

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

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Exhibit P-1

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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 precise¹ 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 precise² 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 2014 and 2018. Because many employees receive no stock awards or bonuses, 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.

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

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 $p = e^{\beta} - 1$ where β 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 age⁸ 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 exempt⁹ 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 management¹⁰ 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

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

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.

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 no stock awards in a given year, the distribution of stock awards differs from Medicare compensation and base pay rate. All employees receive compensation so there are no "zeroes" 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 not the case for stock awards. Many employees receive zero stock awards. The analyses of racial or gender differences must consider both differences in the likelihood of receiving no stock award and in

the size of the stock award, if there were one. The regression technique that appropriately controls for these distributional characteristics of stock awards is a “Tobit.” I use a Tobit regression analysis of stock awards, 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 who receive no, or zero, stock awards. 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.

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 ██████ 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 \$100,000, 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.

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 5,767 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 2,459 and 7,240 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

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

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

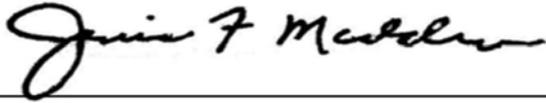
years yield three estimates of the total lost benefits arising from differences in Medicare compensation, not including interest. These totals are reported in the last row of Table 10.

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,
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	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,
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)																		
2013 through 2018 Asian Differences in Medicare Earnings 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	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 through 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 scores 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 coefficients 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 scores 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 coefficients 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 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 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 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 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 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 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

Year	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)			
	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

Year	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)			
	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

Year	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)			
	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

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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

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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

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Philadelphia, PA 19104-6299

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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.

AIIESEC 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).

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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 Ghettos 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.

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- “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.
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- “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 Rebecca 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 Sivitraniidou 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 subcommittee, 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

ORACLE_HQCA_0000089013
ORACLE_HQCA_0000089024
ORACLE_HQCA_0000062858
ORACLE_HQCA_0000089010
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ORACLE_HQCA_0000128178
ORACLE_HQCA_0000128179
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ORACLE_HQCA_0000597172
ORACLE_HQCA_0000597175

ATTACHMENT D
MATERIAL CONSIDERED FOR REPORT

ORACLE_HQCA_0000597177
ORACLE_HQCA_0000597178
ORACLE_HQCA_0000597182
ORACLE_HQCA_0000597892
AllEarnings.xlsx
Application - Candidate Skills.xlsx
Application - CSW History.xlsx
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
DOL0000039944-969
DOL000026402
DOL000034179-34181
DOL000038077-38266
DOL000039913

ATTACHMENT D
MATERIAL CONSIDERED FOR REPORT

DOL000039915

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DOL000039928

Email re: future production ([OFCCP v. Oracle] compliance with 2019-05-16 order re historical data)

Emp_Personal_Experience_Qualification_Assign_Details.xlsx

File Attachments - By Candidate.xlsx

FY13 Last Name A-L Text Fields.xlsx

FY13 Last Name M-Z Text Fields.xlsx

FY14 Last Name A-L Text Fields.xlsx

FY14 Last Name M-Z Text Fields.xlsx

FY15 Last Name A-I Text Fields.xlsx

FY15 Last Name J-R Text Fields.xlsx

FY15 Last Name S-Z Text Fields.xlsx

FY16 Last Name A-I Text Fields.xlsx

FY16 Last Name J-R Text Fields.xlsx

FY16 Last Name S-Z Text Fields.xlsx

FY17 Last Name A-I Text Fields.xlsx

FY17 Last Name J-R Text Fields.xlsx

FY17 Last Name S-Z Text Fields.xlsx

FY18 Text Fields.xlsx

gsi comp history.xls

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

ORACLE_HQCA_0000000464-569

ORACLE_HQCA_000000423-441

ORACLE_HQCA_0000020125-179

ORACLE_HQCA_0000020125-20180

ORACLE_HQCA_0000021846-21849

ATTACHMENT D
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ATTACHMENT D
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ATTACHMENT D
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ATTACHMENT D
MATERIAL CONSIDERED FOR REPORT

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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