch with the company, removes that employee from exposure to on-the-job training. Dr. Saad does not adjust work experience measures for cumulative leaves of absence, but adds a new control variable, cumulative leaves of absence. Leaves of absence affect compensation because they reduce work experience. Women are more likely to take leaves of absence for maternity and child care leave. Dr. Saad's decision to account for leaves of absence as a separate control variable, rather than by adjusting experience controls appropriately, amounts to justifying discrimination against mothers. Women have higher cumulative days of leave of absence because they take parental leave. It is reasonable to account for any ensuing differences in exposure to on-the-job training. The use of a separate variable effectively "marks" mothers and downwardly biases the gender disparity.

Table R4 presents two panels for each of the job functions illustrated in the graph on page 86 of Dr. Saad's July 19, 2019 report. The table first reports Dr. Saad's regression results from the computer backup that he sent to explain his graphics. The graphics show that the only year with a statistically significant gender disparity is 2013 for the PRODDEV job function. The regression model details that yielded that result is reported in the first row of Table R4. The gender coefficient appears in column 1.[9] Column 2 shows the coefficient on his cumulative leave variable, which is -0.0479. Columns 3, 4, and 5 report Dr. Saad's coefficients for Oracle USA tenure, previous

[9] Dr. Saad appears to have adjusted his regression coefficients throughout his report to yield the precise percentage difference, so the coefficient of 0.0177 becomes 1.75%

experience, and total Oracle years (includes experience in acquired companies and Oracle companies that are not Oracle USA).

I note two important aspects of these various types of experience coefficients in Dr. Saad's regressions. First, the coefficients are negative, meaning that employees with more experience receive *lower* compensation than those with less experience. Second, the years of cumulative experience (effectively a motherhood control) is also negative, and at a magnitude that is a multiple of the other experience measures. If experience of any type does not increase compensation, then why would taking a leave of absence (which reduces experience) have a negative effect, and such a large one, on compensation? Why does the cumulative leave in years control have an effect that swamps all of the other experience effects? These results are consistent with the hypothesis that the cumulative leave in years control is not measuring productivity effects of taking a leave but is identifying mothers who receive less compensation. In this case, the coefficient on cumulative years of leave reflects a compensation disparity for mothers. Such a variable should not be included as a control in an analysis of gender disparity.

Dr. Saad's regression analysis underestimates the gender disparity due to the inclusion of a motherhood control. The second panel in Table R4 repeats Dr. Saad's analysis, but corrects his treatment of cumulative years of leave. This panel takes the cumulative years of leave and subtracts it from tenure at Oracle. The re-estimation, then, eliminates the cumulative years of leave variable, reformulates the tenure at Oracle variable and computes the gender disparity, which is the gender coefficient in column 1. This was done for each year, 2013 through 2018. As a result, the gender coefficient for employees in the PRODEV job function increases in absolute value and becomes statistically significant at 3 to 4 standard deviations in each year.

The next two panels on the table perform the same analyses for employees in the INFTECH job function. The results parallel those for PRODEV. The number of women (and of men) employed in INFTECH is much less than in PRODEV, however. As a result, the coefficients of all control variables are less precisely measured. Note that many of the experience controls are not statistically significant. As for PRODEV, the gender coefficient increases in absolute value when the motherhood control is removed. The gender disparity becomes statistically significant in each year except 2016. This is remarkable for a regression that includes over 100 control variables (see column 6) and only 124 to 143 women (see column 7). As I discuss below, Dr. Saad's analyses frequently reduce statistical significance by partitioning the analyses into subdivisions that lead to imprecision.[10]

In summary, education, prior experience, and tenure are exogenous variables. Having obtained a patent could be an exogenous and records of bonuses for getting a patent may reflect that characteristic. Given the evidence of gender and racial disparities in Oracle's job assignments, however, it is likely that this variable is endogenous. Cumulative leaves of absence are also exogenous, but must be considered by adjusting experience controls and not by labeling women taking parental leave.

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[10] I also note that the experience coefficients are quite similar for PRODEV and for INFTECH, further illustrating why it is inappropriate to partition the analyses and lose precision.

## Endogenous Characteristics

Oracle's assignments of employees to specific jobs, including job titles, global career levels, organizational names within Oracle and time in current job are endogenous because Oracle sets the values for these characteristics. If Oracle were truly to discriminate, such discrimination would affect the values of these characteristics, as well as affecting compensation.

In my July 19, 2019 report, I include job titles and career levels in the last analysis reported in the last columns of each panel in Tables 1, 2, and 3. I perform these particular analyses to determine the sources of compensation disparities. I calculate the share of overall compensation disparities arising from pay differences within the same job and differences in job assignments. The analyses controlling for Oracle's job assignments allow me to determine disparities within the same job. The analyses controlling only for exogenous employee characteristics provide me with the complete gender and racial compensation disparities for employees who came to Oracle with the same education and prior experience and who have the same tenure at Oracle. By subtracting the disparity within job from the total disparity, I assess the roles of compensation disparities arising from differences in job assignments and compensation disparities within jobs in creating total disparities. Both women and Asian employees of the same experience and education experienced compensation disparities within job title and global career level, although the size of the disparity was substantially smaller after taking account of the gender and racial differences in Oracle's job assignments.

In my analyses of the effects of current job assignments in my July 19, 2019 report, I did not control for time in current job or for the job's organizational name within Oracle. Dr. Saad includes these two characteristics in his analyses.

*Time in Current Job.*

I do not control for time in current job because the variable is a measure of promotion timing. Adding this variable to the analyses of gender and racial compensation disparities means that the estimated disparities do not include any consideration that promotions may take longer for woman, Asian, and African American employees, with the same experience and time at Oracle. As long as we recognize that this is an endogenous variable, set by Oracle, and therefore potentially reflecting discrimination, however, it can be included in an analysis to measure the effect of differences in current job assignments on gender and racial disparities.

Table R2 shows the effects of adding time in current job to the measurement of the gender disparity at Column 4. As discussed above, this table is adding variables to the analyses shown in Table 1(a) of my earlier report. By comparing the coefficients in Column 4 to those in Column 3, we can see that the time in current job has virtually no effect on the gender disparity, reducing it by between zero and 0.3 percentage points. In all years, the gender disparity within current job is between 4.2 and 5.3 percent and remains highly statistically significant at four standard deviations.

Table R3 shows the effects of adding time in current job to the measurement of the Asian-white disparity at Column 4. As discussed above, this table is adding variables to the analyses shown in Table 2(a) of my earlier report. By comparing the coefficients in Column 4 to those in Column 3, we can see that the time in current job reduces the Asian compensation disparity generally by about ten percent, or between 0.2 and one percentage points. In all years, the Asian disparity within current job is between 2 and 6 percent and remains statistically significant at two to four standard deviations for all years but 2013.

*Organizational Name.*

I also did not control for organizational names in my analyses in my July 19, 2019 report. While I think it reasonable to include time in current job for measuring the extent of compensation disparities coming from within job differences, I do not think it reasonable to include the organizational name for each job. There are four reasons not to include these controls, even when using endogenous controls. First, there is no reason to place equally qualified women, Asians, or African Americans who are in the same job in lower paying organizations within Oracle. Second, labor economic theory indicates that there is no reason for employees to accept less compensation because Oracle makes less money from the product produced at their organization than for the product produced at another organization by identically qualified employees. Third, because employees work in multiple organizations within the same year, organizational names are questionable indicators of productivity differences among employees.[11] Fourth, controls for organizational name add hundreds of variables to the regression analyses undermining the precision of the estimates of gender and racial compensation disparities. I discuss these reasons in more detail below.

[11] At paragraph 116 of his July 19, 2019 report, Dr. Saad describes organization (and his computer backup shows that this is organization name) as correlated "at least in a general way" with products and services worked on. Oracle represented that organization names were cost centers used for tracking various financial outcomes. Oracle went on to say that not every product and service team had an organization name identified with it (Letter of June 29, 2018 from Jinnifer Pitcher to Laura C. Bremer page 8.) If Dr. Saad wants a control for product or services produced, he should use a control variable that actually represents them. Organizational name does not.

In the absence of discrimination, I do not expect that Oracle systematically assigns women, Asians, or African American employees to those organizations within Oracle that yield less profit or are lower paying than those organizations employing men or white employees in the same job with the same education and experience. There is no reason for women, Asian, or African American employees of the same education and experience (exogenous characteristics) as men or white employees to be located in organizations within Oracle that pay them less.

I do not understand why organizational name should lead to any compensation differences among equally skilled employees. Dr. Saad correctly states that pay is a function of productivity. Productivity determines the willingness of employers to pay, or as an economist would explain, the demand for labor at a given pay level. Demand for labor alone, however, does not determine pay. Actual pay also depends on the willingness of employees to work at a given pay level, or as the economist would explain, the supply of labor at a given pay level. While the revenue or profit from a particular product affects the willingness of Oracle to allocate money to pay wages in producing the product, the observed pay to employees also depends on the willingness of Oracle employees to accept lower pay *only because they are creating a less profitable product*. There is no reason for an employee of a given skill level and ability to accept lower pay producing product "A" when the same skills are paid higher for producing product "B." Pay is determined by the intersection of demand for, and supply of, workers. Dr. Saad is ignoring universally accepted theory in labor economics. Labor economists agree that companies selling their product at less profit than do other companies hire fewer workers (because their demand for labor at each wage level is less than for more profitable companies). However, these companies must still pay the workers hired the "competitive wage" (due to the supply of labor being the same for them and for more profitable companies). According to labor economics, any lower profitability translates into fewer workers, but not into lower wages.

Organizational name is a fluid characteristic. Virtually all employees within the job functions included here work in more than one organizational name between 2013 and 2018. Table R5 lists the distribution of the number of different organizations in which the 8,658 employees worked between 2013 and 2018.

Finally, the inclusion of organizational names in the composition analyses compromise the precision with which the effects of gender and race, as well as all other variables in the analysis can be determined. I understand that it might well appear to the lay observer that it is better to be more inclusive; that is, to include all characteristics that might reasonably be expected to influence the compensation, promotions, or job assignments of individual employees at Oracle. Social scientists widely accept, however, that is simply not the case, for two main reasons:

> First, we must consider the *power* of the statistical analyses; that is, the capacity of the data available (number of observations or employees) to measure accurately the effect of each specific characteristic, as the number of characteristics included in the analyses increase while the number of observations (employees) stays the same. There is no "free lunch" in adding thousands more employee attributes to the analyses.[12] The studies or analyses should be designed

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[12] Statistics textbooks warn against putting a large number of variables in any analysis. For example, see Mario F. Triola, *Elementary Statistics*, 9th ed. (Boston: Pearson/Addison-Wesley, 2004): pp. 545-546; Peter Kennedy, *A Guide to Econometrics*, 4th ed. (Cambridge, MA: The MIT Press, 1998): p. 95;

to provide accurate and precise statistical estimates of the effects of gender and race. Adding characteristics that do not matter (in that they do not differ by gender or race after other characteristics are included) decreases the precision, or "accuracy," of the measurement of gender and racial effects.

Second, we must consider whether each *characteristic is "endogenously" determined;* that is, whether the values of attributes included in the analyses might be affected by the very discriminatory behaviors that the statistical analyses are meant to detect. If an attribute is endogenous, then it should not be included in the analyses.

I explain these concerns in more detail below.

In statistical terms, Dr. Saad's analyses include large numbers of organizational name characteristics, including many that are irrelevant, which "use up" the observations on compensation for women, Asian and African American employees to estimate hundreds of irrelevant effects, resulting in too few observations (employees) left to estimate the effects of gender and race. Dr. Saad has added too many controls, or characteristics of workers, to the model for the effects of the characteristics of gender and race to be estimated precisely. The large number of characteristics included in his analyses arises from his decision to include full job title and organizational name and to obtain different measures of the effects of each characteristic within each job function in his analyses of gender disparities. One standard textbook on social science research, for example, reports that most researchers would recommend at least 100 observations for a

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Eric A. Hanushek and John E. Jackson, *Statistical Methods for Social Scientists*, New York: Academic Press, 1977): pp. 93-94.

statistical estimate of *one characteristic* and notes that this value increases when reliable estimates for a subgroup, such as African American employees in this case, are sought.[13]

Table R6 reports the number of estimated effects of characteristics or controls and the number of women, Asian or African American employees in each of Dr. Saad's compensation analyses. The number of characteristics or controls that Dr. Saad includes in his analyses far exceed the standards of the literature, given the number of observations and of women or minority employee observations in particular. Dr. Saad's analyses "wash out" gender and racial effects by taking the relatively small numbers of women, Asian and African American employees, distributing them across the large number of irrelevant effects of attributes to be estimated, yielding too few left to measure gender and racial effects with precision.

Table R2 shows the effects of adding organizational name of current job to the measurement of the gender disparity at Column 5. As discussed above, this table is adding variables to the analyses shown in Table 1a of my earlier report. By comparing the coefficients in Column 5 to those in Column 4, we can see that the organizational name of current job reduces the gender disparity by widely varying amounts over the years. The large variation in gender coefficients across years arises from the imprecision introduced by adding over 500 additional variables to analyses including only about a thousand women. Adding organizational name of current job reduces the estimated disparity arising within the current job by between 7 and 57% or between 0.3 and 2.6

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13 See Royce A. Singleton, Jr., and Bruce C. Straits, *Approaches to Social Research* Third Edition (New York: Oxford University Press, 1999), pp. 166-169.

percentage points. In all years, the gender disparity within current job is between 2 and 4 percent and is statistically significant in only three years, 2015, 2017, and 2018.

Table R3 shows the effects of adding organizational name of current job to the measurement of the Asian disparity at Column 5. As discussed above, this table is adding variables to the analyses shown in Table 2a of my earlier report. By comparing the coefficients in Column 5 to those in Column 4, we can see that the organizational name of current job reduces the racial disparity by widely varying amounts over the years. Adding organizational name of current job reduces the estimated disparity arising within the current job by between 11 and 100% or between 0.7 and 3.6 percentage points. The Asian disparity within current job becomes statistically insignificant in all years.

*Clusters.*

Dr. Saad also implies that differences in job descriptions for the same job title might explain gender and racial differences in compensation. As with the job title, such descriptions are also endogenous variables that are controlled by Oracle and therefore inappropriate to use as controls for statistical tests of whether Oracle discriminates. Dr. Saad describes the differences in words used to identify tasks for employees in the Software Designer 4 job title. In addition to the endogeneity of clusters of word descriptions to Oracle decision making, there are three other problems with considering Dr. Saad's cluster analyses of Software Developer 4 job descriptions as relevant to evidence of the presence or absence of discrimination. First, Dr. Saad's analysis of clusters is descriptive and does not appear to meet standards for scientific explanations. Second, there is no basis for assuming that variations in descriptions within job titles vary systematically by race or gender. Third, Dr. Saad fails to relate these clusters to gender and racial compensation disparities. I discuss each of these problems in more detail below.

Dr. Saad claims that his cluster algorithm created the 24 clusters he identifies for Software Developer 4 job descriptions. The computer backup that he provided does not demonstrate that to be the case. While the sorting of job descriptions into a cluster was done by the computer algorithm, he appears to have arbitrarily determined that 24 clusters should be used. The basis for that determination is not clear to me. His computer backup shows he used a command to set the clusters at 24.[14] Normally, the programmer plots the word correlations on a graph and then assesses the number of clusters that best fit the data. I could not find any evidence of this having happened. Furthermore, there is evidence that Dr. Saad tried different alternatives for the number of clusters. His computer output lists alternatives for 10, 15, or 30 clusters, in addition to the 24 he reports. The bottom line is there is no quantitative or scientific basis for the number of clusters he identifies.

There is no basis for assuming that men and women, Asian and white employees, and African American and white employees in the same job title (and, in my analyses with the same educational attainment and experience) would systematically differ by race or gender in word clusters formed for the same job title. Furthermore, it is not only a race and gender difference in the distribution across clusters that matter, but the differences must also be tied to compensation. Dr. Saad is implicitly assuming that women, Asian, and African American employees systematically select into narrower job descriptions that also systematically differ in compensation from men and white employees who are the

[14] Line 47 of Dr. Saad's program uses the CUTREE function which sets (or forces) the number of clusters at 24

same in experience, education, and job title. He provides no basis for this assumption of the gender or racial inferiority of Oracle employees.

Dr. Saad's data on the Software Designer 4 job descriptions that he sorted, apparently arbitrarily, into 24 clusters include 521 men and women and 491 Asian and white employees. Table R7 shows the results of regressing race or gender alone, then race or gender and education, then race or gender and cluster, then race or gender and cluster and education, on compensation. I report the race or gender coefficients and their significance for each regression, as well as the adjusted $R^2$ for each regression analysis. The cluster control variable has no effect on the measurement of the racial disparity for Asian employees. The cluster variable does decrease the disparity for women by about a third.

**Summary**

The exogenous control variables for employee education, experience, and tenure are appropriate to include in an analysis to evaluate gender and racially discriminatory compensation practices. Being listed on a patent at Oracle may be exogenous (although job assignment evidence suggests otherwise) and, if so, appropriate to include as a control. It is less clear that getting a patent bonus is exogenous. Cumulative years of leave is not appropriate as a separate control, but should be used to adjust experience measures.

Endogenous variables that reflect Oracle decisions about employees are relevant to parsing out the sources of gender and racial compensation disparities, but bias any evaluation of their existence. Job titles and global career levels, and potentially getting a patent, describe Oracle's job placement decisions. Organizational names are problematic even as endogenous variables because they involve the addition of hundreds of control variables that undermine the precision of statistical analyses, among other problems. Dr. Saad suggests forming clusters within job titles, but does not connect them to gender and racial disparities in compensation. For the Software Developer 4 job title, clusters have no effect on the observed racial disparities and a small effect on the observed gender disparity.

**COMPENSATION, INITIAL ASSIGNMENTS, AND PROMOTIONS**

My analyses of gender and racial differences in compensation began with an analysis that compares men and women, and Asian or African American and white employees, who have attained the same educational degrees, are the same age, have the same amount of time (tenure) with the company, and are in jobs with the same descriptors. I use job descriptors as indices or proxies of the substantive or content areas of an employee's education and prior work experience. As explained in my earlier report, my analyses test for the total compensation disparities among employees resulting from compensation differences within job and from different jobs (due to promotion and initial assignment differences) for employees who are comparable in the characteristics that employees control and that are not the results of any potential decisions -- or potential discrimination -- by Oracle.

These analyses clearly established that there were gender and racial disparities in compensation after comparing, or grouping, employees of the same education and experience. I then developed a series of analyses to quantify the role of initial placements in the compensation differences. I analyzed initial and current job assignments.

I found gender and racial disparities in initial assignments. I found that about half of current gender differences in compensation arise from gender differences in job assignments at hire for employees of similar experience and education. I found that differences in assignments after hire as well as current compensation differentials with similar job assignments account for the other half of current compensation differentials by gender.

I found that current Asian-white differences in compensation arise almost entirely from differential job assignments by race for employees of similar experience and education. Additional differences in compensation arise from different compensation for employees with similar current job assignments.

As discussed above, if gender and racial discrimination were to exist, the gender and racial differences in compensation for employees working in the same job are expected to be substantially smaller than the compensation effects arising from gender and racial differences in promotion and initial job assignment. Because gender and racial differences in compensation within the same job would be more apparent to everyone, including employees and management, they are smaller or less likely to occur. In my analyses, I observe that gender and racial differences in compensation within the same job are smaller than racial differences in compensation arising from differences in initial assignments.

Dr. Saad performed some direct evaluations of gender and racial disparities in initial assignments and promotions. I address those studies below.

**Initial Assignments**

I agree with Dr. Saad that the actual jobs in which individuals are placed at various levels at Oracle have detailed, and often very specific, education and job experience requirements. All applicants of the same age, educational attainment, and specialization area are obviously not equally qualified for all of these varied positions. If one were designing a statistical analysis to assign each individual applicant to each job, each of these detailed requirements for jobs and the specific skill set of each individual would have to be included. A statistical model for assigning individuals to particular jobs would be rather silly because many of these requirements do not lend themselves to quantification and the numbers of hires are too few to allow reliable estimation of the effects of the large number of characteristics that such a model would have to include. Fortunately, I am not developing statistical analyses for assigning individuals to jobs. Rather, I am designing analyses to evaluate statistically whether Oracle systematically assigns women, Asian and African American hires to job title and global career levels in a way that is different, and inferior to, the assignments of men or white hires. For this purpose, I do not have to include all of the characteristics by which individuals, or jobs, differ. In this case, we only need to include the characteristics by which the genders or races differ.

Dr. Saad's analyses of initial assignments of new hires by gender and race do not provide the information needed to evaluate whether gender and racial disparities in job assignments at hire account for gender and racial disparities in current compensation. The problems with his analyses include:

- Dr. Saad's studies include too few of the initial job assignments of relevant employees to draw any conclusions about how initial assignments affect the compensation of the much larger groups of employees we both analyze.
- Dr. Saad's studies do not control for exogenous characteristics that plausibly differ by race or gender, including education and job descriptor, and instead include the endogenous characteristics determined by Oracle.
- Dr. Saad's analyses of whether a newly hired employee's global career level assignment was the same, higher, or lower than that of the job requisition do not control for the global career level of the requisition. When this control is added, there is evidence of gender and racial disparities in the global career level of the initial assignment relative to that in the job requisition.

I discuss each of these problems in more detail below.

*Dr. Saad's analyses of initial assignments include a small subset of employees.* Dr. Saad's analyses of gender and racial differentials in assignments at hire include only a minority of the assignments at hire for men and women employed in the Information Technology, Product Development, and Support job functions, or for Asian, African American, and white employees in the Product Development job function between 2013 and 2018. Table R8 reports the number of employees whose initial job assignments are analyzed by Dr. Saad. The Table also reports the total number of initial assignments made by Oracle between 2013 and 2018, indicating that Dr. Saad analyzes fewer than two-thirds of these assignments. In my analyses linking current compensation differences by gender or race to initial assignments, I include all men and women employed in Information Technology, Product Development, and Support job functions and all Asian, African American and white employees in the Product Development job function between 2013 and 2018. My analyses of current compensation and initial assignments show that initial assignments account for about half of the current gender compensation differences and the majority of the current compensation disparities for Asian employees. As Table R8 indicates, Dr. Saad's study of initial assignments includes only 20 to 27% of the initial assignments for these employees. Simply, Dr. Saad's studies of initial assignments include far too few of the relevant employees' initial assignments to determine either the extent of gender or race differences in initial assignments at Oracle, or the effects of those assignments on current compensation.

*Dr. Saad does not include the relevant control variables determined by employees, but includes control variables determined by Oracle.* Dr. Saad does not consider the effects of education on initial assignments of employees. Education is a characteristic determined by the employee (and not affected by Oracle's decision-making) that affects initial assignments. Dr. Saad does not use any measures of education in his analyses of initial assignments, but instead uses global career level and standard job title (both defined and used by Oracle) as non-discriminatory measures of employee qualifications. Dr. Saad's use of these controls in a study whose purpose is to test for gender and racial disparities cannot be justified. The use of these characteristics or controls as indicators of employee qualifications requires an assumption of no discrimination by Oracle. Because the purpose of the test itself is to measure discrimination, such an assumption cannot be justified in testing for discrimination in initial assignments. All of Dr. Saad's analyses of initial assignments are compromised by the failure to include education and the unjustified inclusion of Oracle's decisions on employees.

*Dr. Saad fails to include a critical control variable in his analyses of global career level assignments at hire.* Dr. Saad analyzes the global career level assignments by race and gender for a subset of the hires. The subset includes experienced hires who matched an Oracle job requisition. Dr. Saad argues that prospective employees generally apply for one particular job and, if hired, simply get the job for which they applied. Applicants may be offered a different job, in either a lower or higher global career level, than requested on the application.

In particular he reports that women and Asian hires applied for lower global career level jobs than did men and white hires. He also reports that women, Asian, and African American hires were equally likely as were men and white hires to be assigned the global career level of the job for which they applied.

Dr. Saad fails to take the next step, however, of determining whether jobs advertised at lower global career levels were more likely to be filled at different global levels than those at higher levels, and, if so, whether there were racial or gender differentials in the initial assignment when hired for advertised jobs at the same global career levels. Had he done so, Dr. Saad would have found evidence, for this subset of hires, that women and Asian employees received lower initial global career levels.

Charts R1 and R2 use the graphics and statistical tests that Dr. Saad used in his analyses of "Actual vs. Applied for Job Level" by gender and race, but control for the job's global career level. The charts include the three largest global career levels, IC3, IC4, and IC5, into which employees were hired.

Chart R1 shows that, for job openings at IC3, women were more likely than were men to receive a lower global career level than in the requisition, but less likely to receive a higher level. These gender differences, in isolation, are not statistically significant. For job openings at IC4, the same pattern occurs, but the gender disparity is more striking and is statistically significant in isolation. For job openings at IC5, no women received a higher level (although 6.5% of men did). With only 46 women hired into these jobs, the statistical test for difference lacks precision and is not statistically significant in isolation. Oracle hired over ninety percent of the women in individual contributor jobs, and about eighty percent of women in any job in Dr. Saad's hire dataset, into jobs advertised as IC3, IC4 or IC5. Women's disadvantage increases as the global career level of the advertised job increases. Higher global career level jobs pay more.

Chart R2 repeats the same analyses, comparing Asian and white hires. For job openings at IC3, Asian hires were more likely than white hires to receive a higher level than advertised, and less likely to receive a lower level, but the racial differences were not statistically significant. For job openings at IC4 and IC5, higher paying jobs, the racial pattern is reversed. Asians are less likely to get a higher level than the advertised job for which they applied. These racial disparities are statistically significant in isolation. Oracle hired over ninety percent of Asians in Dr. Saad's hire analysis data set into jobs advertised at IC3, IC4, or IC5. The racial disadvantage of Asian hires increases as the global career level of the advertised job increases. Higher global career level jobs pay more.

Finally, I use regression analysis to test for differences in initial assignments controlling for the "job applied for." I analyze the starting salary for the hired employees whom Dr. Saad matched to a requisition. I control for the exogenous characteristics of race or gender, age, education, and hire year, as well as the job descriptor. I also control for the global career level of the job applied for, as listed on the job requisition. The first column of Table R9 reports the gender disparity in starting pay for women relative to men with the same race, age, educational attainment, hire year, job descriptors, applying to job requisitions with the same global career level. Women average 3.8 percent less starting pay, a gender difference of 3.63 standard deviations. The second column performs the same analysis for Asian employees relative to white employees and finds Asian employees average three percent lower salaries, a racial difference of 2.52 standard deviations. The third column performs the analysis for African American employees. Because there are so few African American employees, the statistics are quite imprecise, but the average salary disparity is seven percent for African American employees of the same gender, age, educational attainment, hire year, job descriptors, applying to job requisitions with the same global career level, as white employees.

In summary, the statistical evidence on initial assignments shows disparities in the salary and the global career levels given to women, Asian, and African American hires. My July 19, 2019 report showed differences in starting salaries arising from differences in starting assignments of global career levels and from differences in starting salaries within the same job and global career level. Once I modify Dr. Saad's analyses of the small subset of hires with job requisition data available to include exogenous characteristics, such as education, and to control for the global career level of the job applied for, the evidence is consistent with gender and racial disparities in initial assignments.

**Promotions and Compensation Growth**

Dr. Saad discusses the OFCCP studies of growth in pay, which he relates to the SAC. I presented no direct study of pay growth in my July 19, 2019 report. Some of my studies in that report are relevant to pay growth, however. I found gender pay differentials of between 10 and 19 percent.[15] when I controlled for race, age, education, time at Oracle, current job descriptor (to indicate area of education and experience), and management. In addition, I found approximately equivalent gender differences in compensation when I use the job at hire (and its global career level) rather than those characteristics of the current job.[16] When I add current job data to the analysis including job at hire data, however, the measured gender disparity (the gender coefficient) is about half of the gender disparity when only the job at hire is included. This statistical result means that the gender disparities in current compensation decrease by more than half when controls for current job assignments are added to job assignments at hire. These changes in gender coefficients can occur only if compensation decisions subsequent to hire contribute to current compensation disparities. The gender coefficient logically can drop in the latter regression only if pay growth after hire is slower for women, in addition to the disadvantages at initial assignment.

My findings for gender disparities contrasted with my findings for the racial disparity in compensation of Asian employees. For Asian employees, I found that most of the current compensation differentials are due to the original job assignments. Once I have controlled for the job assignment at hire (including global career level), the racial

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15 See, for example, Table 1a, columns 6 and 7 from my July 19, 2019 report.

16 See, for example, Table 5a, column 1 from my July 19, 2019 report.

disparity does not change with the addition of controls for current job assignment. The current disparity in compensation for Asian employees must logically arise, then, from the disparities in jobs assigned at hire and to disparities in pay within the current job. Therefore, I found no evidence that there were differences in pay growth for Asian employees, given the initial job assignment.

My findings for racial disparities in the compensation for African Americans were more similar to those for gender than to those for Asian employees. The number of African American employees, however, make it impossible to analyze pay growth with the other controls, which Dr. Saad, or I, include.

Dr. Saad's direct measurement of pay growth, with the correct control variables included, shows *the same phenomena as my indirect approach*. When I revise Dr. Saad's direct measurement of base pay growth as presented in his report at pages 125-127 using the appropriate controls, the results are consistent with the conclusions from my prior analyses, as described above. Dr. Saad regressed the controls listed under each of his pay growth tables on compensation, to get the gender and race coefficients and standard deviations listed in the last two columns of those tables.

Some of the controls he includes undermine the ability of his analysis to measure gender and race effects. First, he effectively controls for the greatest sources of pay changes (which is a problem because that is what he is trying to measure in the first instance), when he adds controls for changes in global career level and job title during the year. Changes in global career level and job title are two of the most important ways for pay to grow. When he adds these controls, his analyses of pay growth no longer include the most important sources of pay growth. He is measuring only the expectedly lower pay growth for those who do not change global career levels or job titles. In technical terms, Dr. Saad placed the "dependent variable" of pay growth or change on both sides of the equation. The explanatory variables must be "independent variables," not measures of the very outcome (dependent variable) the analysis is explaining. Second, Dr. Saad fails to control for pay level at the start of the year. There is generally a statistical tendency for "regression to the mean" (meaning that pay grows the most for the lowest paid and the least for the highest paid). It is also the case that pay growth tends to be greatest for the most recently hired and youngest workers, who are also paid less. In the end, the proof is in the results when this control is included. Prior year pay level is one of the most statistically significant variables in the analysis. The standard deviations on the coefficient for the prior year's pay control range between 7 and 18, far more than for the other 500 controls that Dr. Saad includes in these analyses.

Table R10 shows the results of Dr. Saad's pay growth analyses when we include pay growth from job changes and control for starting pay. The columns follow those in his tables. The first panel compares men and women in Information Technology, Product Development, and Support job functions; the second panel compares Asian and white employees in the Product Development job function. Women of the same experience and education as men had significantly lower pay growth in each year from 2013 through 2016, when measured in isolation. They experienced less growth in 2017 and 2018, but the difference was not significant in isolation. Asian employees of the same experience and education as white employees experienced less pay growth, which is statistically insignificant in isolation, for 2013 through 2017 and equivalent pay growth in 2018.

## CONCLUSIONS

I have not changed the general conclusions reported in my July 19, 2019 report. The studies suggested by Dr. Saad, appropriately modified, strengthen those findings.

My statistical analyses are consistent with the existence of a pattern of gender and racially discriminatory compensation at Oracle. The compensation disadvantage of women is in the range of 10 to 15 percent between 2013 and 2018. These salary disparities, summarized in Table 1 of my July 19, 2019 report, are the results of gender disparities in promotions, in level of initial job assignments, and in compensation within current jobs. The compensation disadvantage of Asian employees is in the range of 10 to 18 percent between 2013 and 2018. These salary disparities, summarized in Table 2 of my July 19, 2019 report, are primarily the results of racial disparities in level of initial job assignments and in compensation within current jobs. The compensation disadvantage of African American employees is in the range of one to thirty percent between 2013 and 2018. These salary disparities, summarized in Table 3 of my July 19, 2019 report, are primarily the results of racial disparities in promotions, in level of initial job assignments, and in compensation within current jobs. The wider range of estimated disparities for African American employees is a statistical artifact of their low representation at Oracle, which decreases the precision of statistical analyses.

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**TABLES**

**Table R1**

**Education Estimates Used to Obtain the Gender and Racial Compensation Disparities for 2018 Reported in My July 19, 2019 Report, Tables 1b and 2b**

| Women-Men | | | Asian-White | | |
|---|---|---|---|---|---|
| **Degree** | **Estimate** | **Stan. Dev.** | **Degree** | **Estimate** | **Stan. Dev.** |
| Doctorate | 0.171 | 3.41 | Doctorate | 0.153 | 2.87 |
| Master | 0.077 | 3.44 | Master | 0.071 | 2.81 |
| No Bachelor | -0.238 | -2.49 | No Bachelor | -0.096 | -0.68 |

| Table R2 | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2013 through 2018 Gender Differences in Medicare Earnings at Oracle Headquarters by Year, with Various Characteristics Controlled** | | | | | | | | | | | | | |
| **Controls for ...** | | | | | | | | | | | | | |
| | | | **Race, Age, Education, Time at Oracle, Job Descriptors, Exempt, Management (1)** | | **Adds Whether Ever Had Patent Bonus (2)** | | **Adds Global Career Level (3)** | | **Adds Time in Current Job (4)** | | **Adds Organization (5)** | |
| **Year** | **Number of Workers** | **% Women** | **Gender Coefficient** | **Stan. Dev.** | **Gender Coefficient** | **Stan. Dev.** | **Gender Coefficient** | **Stan. Dev.** | **Gender Coefficient** | **Stan. Dev.** | **Gender Coefficient** | **Stan. Dev.** |
| 2013 | 4327 | 26.3% | -0.128 | -9.21 | -0.111 | -8.17 | -0.049 | -4.48 | -0.046 | -4.23 | -0.020 | -1.40 |
| 2014 | 4279 | 26.4% | -0.134 | -8.70 | -0.114 | -7.64 | -0.056 | -4.70 | -0.053 | -4.55 | -0.037 | -1.47 |
| 2015 | 4225 | 26.1% | -0.105 | -7.57 | -0.088 | -6.49 | -0.042 | -3.87 | -0.042 | -3.92 | -0.039 | -2.32 |
| 2016 | 4273 | 25.5% | -0.119 | -8.23 | -0.099 | -7.10 | -0.046 | -4.22 | -0.046 | -4.34 | -0.033 | -1.87 |
| 2017 | 4241 | 25.8% | -0.146 | -8.80 | -0.124 | -7.69 | -0.050 | -4.16 | -0.050 | -4.21 | -0.039 | -3.20 |
| 2018 | 4019 | 26.2% | -0.151 | -8.91 | -0.127 | -7.76 | -0.051 | -4.19 | -0.049 | -4.09 | -0.028 | -2.22 |

| Table R3 | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Asian Differences in Medicare Earnings at Oracle Headquarters by Year, with Various Characteristics Controlled | | | | | | | | | | | | |
| Controls for | | | | | | | | | | | | |
| | | | Gender, Age, Education, Time at Oracle, Job Descriptors, Exempt, Management (1) | | Adds Whether Ever Had Patent Bonus (2) | | Adds Global Career Level (3) | | Adds Time in Current Job (4) | | Adds Organization (5) | |
| Year | Number of Workers | % Asian | Race Coefficient | Stan. Dev. | Race Coefficient | Stan. Dev. | Race Coefficient | Stan. Dev. | Race Coefficient | Stan. Dev. | Race Coefficient | Stan. Dev. |
| 2013 | 3584 | 72.5% | -0.123 | -7.27 | -0.104 | -6.35 | -0.034 | -2.58 | -0.024 | -1.84 | -0.006 | -0.32 |
| 2014 | 3534 | 73.7% | -0.177 | -9.32 | -0.155 | -8.41 | -0.070 | -4.79 | -0.061 | -4.20 | -0.054 | -1.45 |
| 2015 | 3471 | 74.4% | -0.156 | -9.08 | -0.135 | -8.05 | -0.065 | -4.84 | -0.059 | -4.42 | -0.023 | -0.97 |
| 2016 | 3470 | 75.9% | -0.125 | -6.95 | -0.102 | -5.86 | -0.030 | -2.22 | -0.027 | -2.02 | 0.004 | 0.17 |
| 2017 | 3494 | 76.5% | -0.131 | -6.31 | -0.106 | -5.33 | -0.037 | -2.43 | -0.031 | -2.04 | -0.017 | -1.07 |
| 2018 | 3300 | 77.4% | -0.138 | -6.37 | -0.114 | -5.51 | -0.035 | -2.27 | -0.033 | -2.13 | -0.025 | -1.55 |

| Table R4<br>Dr. Saad's Compensation Effects of Gender, Motherhood (Years of Cumulative Leaves), and Tenure at Oracle | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Gender (1) | | Cumulative Leave in Years (2) | | Tenure at Oracle (3) | | Previous Experience (4) | | Total Oracle Years (5) | | # Control Variables | # Women |
| | Coef. | Stan. Dev. | Coef. | Stan. Dev. | Coef. | Stan. Dev. | Coef. | Stan. Dev. | Coef. | Stan. Dev. | | |
| Dr. Saad's Computer Backup for Graph for PRODDEV on p. 86 of his report | | | | | | | | | | | | |
| 2013 | -0.0177 | -2.12 | -0.0479 | -3.30 | -0.0096 | -5.70 | -0.0034 | -6.00 | 0.0003 | 0.18 | 551 | 1123 |
| 2014 | -0.0132 | -1.39 | -0.0602 | -3.84 | -0.0080 | -4.22 | -0.0053 | -8.20 | -0.0045 | -2.36 | 527 | 1110 |
| 2015 | -0.0142 | -1.43 | -0.0786 | -4.73 | -0.0087 | -4.68 | -0.0062 | -9.32 | -0.0059 | -3.16 | 487 | 1081 |
| 2016 | -0.0143 | -1.48 | -0.0916 | -5.84 | -0.0071 | -4.25 | -0.0063 | -9.70 | -0.0056 | -3.26 | 432 | 1055 |
| 2017 | -0.0097 | -0.93 | -0.1044 | -6.36 | -0.0080 | -4.78 | -0.0072 | -10.29 | -0.0080 | -4.78 | 414 | 1052 |
| 2018 | -0.0083 | -0.76 | -0.0910 | -5.39 | -0.0062 | -3.74 | -0.0074 | -10.07 | -0.0084 | -4.92 | 368 | 999 |
| Dr. Saad's PRODEV Estimation, removing Cumulative Leave in Years and Correcting Tenure at Oracle | | | | | | | | | | | | |
| 2013 | -0.0297 | -3.82 | | | -0.0093 | -5.53 | -0.0032 | -5.62 | -0.0002 | -0.12 | 550 | 1123 |
| 2014 | -0.0283 | -3.19 | | | -0.0076 | -4.04 | -0.0050 | -7.77 | -0.0050 | -2.67 | 526 | 1110 |
| 2015 | -0.0347 | -3.78 | | | -0.0083 | -4.48 | -0.0059 | -8.83 | -0.0067 | -3.56 | 486 | 1081 |
| 2016 | -0.0381 | -4.25 | | | -0.0068 | -4.08 | -0.0059 | -9.11 | -0.0064 | -3.67 | 431 | 1055 |
| 2017 | -0.0365 | -3.78 | | | -0.0079 | -4.69 | -0.0068 | -9.75 | -0.0063 | -3.63 | 413 | 1052 |
| 2018 | -0.0313 | -3.09 | | | -0.0061 | -3.65 | -0.0071 | -9.58 | -0.0089 | -5.19 | 367 | 999 |
| Dr. Saad's Computer Backup for Graph for INFTECH on p. 86 of his report | | | | | | | | | | | | |
| 2013 | -0.0340 | -1.75 | -0.0693 | -1.55 | -0.0065 | -2.01 | -0.0013 | -1.12 | 0.0011 | 0.36 | 107 | 124 |
| 2014 | -0.0348 | -1.49 | -0.0708 | -1.19 | -0.0090 | -2.34 | -0.0027 | -1.97 | 0.0008 | 0.20 | 102 | 124 |
| 2015 | -0.0367 | -1.67 | -0.1377 | -2.21 | -0.0064 | -1.88 | -0.0028 | -2.12 | -0.0031 | -0.92 | 119 | 136 |
| 2016 | -0.0086 | -0.41 | -0.1345 | -2.14 | -0.0030 | -2.42 | -0.2221 | -1.00 | -0.0021 | -0.71 | 122 | 143 |
| 2017 | -0.0313 | -1.33 | -0.1520 | -2.31 | -0.0051 | -1.55 | -0.0029 | -2.10 | -0.0030 | -0.91 | 116 | 132 |
| 2018 | -0.0589 | -2.37 | -0.0748 | -1.23 | -0.0032 | -0.95 | -0.0023 | -1.67 | -0.0063 | -1.88 | 125 | 127 |
| Dr. Saad's INFTECH Estimation, removing Cumulative Leave in Years and Correcting Time in Company | | | | | | | | | | | | |
| 2013 | -0.0457 | -2.50 | | | -0.0069 | -2.14 | -0.0011 | -0.96 | 0.0014 | 0.44 | 106 | 124 |
| 2014 | -0.0492 | -2.36 | | | -0.0098 | -2.54 | -0.0023 | -1.73 | 0.0014 | 0.38 | 101 | 124 |
| 2015 | -0.0568 | -2.81 | | | -0.0076 | -2.23 | -0.0022 | -1.71 | -0.0022 | -0.67 | 118 | 136 |
| 2016 | -0.0267 | -1.37 | | | -0.0070 | -2.25 | -0.0025 | -2.07 | -0.0018 | -0.61 | 121 | 143 |
| 2017 | -0.0509 | -2.30 | | | -0.0060 | -1.80 | -0.0023 | -1.71 | -0.0026 | -0.78 | 115 | 132 |
| 2018 | -0.0722 | -3.20 | | | -0.0033 | -1.00 | -0.0022 | -1.58 | -0.0063 | -1.88 | 124 | 127 |

**Table R5**

**Counts of Oracle Employees by Number of Organizational Names of Employment between 2013 and 2018**

| Number of Organizational Names | Number of Employees |
|---|---|
| 1 | 31 |
| 2 | 4242 |
| 3 | 2056 |
| 4 | 1254 |
| 5 | 612 |
| 6 | 297 |
| 7 | 105 |
| 8 | 37 |
| 9 | 17 |
| 10 | 5 |
| 11 | 1 |
| 12 | 1 |

| Table R6<br>Counts of Employees and Control Variables in Dr. Saad's Compensation Regressions | | | | | |
|---|---|---|---|---|---|
| Year | Job Functions | Groups Compared | Number of Men/White Employees | Number of Women/Asian/ African American Employees | Number of Control Variables |
| 2013 | INFOTECH | Men/Women | 316 | 124 | 107 |
| 2014 | INFOTECH | Men/Women | 323 | 124 | 102 |
| 2015 | INFOTECH | Men/Women | 420 | 136 | 119 |
| 2016 | INFOTECH | Men/Women | 461 | 143 | 122 |
| 2017 | INFOTECH | Men/Women | 412 | 132 | 116 |
| 2018 | INFOTECH | Men/Women | 394 | 127 | 125 |
| 2013 | PRODEV | Men/Women | 2778 | 1123 | 551 |
| 2014 | PRODEV | Men/Women | 2762 | 1110 | 527 |
| 2015 | PRODEV | Men/Women | 2733 | 1081 | 487 |
| 2016 | PRODEV | Men/Women | 2754 | 1055 | 432 |
| 2017 | PRODEV | Men/Women | 2764 | 1052 | 414 |
| 2018 | PRODEV | Men/Women | 2586 | 999 | 368 |
| 2013 | SUPP | Men/Women | 191 | 42 | 91 |
| 2014 | SUPP | Men/Women | 178 | 42 | 89 |
| 2015 | SUPP | Men/Women | 72 | 31 | 63 |
| 2016 | SUPP | Men/Women | 72 | 23 | 58 |
| 2017 | SUPP | Men/Women | 65 | 20 | 59 |
| 2018 | SUPP | Men/Women | 62 | 21 | 57 |
| 2013 | PRODEV | Asian/White | 1037 | 2746 | 547 |
| 2014 | PRODEV | Asian/White | 992 | 2764 | 524 |
| 2015 | PRODEV | Asian/White | 937 | 2750 | 484 |
| 2016 | PRODEV | Asian/White | 881 | 2778 | 427 |
| 2017 | PRODEV | Asian/White | 849 | 2820 | 412 |
| 2018 | PRODEV | Asian/White | 773 | 2662 | 364 |
| 2013 | PRODEV | African American/White | 1037 | 25 | 375 |
| 2014 | PRODEV | African American/White | 992 | 26 | 359 |
| 2015 | PRODEV | African American/White | 937 | 25 | 329 |
| 2016 | PRODEV | African American/White | 881 | 29 | 298 |
| 2017 | PRODEV | African American/White | 849 | 27 | 289 |
| 2018 | PRODEV | African American/White | 773 | 27 | 251 |

| Table R7<br>Compensation by Race, Gender, and Education<br>of Dr. Saad's 24 Clusters<br>of 521 Software Designer 4 Employees | | | |
|---|---|---|---|
| Control Variables | Race Coefficient | Standard Deviation | Adjusted $R^2$ |
| Asian only | -0.033 | -1.85 | 0.01 |
| plus education | -0.038 | -2.25 | 0.13 |
| plus cluster | -0.036 | -2.07 | 0.09 |
| plus cluster and education | -0.037 | -2.19 | 0.19 |
| Control Variables | Gender Coefficient | Standard Deviation | Adjusted $R^2$ |
| Women only | -0.035 | -1.76 | 0.00 |
| plus education | -0.033 | -1.73 | 0.10 |
| plus cluster | -0.024 | -1.23 | 0.08 |
| plus cluster and education | -0.021 | -1.08 | 0.15 |

Table R8

Dr. Saad's Study of Initial Assignment Differences, by Gender and Race, Omit Most Employees

| | Number of Records Included in Analysis | | |
|---|---|---|---|
| | Men/Women | Asian/White | African American/White |
| Dr. Saad's Initial Assignment Study | 1659 | 1517 | 338 |
| All Employees Hired between 2013 and 2018 | 2819 | 2581 | 504 |
| % included in Dr. Saad's Study | 58.9% | 58.8% | 67.1% |
| Unique Employees included in Medicare Compensation Disparity Analyses | 6758 | 5598 | 1381 |
| % included in Dr. Saad's Study | 24.5% | 27.1% | 24.5% |
| Unique Employees included in Base Pay Disparity Analyses | 7849 | 6480 | 1620 |
| % included in Dr. Saad's Study | 21.1% | 23.4% | 20.9% |

| Table R9<br><br>2013 through 2018 Gender and Racial Differences in Starting Pay at Oracle,<br>Employees Matched to Job Requisitions, Controlling for<br>Race (Gender), Age, Education, Hire Year, Job Descriptor<br>and Global Career Level of Job Requisiiton | | | | | |
|---|---|---|---|---|---|
| | Women Employees | | Asian Employees | | African American Employees |
| Coefficient | -0.038 | | -0.030 | | -0.070 |
| Stan. Dev. | -3.63 | | -2.52 | | -1.06 |
| Number | 841 | | 766 | | 185 |

| Table R10 | | | | | |
|---|---|---|---|---|---|
| Dr. Saad's Pay Growth Analysis, Including Job Changes and Controlling for Starting Pay | | | | | |
| Year | # Obs Used | # Protected Group | Average Pay Growth | Gender or Race Coefficient | Standard Deviation |
| Women Employees | | | | | |
| 2013 | 4565 | 6578 | [redacted] | -0.0039 | -2.07 |
| 2014 | 4528 | 6542 | | -0.0039 | -2.33 |
| 2015 | 4463 | 6478 | | -0.0038 | -2.29 |
| 2016 | 4502 | 6518 | | -0.0030 | -2.20 |
| 2017 | 4441 | 6458 | | -0.0019 | -1.62 |
| 2018 | 4175 | 6193 | | -0.0002 | 0.11 |
| | | | | | |
| Asian Employees | | | | | |
| 2013 | 3774 | 2743 | [redacted] | -0.0016 | -0.74 |
| 2014 | 2745 | 2761 | | -0.0017 | -0.90 |
| 2015 | 3677 | 2743 | | -0.0013 | -0.63 |
| 2016 | 3653 | 2777 | | -0.0025 | -1.58 |
| 2017 | 3666 | 2817 | | -0.0011 | -0.80 |
| 2018 | 3421 | 2652 | | 0.0002 | 0.09 |

## CHARTS

Chart R1
Comparison of Actual vs. Applied-For Global Career Level for Men vs. Women Hires

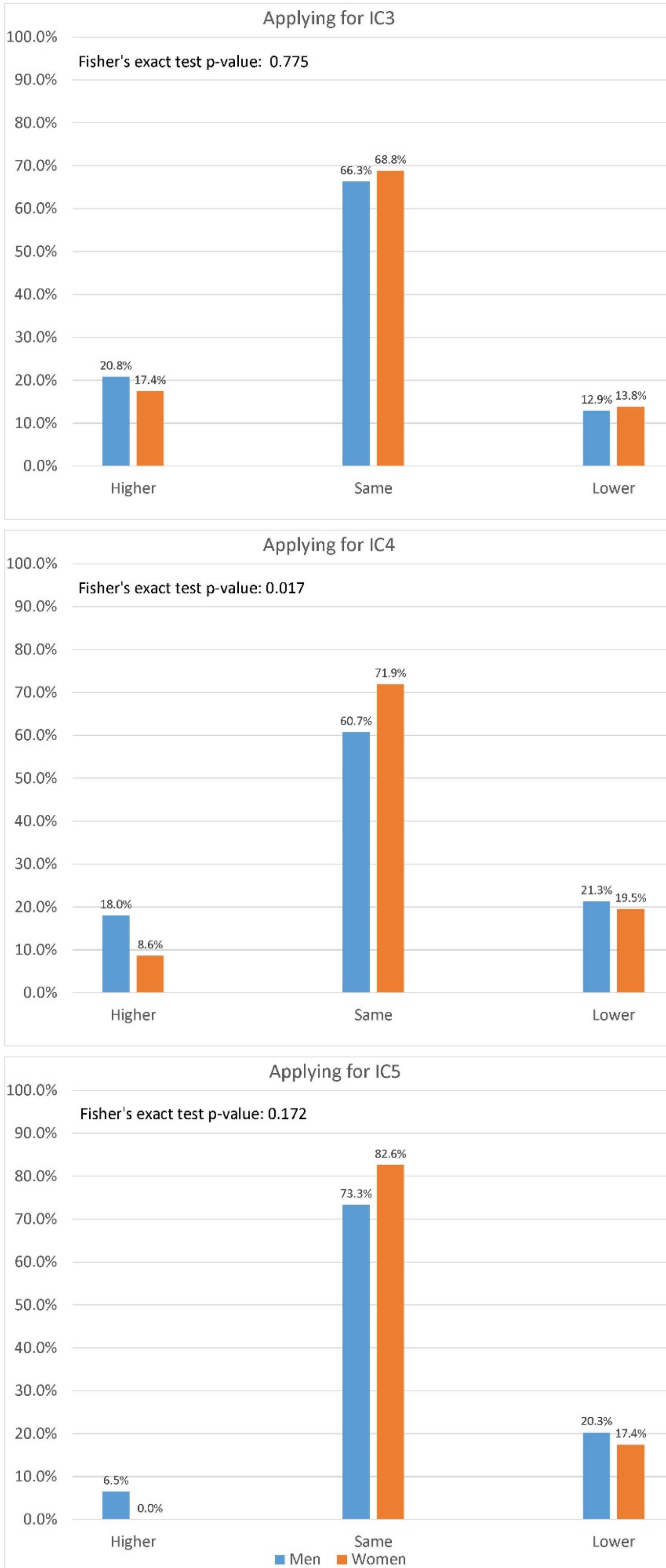
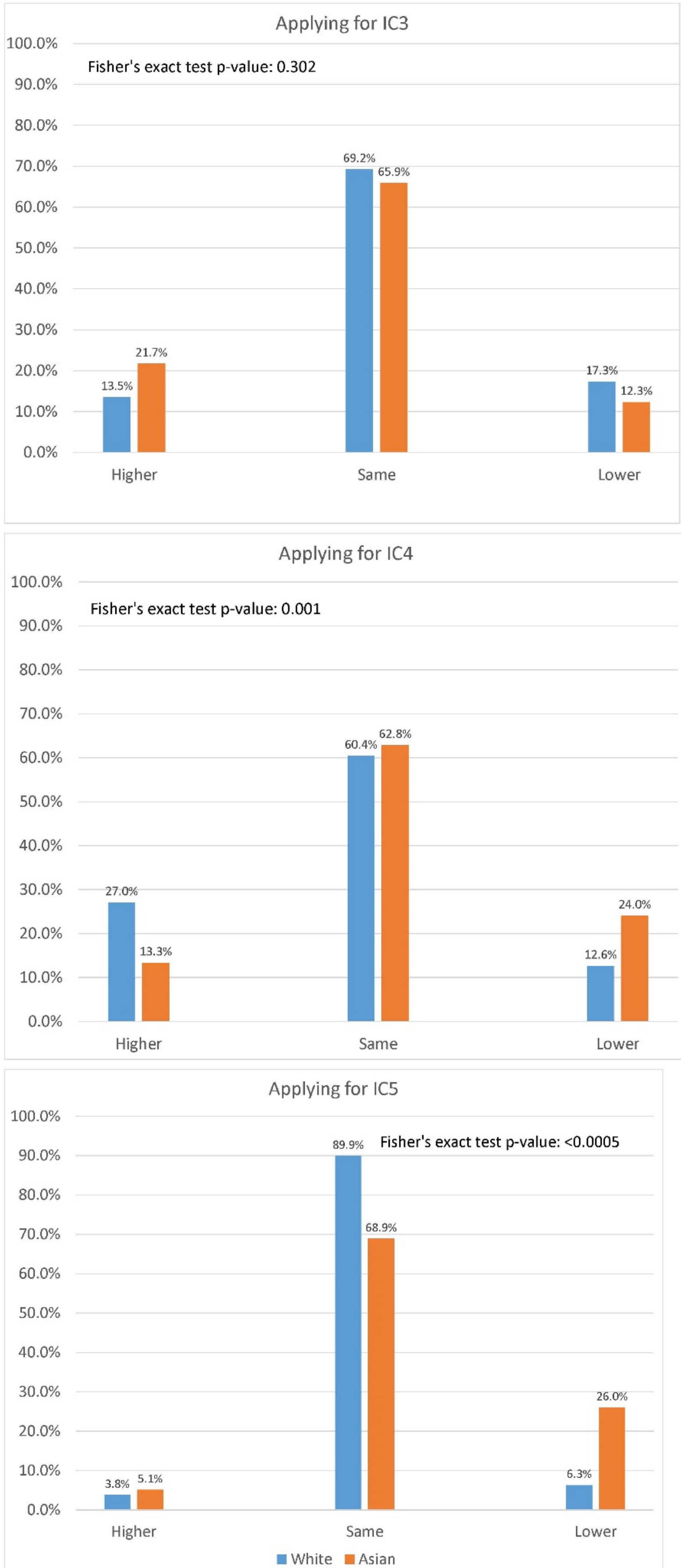


Chart R2

Comparison of Actual vs. Applied-For Global Career Level for White vs. Asian Hires



# DECLARATION OF RIDDELL ISO MOTION TO SEAL

# EXHIBIT C

# EXHIBIT E

EXHIBIT E

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**UNITED STATES DEPARTMENT OF LABOR**
**OFFICE OF ADMINISTRATIVE LAW JUDGES**

**OFFICE OF FEDERAL CONTRACT COMPLIANCE PROGRAMS, UNITED STATES DEPARTMENT OF LABOR,**

Plaintiff,

v.

**ORACLE AMERICA, INC.**

Defendant.

Case No. 2017-OFC-00006

## DECLARATION OF JANICE F. MADDEN

I, Janice F. Madden, state and declare as follows.

1. The Office of Federal Contract Compliance Programs, U.S. Department of Labor has retained me as an expert labor economist and statistician in OFCCP v. Oracle America, Inc. After I submitted my rebuttal expert report, I received Dr. Saad's rebuttal expert report.



EXHIBIT
PENGAD 800-631-6989
9
Saad

2. I have personal knowledge of the matters set forth in this declaration, and I could and would competently testify thereto if called upon to do so.

3. In paragraph 49 of Dr. Saad's rebuttal report, he states "[c]ollege major and field of study are unquestionably omitted variables relevant to Dr. Madden's analysis, and there is no reason to simply assume that they are distributed identically across the demographic groups. There is no evidence that everything left out of Dr. Madden's model is demographically neutral and can be safely ignored."

4. In response to Dr. Saad's claim, I analyze how the addition of college major and field of study affect the race and gender differentials in compensation (that is, the coefficients on race and gender) as originally reported in Tables 1a, 1b, 2a, 2b and 3a of my July 19, 2019 report. I have prepared tables showing the results with the addition of college major and field of study, using the classification of majors designed by Dr. Saad as listed in his rebuttal report.

a. Tables A-1 through A-5 are attached to this declaration as Exhibits A-1, A-2, A-3, A-4, and A-5.
b. Exhibit A-1 is titled "Madden Table 1(a) _ Revised adding Saad's Coded Majors at col5."
c. Exhibit A-2 is titled "Madden Table 1(b) _ Revised adding Saad's Coded Majors at col5."
d. Exhibit A-3 is titled "Madden Table 2(a) _ Revised adding Saad's Coded Majors at col5."
e. Exhibit A-4 is titled " Madden Table 2(b) _ Revised adding Saad's Coded Majors at col5."
f. Exhibit A-5 is titled "Madden Table 3(a) _ Revised adding Saad's Coded Majors at col5."

5. Columns 5 through 8 of Tables A-1 through A-5 report the effects of adding Dr. Saad's college major variable to the original analyses reported in columns 5 through 8 of Tables 1a, 1b, 2a, 2b and 3a of my July 19, 2019 report. Comparisons of the reported coefficients and standard deviations in the two sets of tables (1a, 1b, 2a, 2b, 3a from the original report and Tables A-1 though A-5) show that adding college major has no substantial effect on the size or significance of the race and gender differences in compensation.

6. At pages 54 through 55 of his Rebuttal Report, Dr. Saad discusses the job assignments of hires who were directed to requisition notices posted by Oracle. He analyzes those requisition placements separately by Global Career Level or with no controls for the Global Career Level and then claims that Oracle assigns the hires "irrespective of race or gender" in his rebuttal report. I have analyzed his data on these requisitions to test for the overall race and gender differentials in the global career initial assignments of these requisition-based hires that he claims are gender and race neutral. I attach a summary of this analysis as Exhibit B.

a. Exhibit B is titled "Table Differences in Global Career Level Assignments for Experienced Hires Relative to Requisition Specified Global Career Level, Controlling for Global Career Level in Requisition and Year By Gender and Race in Dr. Saad's Data, 2013-2018"

b. The Exhibit B Table shows statistically significant, or systematic, lower Global Career Level assignments by race (for Asians) and by gender in Global Career Level jobs, after the Global Career Level of the requisition is controlled.

7. Dr. Saad reports the salary ranges in the job functions analyzed in this case. In response, I have prepared a table illustrating the gender and racial disparities within those salary ranges he identifies. Attached as Exhibit C is the chart I created to illustrate the differences in pay for Oracle women, Asian, and black employees compared to whites or male employees in

each pay category. Exhibit C is titled "The Distribution of Dr. Saad's Total Compensation in 2014 by Job Function, Gender, and Race (Higher Compensation Group Noted by Underline and Embolding.)"

8. I re-analyze Dr. Saad's Tables 1-5 from his July 19, 2019 report making two changes. First, I use base pay rather than total compensation and I also add an analysis that removes "organization" from his work-related variables reported in the last column of his tables. These examples are attached as Exhibits D-1 through D-5.

a. Exhibit D-1 is titled "Redo of Saad's Table 1 Using Basepay instead of Total Compensation."

b. Exhibit D-2 is titled "Redo of Saad's Table 2 Using Basepay instead of Total Compensation."

c. Exhibit D-3 is titled "Redo of Saad's Table 3 Using Basepay instead of Total Compensation."

d. Exhibit D-4 is titled "Redo of Saad's Table 4 Using Basepay instead of Total Compensation."

e. Exhibit D-5, titled "Redo of Saad's Table 5 Using Basepay instead of Total Compensation."

9. These tables show statistically significant base pay differences by race and gender using his model (but for base pay rather than total compensation) and also show that when organization name is removed from his model most of the disparities increase and show a greater level of statistical significance.

I declare under penalty of perjury under the laws of the United States of America that the foregoing is true and correct.

Executed on October 11, 2019 in Philadelphia, Pennsylvania.

Janice F. Madden

JANICE F. MADDEN

| Madden Table 1(a) _ Revised adding Saad's Coded Majors at col5 | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Gender Differences in Medicare Earnings at Oracle Headquarters by Year, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | Gender Only (1) | | Adds Race/Ethnicity (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle and Coded Majors (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Women | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score |
| 2013 | 4327 | 26.3% | -0 213 | -11.96 | -0.199 | -11.33 | -0.200 | -12.07 | -0.198 | -11.97 | -0.197 | -12.21 | -0.157 | -10.46 | -0.128 | -9.14 | -0.056 | -5.00 |
| 2014 | 4279 | 26.4% | -0 232 | -11.69 | -0.217 | -11.09 | -0.221 | -11.85 | -0.221 | -11.91 | -0.219 | -12.16 | -0.167 | -10.07 | -0.134 | -8.68 | -0.063 | -5.23 |
| 2015 | 4225 | 26.1% | -0.188 | -10.60 | -0.173 | -9.94 | -0.174 | -10.61 | -0.174 | -10.62 | -0.174 | -10.90 | -0.132 | -8 92 | -0.104 | -7.53 | -0.046 | -4.25 |
| 2016 | 4273 | 25.5% | -0.199 | -10.63 | -0.189 | -10.23 | -0.198 | -11.35 | -0.200 | -11.53 | -0.197 | -11.58 | -0.149 | -9 66 | -0.118 | -8.21 | -0.052 | -4.74 |
| 2017 | 4241 | 25.8% | -0 237 | -11.05 | -0.228 | -10.72 | -0.231 | -11.46 | -0.234 | -11.72 | -0.236 | -11.97 | -0.177 | -9 88 | -0.145 | -8.75 | -0.058 | -4.71 |
| 2018 | 4019 | 26.2% | -0 242 | -11.23 | -0.235 | -11.02 | -0.231 | -11.38 | -0.234 | -11.53 | -0.235 | -11.80 | -0.185 | -10.10 | -0.150 | -8.83 | -0.058 | -4.69 |

**Ex. A-1**

| Madden Table 1(b) _ Revised adding Saad's Coded Majors at col5 | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Gender Differences in Medicare Earnings at Oracle Headquarters by Year, Employees with Recorded Education Characteristics, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | Gender Only (1) | | Adds Race/Ethnicity (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle and Coded Majors (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Women | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score | Gender Coefficient | t score |
| 2013 | 1448 | 25.8% | -0.146 | -5 93 | -0.138 | -5.73 | -0.143 | -6 38 | -0.134 | -5.99 | -0.138 | -6 23 | -0.127 | -5.73 | -0.102 | -4 97 | -0 040 | -2.30 |
| 2014 | 1530 | 24.8% | -0.166 | -6.77 | -0.163 | -6.82 | -0.167 | -7.41 | -0.161 | -7.17 | -0.166 | -7.41 | -0.145 | -6.59 | -0.113 | -5.61 | -0 052 | -3.20 |
| 2015 | 1625 | 24.2% | -0.141 | -6 50 | -0.137 | -6.46 | -0.145 | -7 23 | -0.139 | -6.99 | -0.139 | -7 03 | -0.114 | -5.86 | -0.084 | -4.70 | -0 036 | -2.56 |
| 2016 | 1814 | 22.9% | -0.159 | -7.11 | -0.161 | -7.31 | -0.180 | -8 85 | -0.177 | -8.75 | -0.177 | -8.75 | -0.151 | -7.64 | -0.116 | -6 31 | -0 051 | -3.69 |
| 2017 | 1974 | 23.8% | -0.194 | -7 56 | -0.195 | -7.73 | -0.200 | -8.72 | -0.192 | -8.44 | -0.198 | -8.67 | -0.169 | -7.50 | -0.132 | -6 34 | -0 050 | -2.99 |
| 2018 | 1737 | 24.5% | -0.207 | -7 89 | -0.211 | -8.14 | -0.215 | -8 80 | -0 210 | -8.62 | -0.216 | -8 90 | -0.190 | -7.93 | -0.160 | -7.19 | -0 063 | -3.72 |

**Ex. A-2**

| Madden Table 2(a) _ Revised adding Saad's Coded Majors at col5<br>2013 through 2018 Asian Differences in Medicare Earnings at Oracle Headquarters by Year,<br>with Various Characteristics Controlled<br>Controls for ... | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Asian Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle and Coded Majors (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Asian | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score |
| 2013 | 3584 | 72.5% | -0.237 | -12.14 | -0.220 | -11.40 | -0.125 | -6.39 | -0.128 | -6.50 | -0.121 | -6.27 | -0.111 | -6.07 | -0.122 | -7.21 | -0.040 | -2.94 |
| 2014 | 3534 | 73.7% | -0.295 | -13.38 | -0.278 | -12.76 | -0.184 | -8.27 | -0.191 | -8.49 | -0.180 | -8.26 | -0.175 | -8.54 | -0.176 | -9.23 | -0.078 | -5.19 |
| 2015 | 3470 | 74.4% | -0.269 | -13.55 | -0.255 | -12.98 | -0.158 | -8.00 | -0.167 | -8.41 | -0.161 | -8.26 | -0.154 | -8.34 | -0.157 | -9.11 | -0.072 | -5.33 |
| 2016 | 3470 | 75.9% | -0.230 | -10.76 | -0.216 | -10.23 | -0.123 | -5.80 | -0.129 | -6.03 | -0.119 | -5.67 | -0.113 | -5.76 | -0.125 | -6.88 | -0.037 | -2.67 |
| 2017 | 3494 | 76.5% | -0.235 | -9.51 | -0.220 | -9.02 | -0.126 | -5.14 | -0.132 | -5.33 | -0.121 | -4.98 | -0.104 | -4.62 | -0.133 | -6.39 | -0.046 | -2.94 |
| 2018 | 3300 | 77.4% | -0.223 | -8.74 | -0.208 | -8.28 | -0.121 | -4.74 | -0.130 | -5.04 | -0.127 | -5.02 | -0.105 | -4.45 | -0.141 | -6.50 | -0.042 | -2.65 |

**Ex. A-3**

| Madden Table 2(b) _ Revised adding Saad's Coded Majors at col5 | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 thorugh 2018 Asian Differences in Medicare Earnings at Oracle Headquarters by Year, Employees with Recorded Educational Characteristics, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | Asian Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle and Coded Majors (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % Asian | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score |
| 2013 | 1173 | 76.1% | -0.220 | -7.72 | -0.209 | -7.40 | -0.123 | -4.41 | -0.128 | -4.40 | -0.125 | -4.36 | -0.118 | -4.16 | -0.124 | -4.78 | -0 034 | -1.55 |
| 2014 | 1222 | 77.2% | -0.253 | -8 84 | -0.247 | -8.75 | -0.168 | -5 96 | -0.184 | -6.27 | -0.181 | -6.22 | -0.175 | -6.12 | -0.166 | -6.36 | -0 061 | -2.90 |
| 2015 | 1299 | 77.0% | -0.219 | -8 89 | -0.214 | -8.78 | -0.149 | -6.11 | -0.166 | -6.54 | -0.161 | -6.39 | -0.161 | -6 55 | -0.154 | -6.83 | -0 064 | -3.62 |
| 2016 | 1417 | 80.2% | -0.208 | -7.70 | -0.205 | -7.71 | -0.133 | -5.12 | -0.150 | -5.57 | -0.146 | -5.46 | -0.133 | -5 09 | -0.137 | -5.68 | -0 054 | -3.00 |
| 2017 | 1587 | 81.0% | -0.229 | -7.17 | -0.228 | -7.27 | -0.129 | -4 34 | -0.148 | -4.79 | -0.147 | -4.76 | -0.131 | -4 27 | -0.165 | -5.83 | -0 080 | -3.53 |
| 2018 | 1396 | 82.3% | -0.175 | -5.17 | -0.178 | -5.35 | -0.100 | -3 04 | -0.134 | -3.89 | -0.137 | -3.99 | -0.109 | -3 22 | -0.148 | -4.73 | -0 069 | -2.92 |

**Ex. A-4**

| Madden Table 3(a) _ Revised adding Saad's Coded Majors at col5 | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 African American Differences in Medicare Earnings at Oracle Headquarters by Year, with Various Characteristics Considered | | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | | |
| | | | African American Only (1) | | Adds Gender (2) | | Adds Age (3) | | Adds Education (4) | | Adds Time at Oracle and Coded Majors (5) | | Adds Exempt/Non Exempt and Job Descriptor (6) | | Adds Management Control (7) | | Adds Global Career Level (8) | |
| Year | Number of Workers | % African American | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score | Race Coefficient | t score |
| 2013 | 1008 | 2.3% | -0.229 | -1 84 | -0.219 | -1.78 | -0.148 | -1.25 | -0.152 | -1.28 | -0.133 | -1.16 | -0.090 | -0.90 | -0.002 | -0.03 | 0.028 | 0.38 |
| 2014 | 954 | 2.4% | -0.490 | -3.43 | -0.459 | -3.24 | -0.391 | -2.83 | -0.406 | -2.94 | -0.372 | -2.83 | -0.307 | -2.70 | -0.193 | -1.84 | -0.089 | -1.13 |
| 2015 | 916 | 2.8% | -0.431 | -3.73 | -0.412 | -3.58 | -0.335 | -2.99 | -0.356 | -3.18 | -0.330 | -3.03 | -0.295 | -3.05 | -0.221 | -2.48 | -0.082 | -1.19 |
| 2016 | 867 | 3.5% | -0.501 | -4.46 | -0.479 | -4.27 | -0.343 | -3.15 | -0.345 | -3.17 | -0.329 | -3.09 | -0.267 | -2.93 | -0.199 | -2.37 | -0.072 | -1.15 |
| 2017 | 848 | 3.3% | -0.538 | -4.19 | -0.508 | -3.97 | -0.446 | -3.53 | -0.426 | -3.38 | -0.397 | -3.23 | -0.311 | -2.88 | -0.250 | -2.52 | -0.121 | -1.71 |
| 2018 | 772 | 3.5% | -0.514 | -3 88 | -0.495 | -3.75 | -0.410 | -3.15 | -0.384 | -2.98 | -0.355 | -2.83 | -0.217 | -1.98 | -0.199 | -1.98 | -0.072 | -1.04 |

**Ex. A-5**

| Table<br>Differences in Global Career Level Asssignments for Experienced Hires<br>Relative to Requisition Specified Global Career Level<br>Controlling for Global Career Level in Requisition and Year<br>By Gender and Race in Dr. Saad's Data, 2013-2018 | | | | |
|---|---|---|---|---|
| | Global Career Level Assignment Differences | | | |
| | Lower | Probability Difference Is Due to Chance | Higher | Probability Difference Is Due to Chance |
| Women relative to men | 0 | na | -12.2 | 0.042 |
| Asian relative to white hires | 17.4 | 0.003 | -5.7 | 0.316 |

**Ex. B**

| The Distribution of Dr. Saad's Total Compensation in 2014 by Job Function, Gender, and Race (Higher Compensation Group Noted by Underline and Embolding) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Job Function/Gender/Race | N | Mean | Minimum | 10th Percentile | 50th Percentile | 90th Percentile | Maximum |
| PRODEV | | | | | | | |
| Men | 2742 | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] |
| Women | 1089 | $ | $ | $ | $ | $ | $ |
| Women's Compensation as % of Men's to Men | | 69.5% | 69.8% | 88.5% | 80.4% | 64.6% | 19.6% |
| Whites | 968 | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] |
| Asians | 2747 | $ | $ | $ | $ | $ | $ |
| Asian Employee Compensation as % of White Employee Compensation | | 74.6% | 102.8% | 97.1% | 81.8% | 67.0% | 71.0% |
| African Americans | 26 | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] |
| African American Employee Compensation as % of White Employee Compensation | | 53.2% | 181.8% | 90.3% | 70.5% | 50.2% | 3.0% |
| SUPP | | | | | | | |
| Men | 177 | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] |
| Women | 42 | $ | $ | $ | $ | $ | $ |
| Women's Compensation as % of Men's to Men | | 71.6% | 71.6% | 87.5% | 87.1% | 73.9% | 21.5% |
| INFTECH | | | | | | | |
| Men | 323 | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] | $ [redacted] |
| Women | 122 | $ | $ | $ | $ | $ | $ |
| Women's Compensation as % of Men's to Men | | 86.1% | 112.3% | 109.2% | 93.7% | 79.3% | 29.4% |

**Ex. C**

**Redo of Saad's Table 1 Using Basepay instead of Total Compensation**

**2013 through 2018 Gender Differences in Base Pay at Oracle Headquarters by Year, with Various Characteristics Controlled**

**- Full-Year Incumbents in the INFTECH Job Function -**

| | | | Controls for ... | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Gender Only (1) | | Adds Race/Ethnicity (2) | | Adds Refined Age Variable (3) | | Adds Education (4) | | Adds Refined Tenure Variables (5) | | Adds Work-Related Variables (6) | | Removes Organization Name (7) | |
| Year | Number of Workers | % Women | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV |
| 2013 | 440 | 28.2% | -0.037 | -1.18 | -0.045 | -1.45 | -0.046 | -1.47 | -0.047 | -1.48 | -0.016 | -0.49 | -0.026 | -1.79 | -0.028 | -1.93 |
| 2014 | 447 | 27.7% | -0.051 | -1.50 | -0.056 | -1.68 | -0.056 | -1.69 | -0.050 | -1.49 | -0.009 | -0.25 | -0.037 | -2.40 | -0.038 | -2.55 |
| 2015 | 556 | 24.5% | -0.077 | -2.50 | -0.077 | -2.56 | -0.078 | -2.59 | -0.076 | -2.53 | -0.028 | -0.85 | -0.026 | -1.88 | -0.037 | -2.59 |
| 2016 | 604 | 23.7% | -0.097 | -3.23 | -0.097 | -3.31 | -0.098 | -3.35 | -0.098 | -3.37 | -0.056 | -1.79 | -0.024 | -1.71 | -0.034 | -2.37 |
| 2017 | 544 | 24.3% | -0.093 | -2.94 | -0.095 | -3.04 | -0.095 | -3.06 | -0.096 | -3.08 | -0.045 | -1.38 | -0.036 | -2.37 | -0.040 | -2.69 |
| 2018 | 521 | 24.4% | -0.085 | -2.68 | -0.087 | -2.79 | -0.087 | -2.81 | -0.087 | -2.81 | -0.038 | -1.15 | -0.043 | -2.66 | -0.037 | -2.36 |

**Ex. D-1**

| Redo of Saad's Table 2 Using Basepay instead of Total Compensation | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Gender Differences in Base Pay at Oracle Headquarters by Year, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | |
| - Full-Year Incumbents in the PRODEV Job Function - | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | |
| | | | Gender Only (1) | | Adds Race/Ethnicity (2) | | Adds Refined Age Variable (3) | | Adds Education (4) | | Adds Refined Tenure Variables (5) | | Adds Work-Related Variables (6) | | Removes Organization Name (7) | |
| Year | Number of Workers | % Women | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV |
| 2013 | 3901 | 28.8% | -0.171 | -17.45 | -0.160 | -16.65 | -0.159 | -16.60 | -0.159 | -16.69 | -0.130 | -14.07 | -0.010 | -2.10 | -0.022 | -4.21 |
| 2014 | 3872 | 28.7% | -0.165 | -16.39 | -0.155 | -15.65 | -0.154 | -15.54 | -0.155 | -15.63 | -0.130 | -13.91 | -0.010 | -1.89 | -0.022 | -4.04 |
| 2015 | 3814 | 28.3% | -0.163 | -16.21 | -0.152 | -15.42 | -0.157 | -15.26 | -0.152 | -15.44 | -0.126 | -13.22 | -0.013 | -2.64 | -0.024 | -4.53 |
| 2016 | 3809 | 27.7% | -0.157 | -15.26 | -0.148 | -14.62 | -0.147 | -14.50 | -0.149 | -14.73 | -0.129 | -13.30 | -0.012 | -2.38 | -0.022 | -4.12 |
| 2017 | 3816 | 27.6% | -0.155 | -15.58 | -0.149 | -15.08 | -0.146 | -14.89 | -0.149 | -15.24 | -0.130 | -13.83 | -0.013 | -2.54 | -0.023 | -4.42 |
| 2018 | 3585 | 27.9% | -0.160 | -14.86 | -0.155 | -14.59 | -0.153 | -14.46 | -0.155 | -14.72 | -0.135 | -13.32 | -0.015 | -2.73 | -0.023 | -4.14 |

**Ex. D-2**

Redo of Saad's Table 3 Using Basepay instead of Total Compensation

2013 through 2018 Gender Differences in Base Pay at Oracle Headquarters by Year, with Various Characteristics Controlled

- Full-Year Incumbents in the SUPP Job Function -

Controls for ...

| | | | Gender Only (1) | | Adds Race/Ethnicity (2) | | Adds Refined Age Variable (3) | | Adds Education (4) | | Adds Refined Tenure Variables (5) | | Adds Work-Related Variables (6) | | Removes Organization Name (7) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | Number of Workers | % Women | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV | Gender Coefficient | ST DEV |
| 2013 | 233 | 18.0% | -0.179 | -3.85 | -0.185 | -3.98 | -0.191 | -4.05 | -0.198 | -4.22 | -0.169 | -3.51 | -0.050 | -2.06 | -0.061 | -2.69 |
| 2014 | 220 | 19.1% | -0.152 | -3.24 | -0.159 | -3.34 | -0.169 | -3.54 | -0.172 | -3.62 | -0.122 | -2.52 | -0.044 | -2.16 | -0.052 | -2.47 |
| 2015 | 103 | 30.1% | -0.136 | -1.84 | -0.126 | -1.65 | -0.144 | -1.88 | -0.146 | -1.84 | -0.084 | -0.96 | 0.016 | 0.32 | -0.029 | -0.76 |
| 2016 | 95 | 24.2% | -0.123 | -1.43 | -0.127 | -1.45 | -0.150 | -1.65 | -0.144 | -1.57 | -0.110 | -0.97 | 0.011 | 0.14 | -0.065 | -1.51 |
| 2017 | 85 | 23.5% | -0.090 | -0.09 | -0.091 | -0.91 | -0.110 | -1.04 | -0.097 | -0.90 | -0.049 | -0.41 | -0.161 | -3.19 | -0.073 | -1.70 |
| 2018 | 83 | 25.3% | -0.103 | -1.07 | -0.106 | -1.07 | -0.146 | -1.41 | -0.133 | -1.26 | -0.032 | -0.27 | 0.018 | 0.24 | -0.044 | -0.89 |

**Ex. D-3**

| Redo of Saad's Table 4 Using Basepay instead of Total Compensation | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 through 2018 Asian Differences in Base Pay at Oracle Headquarters by Year, with Various Characteristics Controlled | | | | | | | | | | | | | | | | | |
| - Full-Year Incumbents in the PRODEV Job Function - | | | | | | | | | | | | | | | | | |
| Controls for ... | | | | | | | | | | | | | | | | | |
| | | | Asian Only (1) | | Adds Gender (2) | | Adds Refined Age Variable (3) | | Adds Education (4) | | Adds Refined Tenure Variables (5) | | Adds Work-Related Variables (6) | | Removes Organization Name (7) | |
| Year | Number of Workers | % Women | Asian Coefficient | ST DEV | Asian Coefficient | ST DEV | Asian Coefficient | ST DEV | Asian Coefficient | ST DEV | Asian Coefficient | ST DEV | Asian Coefficient | ST DEV | Asian Coefficient | ST DEV |
| 2013 | 3783 | 72.6% | -0.138 | -13.54 | -0.123 | -12.51 | -0.107 | -10.46 | -0.103 | -10.03 | -0.068 | -7.10 | -0.014 | -2.73 | -0.027 | -5.00 |
| 2014 | 3756 | 73.6% | -0.134 | -12.67 | -0.121 | -11.76 | -0.107 | -10.00 | -0.105 | -9.70 | -0.073 | -7.35 | -0.009 | -1.62 | -0.027 | -4.77 |
| 2015 | 3687 | 74.6% | -0.135 | -12.71 | -0.122 | -11.76 | -0.111 | -10.27 | -0.109 | -10.07 | -0.076 | -7.52 | -0.010 | -1.83 | -0.028 | -4.93 |
| 2016 | 3659 | 75.9% | -0.121 | -10.88 | -0.109 | -10.07 | -0.098 | -8.79 | -0.096 | -8.46 | -0.062 | -5.95 | -0.012 | -2.14 | -0.025 | -4.27 |
| 2017 | 3669 | 76.9% | -0.113 | -10.38 | -0.102 | -9.66 | -0.085 | -7.86 | -0.078 | -7.11 | -0.049 | -4.78 | -0.014 | -2.56 | -0.023 | -4.18 |
| 2018 | 3435 | 77.5% | -0.110 | -9.20 | -0.100 | -8.58 | -0.085 | -7.06 | -0.078 | -6.10 | -0.052 | -4.55 | -0.010 | -1.62 | -0.024 | -3.89 |

**Ex. D-4**

Redo of Saad's Table 5 Using Basepay instead of Total Compensation

2013 through 2018 African-American Differences in Base Pay at Oracle Headquarters by Year, with Various Characteristics Controlled

- Full-Year Incumbents in the PRODEV Job Function -

| | | | Controls for ... | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | African-American Only (1) | | Adds Gender (2) | | Adds Refined Age Variable (3) | | Adds Education (4) | | Adds Refined Tenure Variables (5) | | Adds Work-Related Variables (6) | | Removes Organization Name (7) | |
| Year | Number of Workers | % Women | Black Coefficient | ST DEV | Black Coefficient | ST DEV | Black Coefficient | ST DEV | Black Coefficient | ST DEV | Black Coefficient | ST DEV | Black Coefficient | ST DEV | Black Coefficient | ST DEV |
| 2013 | 1062 | 2.4% | -0.189 | -2.87 | -0.180 | -2.80 | -0.181 | -2.81 | -0.187 | -2.91 | -0.158 | -2.72 | 0.011 | 0.35 | -0.035 | -1.16 |
| 2014 | 1018 | 2.6% | -0.238 | -3.56 | -0.227 | -3.45 | -0.230 | -3.48 | -0.242 | -3.66 | -0.211 | -3.59 | 0.008 | 0.24 | -0.041 | -1.32 |
| 2015 | 962 | 2.6% | -0.266 | -4.07 | -0.253 | -3.93 | -0.258 | -4.00 | -0.272 | -4.22 | -0.239 | -4.07 | -0.005 | -0.15 | -0.067 | -2.12 |
| 2016 | 910 | 3.2% | -0.292 | -4.76 | -0.277 | -4.57 | -0.281 | -4.63 | -0.284 | -4.69 | -0.219 | -3.91 | -0.026 | -0.81 | -0.073 | -2.46 |
| 2017 | 876 | 3.1% | -0.310 | -5.00 | -0.291 | -4.77 | -0.292 | -4.78 | -0.289 | -4.71 | -0.238 | -4.23 | -0.059 | -1.81 | -0.099 | -3.33 |
| 2018 | 800 | 3.4% | -0.324 | -4.94 | -0.311 | -4.81 | -0.312 | -4.82 | -0.307 | -4.75 | -0.262 | -4.36 | -0.090 | -2.68 | -0.104 | -3.18 |

**Ex. D-5**