UNITED STATES DEPARTMENT OF LABOR
OFFICE OF ADMINISTRATIVE LAW JUDGES

OFFICE OF FEDERAL CONTRACT COMPLIANCE PROGRAMS, UNITED STATES DEPARTMENT OF LABOR, Plaintiff, v. ORACLE AMERICA, INC., Defendant.	OALJ Case No. 2017-OFC-00006 OFCCP No. R00192699 **DECLARATION OF ERIN CONNELL IN SUPPORT OF DEFENDANT ORACLE AMERICA, INC.'S MOTION FOR SUMMARY JUDGMENT OR, IN THE ALTERNATIVE, FOR PARTIAL SUMMARY JUDGMENT** **EXHIBITS VOLUME 2 OF 3**

REDACTED PURSUANT TO COURT ORDER

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Office of Administrative Law Judges
San Francisco, CA

Exhibit M

EXPERT REPORT OF ALI SAAD, Ph.D.

In the matter of
Office of Federal Contract Compliance Programs,
United States Department of Labor, Plaintiff,
v.
Oracle America, Inc., Defendant.

OALJ Case No. 2017-OFC-00006

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ASSIGNMENT

1. I was retained by counsel for defendant Oracle America, Inc. ("Oracle") in my capacity as a labor economist to evaluate the claims made by the OFCCP in their Second Amended Complaint ("SAC") against Oracle. The OFCCP alleges that its "continued evaluation of Oracle's employment practices reveals widespread discrimination at HQCA" – in particular, "that Oracle discriminated against women, Asians, and African Americans or Blacks in compensation."[1] The OFCCP further alleges that "Oracle paid women and Asians less at hire, either by suppressing their pay relative to other employees in the same or comparable job, or by hiring them for lower-paid jobs," and that Oracle "place[s] [female, Asian, and Black or African American] employees in lower global career levels."[2] To address these allegations from a statistical perspective I was provided with electronic human resources data, payroll data, performance review system data, and other documents related to Oracle, including depositions and company policy documents. I have been provided with the OFCCP's backup materials that produced the numbers contained in the SAC, and have thus been able to fully replicate and evaluate those analyses. My initial report responds to the allegations and the associated analyses summarized in the SAC. I may supplement this report at a later date if additional relevant information is made available to me.

QUALIFICATIONS

2. I am the Managing Partner of Resolution Economics Group LLC, a firm whose activities include performing economic and statistical analyses in connection with litigation and other consulting matters. Before beginning my consulting career I was a tenure track member of the faculty of the economics and finance department at Baruch College of The City University of New York. While there I taught labor

[1] Second Amended Complaint, in the matter of *Office of Federal Contract Compliance Programs, United States Department of Labor, Plaintiff, v. Oracle America Inc., Defendant*, United States Department of Labor, Office of Administrative Law Judges, OALJ Case No. 2017-OFC-00006 OFCCP No. R00192699, March 8, 2019, paragraph 11.
[2] SAC, paragraph 22.

economics, micro and macroeconomics, econometrics, and economic history. In connection with my consulting, I have extensive experience providing statistical and economic analyses in connection with company pay equity studies, evaluations of compensation systems, and class action employment cases, including employment discrimination and wage and hour matters. I have also published and lectured on these topics. A consistent focus of my work has involved economic and statistical analysis related to claims of systemic gender discrimination. In the litigation context, I have significant experience in analyzing complex data for the purpose of assisting counsel in evaluating both class certification and liability, including in compensation discrimination cases. I hold a Ph.D. in Economics from The University of Chicago, and a B.A. in History and Economics from The University of Pennsylvania. I have been qualified as an expert witness in both Federal and State Courts. My resume, including all publications and testimony over the past four years, is attached to this report as Attachment A. My firm bills for my services at my current hourly rate of $750 per hour.

DATA AND DOCUMENTS

3. I was provided by Counsel with databases, depositions, and other documents. In addition, I collected publicly available data, and relied on additional secondary materials. The materials I was provided for consideration in connection with my analysis and opinions are listed in Attachment B.

SUMMARY OF FINDINGS

4. I have been asked to evaluate and respond to the statistical analyses described in the SAC, and the claims that the OFCCP makes on the basis on them. In sum, it is my professional opinion that the OFCCP ignored the complexity of work employees perform at Oracle and applied an overly simplistic model of compensation. They mis-measured variables—including the key outcome variable, total

compensation—and omitted other important variables that would serve to similarly situate employees from a labor economics perspective. When additional variables readily available in the data are introduced even into their aggregated models – which I show mask considerable variation in outcomes – the results OFCCP claims to have found no longer exist. In addition, their statistical models of starting pay and "assignment" are also fundamentally mis-specified and contrary to the statements found in the SAC, do not lend support to the OFCCP's claims regarding pay discrimination. OFCCP's results do not stand up under scientific scrutiny and are an unreliable basis for drawing conclusions about compensation at Oracle.

5. In the SAC, the OFCCP claims that Oracle engages in "widespread discrimination at HQCA" – i.e., at Oracle's headquarters location in Redwood Shores, California.[3] It is my understanding that the claims relate to the pay of women, Asians, and African-Americans. It is also my understanding that of the 16 high-level job functions at Oracle HQCA, the OFCCP only brings claims related to three of them.[4] The OFCCP's primary focus is on pay, with other analyses such as starting pay and job "assignment" relied upon by them in support of their pay analyses.

6. To support their claims of discriminatory pay disparities, in their SAC the OFCCP presents a series of tables summarizing statistical analyses performed by year and by each of the three job functions OFCCP alleges are at issue. The statistical method OFCCP used to study pay is multiple regression analysis, which in general terms seeks to study the relationship of pay to a set of factors thought to influence pay, and once these factors are properly identified and measured, to then determine whether gender or race are also factors that appear to impact or relate pay. Multiple regression is a technique that is often used by labor economists to study pay and when used properly, can be effective and informative. However, when it is not used correctly, conclusions based on regression results can be highly misleading.

[3] SAC, paragraph 11.

[4] Job functions are broadly interpreted as the general "type" of work, such as Sales, Administration, etc. (Waggoner, Kate_2019.05.01_Depo Ex 03.PDF, ORACLE_HQCA_0000042098-20) The three Job Functions at issue in this case are Product Development, Information Technology, and Support.

7. As discussed below, it is my opinion that the analyses presented by OFCCP in the SAC were not performed correctly, because they leave out or mis-measure a number of important pay-related factors and also because they aggregate the statistical analysis over employees who are too diverse for the model they use.[5] As a result, from a labor economics perspective, the analyses presented in the SAC do not serve to similarly situate employees with respect to the work they are doing at Oracle, which is highly complex and widely varying, or with respect to the skills and abilities that they bring to bear on that work. Furthermore, it does not appear that OFCCP's analyses in the SAC accurately model or reflect Oracle's pay system and practices, which involve decisions by multiple managers within different lines of business (LOBs) that cut across the three job functions OFCCP examined. For these reasons, and as explained more fully below, the pay analyses presented in the SAC are not a reliable basis upon which to conclude that Oracle's managers discriminated against women or minorities with respect to pay. I show that introducing additional readily available variables from the data that more closely track work performed and employee skills and abilities – even if one maintains the highly aggregated structure OFCCP selected – generates entirely different results that are inconsistent with an allegation of a pervasive pattern of discrimination.

<u>Multiple regression analysis can be a useful tool, but can be misused and generate misleading results if not appropriately tailored to the particular data and practices being studied.</u>

8. Before getting into the details of why the OFCCP's multiple regression analyses in this case are flawed, it is important to first discuss this technique in general terms. Multiple regression is a statistical tool that is designed to explain or relate a variable of interest, such as pay, to a number of factors we think may impact pay, in order to understand what factors drive pay and by how much. For example, in many companies we would expect something like education to impact pay. Suppose we want to know by how much a Ph.D. increases pay when compared to a B.A. or M.A. degree. It would be incorrect to simply compare the average earnings of employees with a Ph.D. to the average earnings of employees with either

[5] Because I was provided with the backup computer programs and data sets used to create the results in the SAC, I have been able to fully review and evaluate the methodology used by the OFCCP.

a B.A. or an M.A. The reason is clear: employees with a Ph.D. might have not only more education than the other two education groups, but may also possess more (or less) relevant work experience. They may also be concentrated in different places within the company relative to the other two groups – that is, they may work on different types of projects, in different departments, or in different kinds of roles. Given these issues, simply comparing average pay by educational grouping will not tell us the impact of a Ph.D. *alone* on pay; it will mix the effects of a number of other factors that happen to correlate to having a Ph.D. We want to understand what difference having a Ph.D. makes *holding constant* relevant work experience, work department, etc. A multiple regression allows you to figure this out by simultaneously measuring the impact of all factors, which permits the analyst to isolate the impact of any one factor alone. In this way, you can, for example, say that a Ph.D. raises earnings by $10,000 per year, holding other job-related factors in the model constant.[6] Similarly – and as particularly relevant here – one can in theory use multiple regression to study whether employees' gender or race influences pay, holding other job-related factors in the model constant, as a way to investigate whether the data is consistent with a hypothesis of pay discrimination. Of course, in order to conclude that gender or race are related to pay, one would first have to model the other pay related factors correctly, because if those factors are incomplete or are not measured correctly, it could produce a "false positive," where we conclude we find that gender is related to pay when in fact we left out a pay related variable that would have eliminated this finding.

9. Getting the regression model right is crucially important if one attempts to use these analyses in discrimination cases, because discrimination itself is not something an analyst can observe. Unlike prior educational attainment, or the current job title a person person occupies – whose effects on pay can be *directly* measured because the factors causing these effects can themselves be directly measured – "discrimination" can ever only be inferred. This is because the variable used to infer it (gender or race) is

[6] In a preview of something I will discuss below, however, simply including a relevant factor (or set of factors) in a model may not be sufficient. For example, if the nature of the project worked on also influences pay, and if Ph.Ds. tend to work on different projects than employees without Ph.Ds., leaving out project in the multiple regression would distort the measured impact of (or "coefficient for") a Ph.D. on pay by conflating the impact of project with the impact of educational degree.

only a proxy and not a directly observable pay-impacting variable such as education.[7] But that inference will be inappropriate and unsupported if the model is poorly constructed or omits important factors that influence pay for employees in the model. In such a circumstance, the impact of those other omitted factors on pay may end up erroneously being attributed to some factor that *is* in the model, like gender or race. Because these types of errors are found throughout the OFCCP's models, their analyses are unreliable and do not support their conclusions about the impact of gender or race on pay at Oracle.

<u>The OFCCP's pay analysis is flawed and does not support any inference of pervasive pay discrimination against women, Asians, or African-Americans.</u>

<u>The OFCCP fails to measure pay – the variable they are studying – correctly.</u>

10. The problems with the OFCCP's statistical analyses start right up front with their measure of total compensation, which is used to generate the alleged pay differences and very high damages estimates presented in the SAC. This is because the OFCCP measures total compensation incorrectly. Instead of identifying and analyzing the specific compensation awarded to each employee for work performed in a given year by summing up base pay, annual bonus, and shares or options awarded *in that year*, the OFCCP uses a measure of W-2 take-home pay that does not align stock awards to the year in which they were actually earned, and is impacted by employee choices (for example, regarding how much to place in their 401(k) or whether to exercise stock options earned in previous years). An employee's W-2 earnings can include compensation that was awarded years earlier, even back to when they were hired or were in a different job or department. If the purpose of the regression analysis is to compare earnings of employees in a particular year based on their pay-related characteristics measured that same year, one should not use the W-2 data. Because the OFCCP does not measure employee pay correctly, they fail to correctly evaluate the impact of other factors on the pay actually received by different employees in a given year.

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[7] I put "discrimination" in quotes here to reflect the fact that a regression analysis cannot on its own conclude there is discrimination from an analytical perspective. Instead, gender or race differences should be referred to as "unexplained" gender or race differences, given the variables included in the model. The reader should understand that when I use the term discrimination here and elsewhere in this exposition I am simply referring to unexplained adverse differences by gender or race.

The OFCCP fails to distinguish employees performing different work.

11. Another fundamental flaw is that the OFCCP's model effectively groups together employees who are not performing similar work from a labor economics perspective, making any comparisons between employees in those groups irrelevant at best and misleading at worst.

12. The OFCCP's analysis aggregates together all employees who share a high-level Job Function like "Product Development" or "Support." OFCCP's model then controls for differences among employees within these functions using a handful of variables, as described in the SAC.[8] Four of the seven variables in OFCCP's model – standard job title (or job code), job specialty, global career level ("GCL"), and FLSA exempt status – all boil down to a single variable. This is because a given standard job title is associated in a given year with only one job specialty, one GCL, and one FLSA exempt status, so adding those latter three variables adds nothing to the analysis. As a result, their models really only control for four factors: standard job title, part-time/full-time, time in company, and "previous experience."

13. The first of these four factors – standard job title – appears intended to describe the work performed by a given employee; the next three – part-time/full-time, time in company and previous experience – appear intended to describe features of individual employees that might make them more or less `productive in that work. But none of these factors – viewed in isolation or together – suffice for those purposes. For example, one of the variables OFCCP uses to distinguish employees in their current positions – part-time versus full-time – has very little impact, as 99% of the employees in the analysis are full-time.

14. Perhaps most importantly, from a labor economist's perspective the control for Oracle "standard job title" is not sufficient to similarly situate employees in the regression analysis. As shown in detail below, standard job title does not accurately specify the nature of work performed by different employees. Employees performing highly similar work would generally be expected to be paid within a relatively

[8] The pay-related factors they control for in their models are "time in company, previous experience, FLSA exempt status, part time or full time, global career level, job specialty and standard job title." SAC, paragraph 13.

narrow range; the underlying economic principle that generates this result is that a company will generally not choose to pay one employee (say) five times more than the employee next to her if they are truly doing similar work and contributing similar value to the company. But at Oracle, employees within the same standard job title often earn vastly different amounts, even after controlling for the other factors in OFCCP's model. By way of example, employees in one of the largest job titles in the data, Software Developer 4s, earned total compensation ranging from [redacted] in 2014. Simply sharing a standard job title does not serve as a sufficient measure of work performed, and does not do enough on its own to similarly situate employees from a labor economics perspective. Standard job titles instead appear to be a system of classification – much like job function, job specialty, and GCL – that groups together employees whose work may share some general features but in fact differ significantly. This wide range in pay for Software Developer 4 holds up even when taking the other variables into account that the OFCCP uses in its regression model.

<u>The OFCCP's models ignore relevant experience and other important factors impacting pay.</u>

15. The OFCCP introduces two additional factors into its analyses as purported controls for relevant, job-related experience. But these measures are completely inadequate given the characteristics of the work and workers at Oracle, and the diverse set of jobs and employees across the three Job Functions they have analyzed. As for "previous experience," the measure used by OFCCP is simply the employee's age minus 18 minus years since hire at Oracle America, Inc. There are several things wrong with this measure.

a. First, the number of years is not important on its own. Instead, what also matters to a labor economist is what *type* of work was performed prior to working at Oracle America, Inc. Was it years of technology work, and if so, what specific type? Where was the work performed – another leading international technology company, or a small startup? OFCCP's model does nothing to capture these differences in *relevant* prior experience, which can matter significantly for pay decisions.

b. Second, the OFCCP fails to measure and take account of number of years employees may have worked at an Oracle affiliate overseas or in an acquired firm. Many employees in the data previously worked at an Oracle affiliate outside of the USA, which plausibly constitutes relevant experience in many cases, as would work performed at a company later purchased by Oracle to continue its work "in house." OFCCP's model does not credit these employees with this type of experience.

c. Finally, the number of pre-Oracle work years in OFCCP's model does not account for leaves of absence, periods of unemployment or being absent from the labor force, and thus does not actually compare employees who have spent equivalent amounts of time at work, enhancing their job-related skills and abilities. In the context of gender, this can be particularly important; there is a large body of labor economics research that examines the differences between male and female labor force participation and leave-taking, and the consequent impact on work experience and hence earnings.[9]

16. The points above relate to problems with the variables the OFCCP *did* use. However, as I detail below, they failed to use many other variables that are also important in explaining pay at Oracle. Examples are: whether or not an employee had a patent, employee tenure in current standard job title, employee tenure at non-USA Oracle affiliates, organization variables that relate to the types of work and products employees work on, and other variables that can be created with the information provided that allow refinements to the very coarse standard job title control the OFCCP's model relies upon. It is my

[9] Hellerstein, Judith K. and David Neumark, (2006) "Using matched employer-employee data to study labor market discrimination," *Handbook on the Economics of Discrimination*, edited by William M. Rogers III, Edward Elgar, pp. 34. Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz (2010). "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors." *American Economic Journal: Applied Economics*,2(3): 228-55. Goldin, Claudia. (2014) "A grand gender convergence: Its last chapter." *The American Economic Review* 104, no. 4: 1091-1119. Blau, Francine D., and Lawrence M. Kahn. (2017) "The gender wage gap: Extent, trends, and explanations." *Journal of Economic Literature* 55, no. 3: 789-865. Spivey, Christy (2005). "Time off at what price? The effects of career interruptions on earnings" *ILR Review*, *59*(1): 119-140. Waldfogel, Jane (1998). "Understanding the "family gap" in pay for women with children." *Journal of Economic Perspectives*, 12(1): 137-156. Angrist, Joshua D., Stacey H. Chen, and Jae Song. (2011) "Long-Term Consequences of Vietnam-Era Conscription: New Estimates Using Social Security Data." *American Economic Review*, 101 (3): 334-38.

understanding that all of this information was available to the OFCCP at the time they filed the SAC, and yet none of it was used in producing the statistical results summarized in the SAC

17. In a complex workforce such as that at Oracle, many variables are correlated to one another. It is all the more important therefore to get the basic model right before attempting to infer that there is any relationship at all, let alone a meaningful one, between pay and gender or race. But the flaws in the OFCCP's models are so fundamental and pervasive that they are not a statistically sound or reliable basis on which to draw inferences regarding the key issue the OFCCP is focused on: whether there are adverse pay outcomes for women and minorities in the segments of Oracle being studied.

<u>Correcting these errors eliminates the adverse results OFCCP claims to have found.</u>

18. I have performed a number of alternative analyses of compensation – starting with the OFCCP's model, leaving intact its aggregation up to job function (which I do not concede as correct), and introducing additional refinements that are readily available in the data in this case – and I reach very different conclusions. In the analytical work I performed, I have added a number of variables that are related to pay and have corrected the various measurement errors in the OFCCP's model. I find that the pay differences shrink considerably and the majority are not statistically significant. In fact, I find a number of positive relationships between total compensation and gender or race, respectively, undermining the claim that there is a consistent pattern of results adverse to women and minorities. These results do not support an inference of pay discrimination; instead, they are inconsistent with a hypothesis that Oracle managers systematically treat women, Asians, or African-Americans worse than white male employees with respect to pay.

<u>The OFCCP presents misleading bottom-line averages over broad groups of employees in different levels and management chains, obscuring substantial variability that undermines their claim of a pattern of company-wide pay discrimination.</u>

19. The issues above highlight one type of way in which the OFCCP's analyses in the SAC suffer from what economists call "specification bias" – that is, the bias that occurs where variables are measured

incorrectly (prior experience, job performed, etc.), or when important variables are left out (type of prior experience, Oracle affiliate experience, patent activity, leaves of absence, etc.).

20. Closely related to this type of specification bias is another problem: one that results from applying a single model across too broad and diverse a group of employees. This is problematic – even in instances where a model is well-designed – because pay regressions by their nature only produce results that show the *average effect* of each factor studied on employee pay. Here, given the stark differences in the type and level of work performed by different employees across and within the three high-level Job Functions, this average can be highly misleading. The average can significantly overstate the value of a given factor (say, time at Oracle America) for some employees, and understate it for others. As a result, the one-size-fits-all model does not properly account for the differing impact of different pay-related factors in different types of roles, which undermines the reliability of conclusions about the impact of these and other factors – including gender and race – on pay.

21. To summarize: The problem associated with running a regression model on a widely varying employee population is that when a model mixes apples and oranges into one pooled analysis, and estimates only the *average* impact of each variable (as regression models by design do), that average masks considerable underlying variability.[10] The differences among employees created by their diverse attributes and a diverse spectrum of types of work that generate this variability could be addressed through more refined groupings or pay factors, which in turn would give more reliable measurements of pay outcomes and differences. But OFCCP's analyses do not incorporate the needed refinements.

22. Another symptom of the "specification bias" created by performing overly aggregated regression models like the one OFCCP used is that they do a poor job of predicting pay for individual employees. For example, if a well-specified model is applied to an employee population in which the included factors impact pay in a consistent manner, knowing the characteristics of a particular individual would permit the analyst to use the regression coefficients (averages based on the group) to compute what is referred to as

[10] The fact that a variable is statistically significant does not fully cure this problem, since statistical significance is not simply an indicator of the average effect being the product of tightly bunched separate effects per employee, but also by very large numbers of observations in the data.

"predicted" or "fitted" pay. One can compare the "predicted" or "fitted" value for a given employee – which is what the regression says "should be" the pay of an individual based on the average regression outcomes of the included factors across *all* employees – to the actual pay of *that* person. If the differences between actual pay and a model's predictions of pay are substantial for many individual employees, that can indicate either: (a) a poorly designed model (i.e., one that omits or mis-measures important factors), or (b) a model applied to such a diverse employee group that even if it has all the right variables for analysis of some more homogeneous subset, those variables apply in very imprecise ways to many individual employees in an overly aggregated situation. Such a dispersed set of predictions should indicate to the analyst trying a one-size-fits-all approach that something is wrong with the model: either its structure, or its application to dissimilar employees. And that is precisely what one sees in the results generated by the OFCCP's model when they are carefully examined, rather than obscured by presenting only average, group-wide results.

23. Another problem with the bottom-line results that OFCCP presented in the SAC is that they are inconsistent with outcomes that OFCCP's own model generated for other employees at HQCA, but that OFCCP failed to report. As noted above, the OFCCP has focused only on three of the 16 job functions at Oracle HQCA. This is because the model they used as a basis for the NOV – which is essentially the same model carried forward into the SAC – failed to find any pay differences for women and race groups in a variety of pockets of that data. They did not report these statistically insignificant results in their NOV or SAC, but their backup contains them. In addition, the backup underlying the SAC contains many other results of running the exact same models on other employee groupings at HQCA, which show no statistically significant relationships between gender or race. These findings undermine any inference that Oracle's managers consistently and systemically discriminate against women and minorities when it comes to pay, and instead are consistent with the OFCCP having a poorly specified model that does not generate reliable or meaningful conclusions.

The OFCCP's starting pay analysis is seriously flawed

24. The OFCCP's claim that they have identified "causes" of the pay discrimination they allege is also analytically unsupported. First, the OFCCP alleges in the SAC that Oracle "relied" on prior pay in setting starting pay, with the result that protected groups end up with lower pay once in the company.[11] But their starting pay analysis groups together all employees hired into the same global career level, without any control for even the standard job title into which an employee was hired or to which she applied. Such an analysis is completely incorrect in the context of Oracle: GCLs are very broad employee groupings, within which there can be many different jobs and types of work. Requisitions for hire are not posted by "global career level" – they are at the standard job title level and, as I demonstrate below, further specify very detailed types of skills and experience relevant to different posted positions under the same standard job title. At the very least, to be consistent with their overall compensation models, OFCCP should have conducted their starting pay analysis by controlling for standard job title. Below, I show that when properly done, there is no difference in starting pay adverse to women, Asians, or African-Americans.

25. In addition, the OFCCP's starting pay model does not demonstrate any causal connection between prior pay and starting pay at Oracle, but instead only a correlation. But there is a common-sense reason why one would expect to see a strong correlation between prior pay and starting pay for hires into any company, even absent any "reliance" on (or even knowledge of) applicants' prior pay. To the extent that particular skills are sought at the target company, applicants with those skills—who are already getting paid elsewhere for the value of those skills—will generally be the ones hired. I demonstrate below that this correlation is found in the economy as a whole.

26. For the OFCCP to support any stronger causal claims given the expected background correlation, they would have to show that ***holding constant the skills brought to the table by applicants***, starting pay decisions by Oracle managers deviate from these skills in ways only explained by reliance on prior pay itself. But the OFCCP has not suggested this at all, much less shown it.

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[11] SAC, paragraph 32.

The OFCCP's "job assignment" analysis is flawed because it ignores the job application process.

27. The OFCCP also attempts to argue that Oracle "assigns" or channels women and minorities into lower-level (and thus lower-paying) jobs.[12] But the analysis they offer as support for this claim—focused exclusively on so-called "experienced" hires—simply looks at the standard job titles and associated global career levels into which various employees are hired, with no regard to the position(s) at Oracle for which they actually *applied*. The OFCCP's analysis thus does not focus on decisions made by Oracle, but instead just catalogs where workers arriving to Oracle via the experienced labor market end up when they join Oracle. In additiona, the OFCCP does not utilize the extensive data and information available regarding the external applicant process (which I understand was available to the OFCCP), which makes clear that applicants apply against and are hired into particular, position-specific requisitions. Once one uses this data, and analyzes hires in light of the postings to which candidates applied, there is no meaningful difference in where applicants of different genders or races end up: the vast majority of successful applicants—men, women, whites, and minorities—start in the standard job title and global career level associated with the position to which they applied. The OFCCP's analysis ignores the application process altogether and thus does not demonstrate any "assignment" by Oracle adverse to women or minorities.[13]

There is no gender or race difference in pay growth.

28. The OFCCP also analyzed growth in base pay in Product Development from 2003-2016 and concluded that Asians and women "experienced slower wage growth […] to a statistically significant degree," though they do not show or otherwise describe in the SAC the statistical coefficients they claim to have generated.[14] They also did not analyze women in the other two job functions to show that their argument was consistent across the company. Their model also does not account for whether someone took a leave of absence during the year, whether they received a patent bonus during the year, their career

[12] SAC, paragraphs 18-21.
[13] The OFCCP presents no analysis of the steering of applicants to apply to positions below their true capabilities, nor does the OFCCP mention this issue.
[14] SAC, paragraphs 30-31.

level or their organization. A corrected model shows there is no pattern of statistically significant differences in wage growth by gender in any of the three job functions. Among Asians in PRODEV, there are also no statistically significant differences in wage growth. These findings are inconsistent with the OFCCP hypothesis that pay differences between men and women, or between Asians and Whites, widen over time.

<u>The OFCCP selectively reported results in the SAC.</u>

29. The OFCCP claims that women are discriminated against in the PRODEV, INFTECH and SUPPORT job functions, as are Asians in PRODEV, but not Asians in INFTECH and SUPPORT. In addition, the OFCCP reported only half of their results regarding initial placement for Asians in PRODEV. The SAC describes how Asians are 49% as likely as Whites in PRODEV to be "assigned" into higher global career levels as managers. Their back-up also contains unreported results for non-managers in the IC career levels. In the IC career levels, their own results show that Asians are *more likely* to be placed in the higher levels than are Whites, though the difference is not statistically significant.

30. The OFCCP also claims in the SAC that pay disparities between men and women widen the longer they are at Oracle. However, they only show the results for women in PRODEV. When I apply thethe OFCCP's statistical model to women in INFTECH, I find that the pay gap generated by their model is adverse to women and statistically significant in the 1-3 year tenure group, but that this gap falls in size with tenure and is positive for women in the highest tenure band. In SUPPORT the trend is similar to PRODEV but the pay gap in the youngest tenure band is not statistically significantly different from zero, which would imply (according to the OFCCP interpretation of these analyses) that Oracle does not suppress pay early on but suddenly decides to do so later. There are methodological issues with these analyses, but these results are based on the OFCCP methods and the results they chose not to present, and demonstrate how the OFCCP's claims lack support from within their own analyses.

There is no basis to conclude that damages are owed.

31. In the SAC, the OFCCP computes alleged damages for women, Asians, and African-Americans in a formulaic fashion based on the average pay gaps generated by their statistical model. The refined analyses presented herein show that there is no pattern of adverse pay results for women. Thus, from a statistical perspective, there are no damages to estimate for them.

32. My refined analyses also show that there is no unexplained pay disparity between Asians and white employees, and thus no basis for damages. It is worth noting that the OFCCP's calculation of damages for Asians in the SAC are in fact calculated only for Asian men (because Asian women were included in their damages calculations for women), but the OFCCP failed to use an Asian men-only version of their model to estimate these damages. When their analysis is restricted just to Asian men, even using their flawed model, there are no statistically significant pay gaps in half of the years they analyze, meaning there is no evidence of a systematic pattern of adverse outcomes upon which to base damages.

33. The OFCCP also claims in the SAC that African American employees are owed damages, but their analysis for this employee group alone was based on base salary, not total compensation. The focus on base pay rather than total compensation for African-Americans alone is entirely unexplained in the SAC. Employees at Oracle earn total compensation, not base pay alone. When OFCCP's pay model is run using their measure of total compensation (flawed though it is), their own model shows no statistically significant differences in total compensation between African-American and white employees. Again, their own model shows that no damages are owed.

34. In summary, and to wrap up this overview, the OFCCP has applied overly simplistic statistical methods in their pay analyses, fraught with mis-measured and/or missing variables. They have used unsupportable approaches and mis-specified models in their starting pay and "assignment" analyses. Oracle is a large, sophisticated technology company that employs people doing varied and highly complex work. The simplistic approach of the OFCCP – which ignores crucial facts about the specific work and workers at Oracle – fails to produce any reliable results, and OFCCP's conclusions based on their simplistic model do not stand up to scrutiny. Even if one adopts the aggregated approach OFCCP

uses, modifications to their model based on readily available information they had but did not use yield results that are not significant and do not suggest any pattern of pay discrimination. I now proceed to explain each of these findings in more detail, and begin – as one should when seeking to study compensation at a company – with a careful look at the specific company and employees at issue.

ORACLE IS A HIGHLY DIFFERENTIATED AND EVOLVING TECHNOLOGY COMPANY, WHOSE EMPLOYEES PERFORM A WIDE ARRAY OF WORK THAT REQUIRES VARYING SKILLS, ABILITIES, AND COMPETENCIES AND CONTRIBUTE DIFFERENT VALUE TO THE COMPANY

Oracle is a large complex company with widely varying employees working on complex products and services

35. The Oracle Corporation (the parent company of Oracle America, Inc.[15]) is a global company offering a wide variety of complex products and services. It employs 137,000 people worldwide, including 38,000 developers and engineers, 14,000 support and services specialists and 19,000 implementation consultants. Oracle employees hold more than 18,000 patents worldwide.[16] The products the company focuses on change over time, such that over a five year period many products cease to be a focus for the company, while others emerge and become business critical.[17]

36. The employee groups at issue in this case span three job functions (Product Development, Information Technology, and Support) at Oracle's headquarters location HQCA. The employees at

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[15] https://www.sec.gov/Archives/edgar/data/1341439/000119312510151896/dex2101.htm, accessed July 19, 2019.
[16] http://www.oracle.com/us/corporate/oracle-fact-sheet-079219.pdf, accessed June 18, 2019.
[17] "Because not all products and services have the same value to Oracle, the value of the skills, duties, and responsibilities necessary to develop, enhance, or service Oracle's wide array of products and services also differs and changes over time. For example, (and there are plenty more, twenty years ago, employees skilled in Siebel technologies were highly sought after in the marketplace. Today, by contrast, there is high demand for (and comparatively limited supply of) employees with experience specifically in cloud-based technologies and artificial intelligence. As technology continually changes and develops, the competition and market demand for employees skilled in the latest technologies also changes, meaning the value to Oracle of various skills, duties and knowledge also fluctuates over time." Declaration of Steven Miranda in Support of Defendant Oracle America, Inc.'s Motions for Summary Judgment or, in the Alternative, Summary Adjudication, in the matter of *Rong Jewett, Sophy Wang, Xian Murray, Elizabeth Sue Petersen, Marilyn Clark and Manjari Kant, v. Oracle America, Inc.*, Superior Court of the State of California, County of San Mateo, Case No. 17CIV02669, January 17, 2019, paragraph 7 (ORACLE_HQCA_0000607281.pdf)

HQCA in the job functions at issue are very diverse: they span dozens of different standard job titles, from employees in entry-level positions straight out of college up to Senior Vice Presidents with 30 or more years of work experience.

37. There are 8,465 unique employees at HQCA in the PRODEV, INFTECH and SUPPORT job functions from 2013-2018. [18] There are 6,035 employees who are female in any of the three job functions, or are Asian or African American employees in PRODEV. This protected group of employees occupied 142 different standard job titles from 2013-2018 and worked in hundreds of different organizations on hundreds of different products.[19] Among this population OFCCP contends experienced discrimination from 2013-2018 (women in PRODEV, INFTECH, or SUPPORT; Asians and African-Americans in PRODEV only), 30.8% were identified in the data in any given year-end as Managers (i.e., had responsibility for supervising two or more employees) and 69.2% were identified as Individual Contributors (ICs).[20] Most (80.7%) of the ICs in the population OFCCP contends experienced discrimination reported to a manager also covered by OFCCP's claims.

38. Reflecting the wide range of roles these employees occupy, annual base salaries for full-time, full-year employees from 2013-2018 at HQCA ranged from [redacted] However, a large part of compensation at Oracle—particularly for [redacted]

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[18] 214 employees from data are excluded in this count because they start working in PRODEV, INFTECH, and SUPP job functions at HQCA after 1/1/2019. 86% of these employees work on a NetSuite product and moved from US-CA-San Mateo-2955 Campus Drive to HQCA on 1/3/2019 and 1/7/2019.

[19] https://www.oracle.com/products/oracle-a-z.html, accessed July 16, 2019.

[20] There are two main career paths for employees in these job functions at Oracle. Individual Contributors focus more on the technical aspects of products and services relative to Managers who oversee and coordinate projects. Each path is marked by Career Levels, with higher levels indicating increased scope and responsibility, but the two paths are not linked. For example, an IC2 is not the equivalent of an M2; an IC3 being promoted to manager would not automatically move into M4. It depends on the "scope and complexity of the position, and whether or not the employee has previous management experience." (ORACLE_HQCA_0000000407_Global Compensation Training - 2011 Managing Pay Final (Native).PPTX)

employees—is comprised of bonus and equity awards.[21] Total annual compensation for these same employees thus ranged from [redacted]

39. Table 1 summarizes total compensation in 2014 for full-time, full-year employees aggregated up to job function. The first row indicates that there were 445 employees in the INFTECH job function, for whom the average total compensation was [redacted] Imagine lining up these employees from lowest salary to highest. The lowest annual compensation was [redacted] and the highest was [redacted] The median employee is in the middle – 50% of employees earned more and 50% earned less. Salaries in the PRODEV job function – where hundreds of hardware developers, software developers, and application developers work – earn [redacted]n average, but the range of total compensation spans from [redacted] to [redacted] In the smallest of the job functions, SUPPORT, compensation ranges from [redacted] to [redacted] with an average of [redacted]

The Distribution of Total Compensation in 2014 by Job Function

Job Function	N	Mean	Minimum	10th Percentile	50th Percentile	90th Percentile	Maximum
INFTECH	[redacted]						
PRODEV							
SUPPORT							

40. The range is from just under [redacted] for each of the Job Functions, to over [redacted] in INFTECH, over [redacted]n PRODEV, and over [redacted] in SUPPORT. These numbers include both the highest and lowest paid employees, but the range continues to be wide when ignoring these extreme values. The middle 80% of employees – those between the 10th and 90th percentiles in each job

[21] Total compensation equals base pay plus bonuses and stocks awarded that year. See US Manager's Orientation presentation dated December 6, 2016 (ORACLE_HQCA_0000042091_MASTER US Manager Orientation 1201 (Native).PPTX) which describes the components of compensation and divides it into base pay, short-term incentives (bonuses), and long-term incentives (stock options and restricted stock units).

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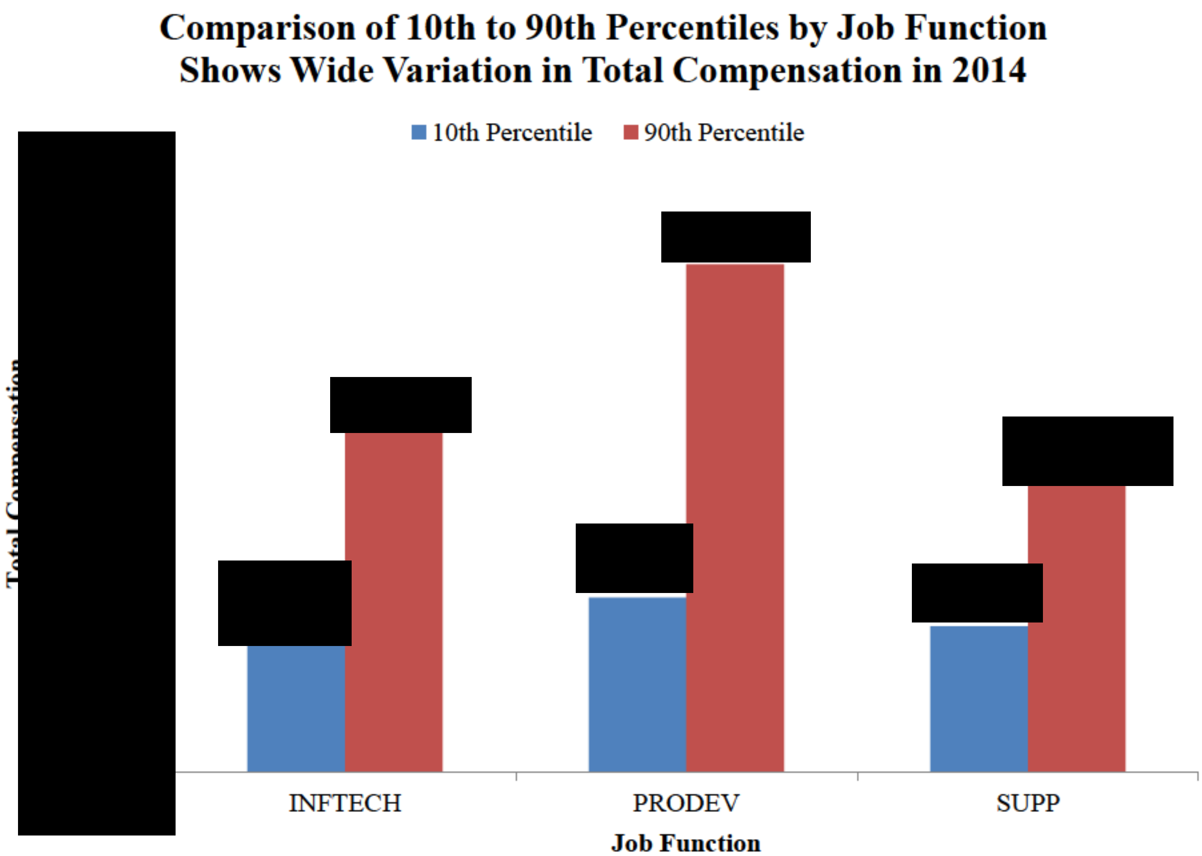
function - are shown below. Employees in INFTECH received between [redacted] while the corresponding ranges in PRODEV and SUPPORT were [redacted] respectively. These ranges are very substantial, even after eliminating the top and bottom 10% of employees.



Career paths at Oracle

41. Career Levels at Oracle reflect how the skills and scope of work increase with advancement within a given job family.[22] There are two Career Level tracks: "IC," indicating "individual contributor,"

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[22] "The career levels are a standard set of broad, hierarchical categories related to the level at which a job is performed. The career level structure has two tracks: Management and Individual Contributor. Management is defined as one who is directly responsible for the practice or process of managing two or more employees (with hire/fire authority). Individual contributor is defined as a single incumbent with no management responsibility. In some cases, however, an individual contributor may operate as a team leader or manage one employee." (ORACLE_HQCA_0000022906 Career Level Guidelines Matrix

and "M," indicating "managerial." The Manager path is for employees who manage two or more people. Individual Contributors work on a technical expertise track and may supervise one employee. The table below comes from Oracle's internal documentation of the Individual Contributor track, and provides a high-level description of the general progression. It is my understanding that as one moves up the career path, the scope of work a given employee performs in his or her particular job family and role generally becomes more complex and the degree of autonomy increases, along with responsibility.

Individual Contributor Career Level Guidelines			
	Contribution	**Knowledge and Skills**	**Job Complexity/Scope**
IC1 - Learning	**Contributes through FOLLOWING DIRECTIONS: Activity with guidance and problem solving with assistance.**	Learns to use professional concepts. Applies company policies and procedures to resolve routine issues.	Works on problems of limited scope. Follows standard practices and procedures in analyzing situations or data from which answers can be readily obtained. Builds stable working relationships internally.
IC2 - Developing	**Contributes INDEPENDENTLY: Completes own role largely independently with some assistance and guidance.**	Developing professional expertise, applies company policies and procedures to resolve a variety of issues.	Works on problems of moderate scope where analysis of situations or data requires a review of a variety of factors. Exercises judgment within defined procedures and practices to determine appropriate action. Builds productive working relationships internally and externally.

Oracle.xls). Oracle also refers to these as a "knowledge leader (individual contributor role) or a "people leader" (manager role)." Oracle U.S. Employee Handbook, p. 43. (ORACLE_HQCA_0000000464)

IC3 - Career (Team Lead)	**Contributes through EXPERTISE: Duties and tasks are varied and are complex requiring independent judgment.**	A seasoned, experienced professional with a full understanding of area of specialization; resolves a wide range of issues in creative ways. This job is the fully qualified, career-oriented, journey-level position.	Works on problems of diverse scope where analysis of data requires evaluation of identifiable factors. Demonstrates good judgment in selecting methods and techniques for obtaining solutions. Networks with senior internal and external personnel in own area of expertise.
IC4 - Advanced (Mentor)	**Contributes through OTHERS: Leading contributor providing direction and mentoring to others.**	Having wide-ranging experience, uses professional concepts and company objectives to resolve complex issues in creative and effective ways. Some barriers to entry exist at this level (i.e., dept/peer review). Level at which career may plateau.	Works on complex issues where analysis of situations or data requires an in-depth evaluation of variable factors. Exercises judgment in selecting methods, techniques and evaluation criteria for obtaining results. Networks with key contacts outside own area of expertise.
IC5 - Guru (Internal Expert)	**Contributes through LEADERSHIP: Manages and plans implementation of company policy for achieving business goals.**	Having broad expertise or unique knowledge, uses skills to contribute to development of company objectives and principles and to achieve goals in creative and effective ways. Barriers to entry such as technical committee review exist at this level.	Works on significant and unique issues where analysis of situations or data requires an evaluation of intangibles. Exercises independent judgment in methods, techniques and evaluation criteria for obtaining results. Creates formal networks involving coordination among groups.

IC6 - Architect (Internal/External Expert)	**Contributes through STRATEGY: Develops and advises on company policy, contributing through strategy definition and implementation.**	As an expert in the field, uses professional concepts in developing resolution to critical issues and broad design matters. Significant barriers to entry (i.e., top management review, approval) exist at this level.	Works on issues that impact design/selling success or address future concepts, products or technologies. Creates formal networks with key decision makers and serves as external spokesperson for the organization.
Source: ORACLE_HeadquartersCA_0000022906 Career Level Guidelines Matrix Oracle.xls			

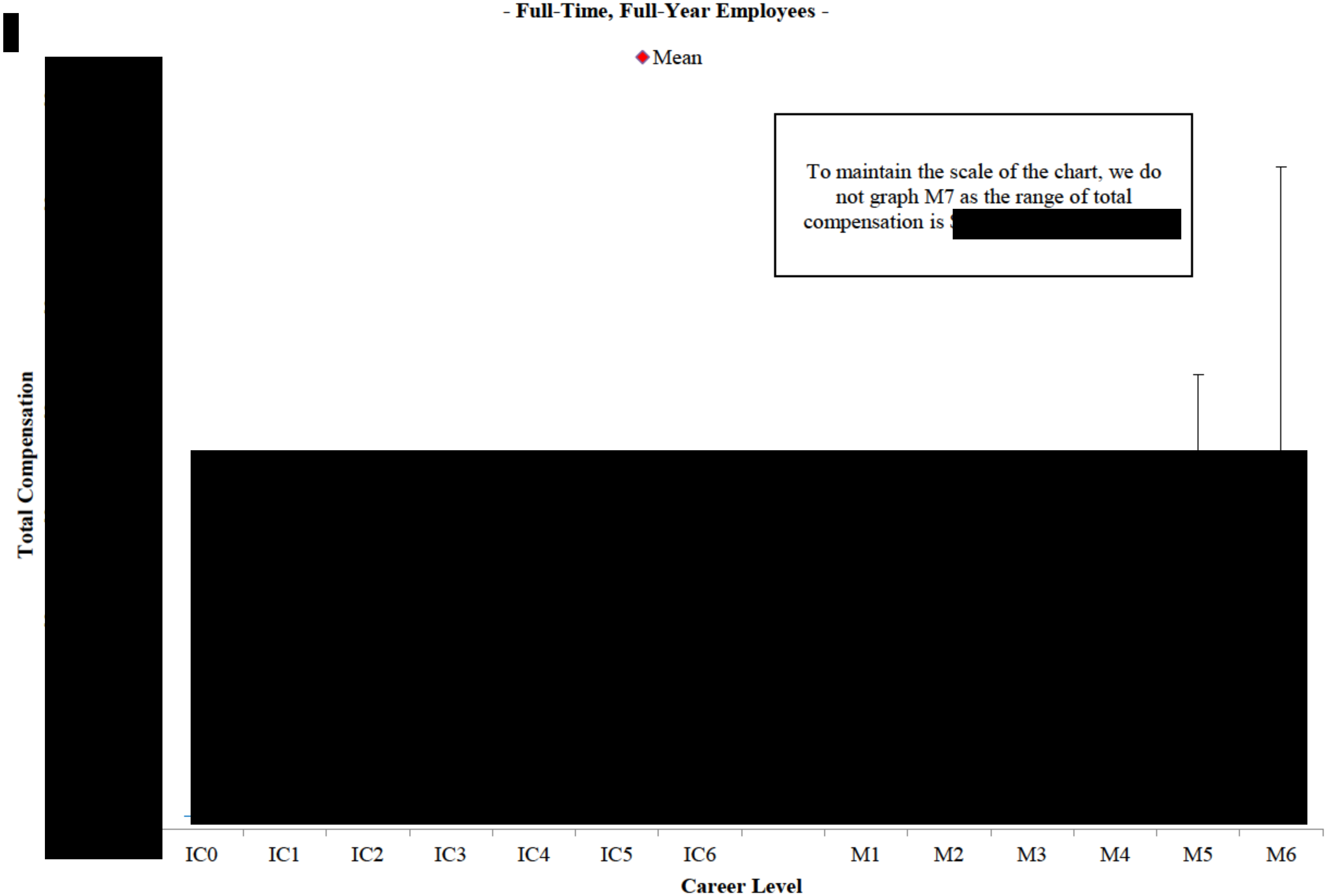
42. Looking at the boxplot charts for Career Level below, one sees very wide ranges of pay within each career level, and one also sees considerable pay overlap between the Career Levels. Boxplots work as follows: The average is indicated by the red diamond. The bottom of the blue box indicates the 10^{th} percentile, the top of the blue box indicates the 90^{th} percentile, and the line inside the box indicates the median or 50^{th} percentile. The vertical lines extending beyond the boxes indicate the minimum and maximum compensation.

43. For example, Career Level IC4 has a total compensation range from [redacted] for full -time full-year employees at Headquarters during 2014. IC3 has a range of [redacted] The 10^{th} and 90^{th} percentiles for IC3 are [redacted] respectively, which [redacted]. As another example, in the M levels, a similar comparison of M3 and M4 also reveals [redacted] In fact, for each adjacent pair of Career Levels in both the IC and M levels there is [redacted], with the exception of level M1, which has only 2 employees so that a range is not well defined. The chart summarizes the dollar figures in the table with vertical bars, and one can see that there is [redacted]. The next chart summarizes the data for the 10^{th} and the 90^{th} percentiles, which reveals [redacted], indicating that there is a lot of flexibility for managers to make individualized pay decisions. The graph also reveals the wide range in total compensation within each of the career levels (with wider ranges at higher career

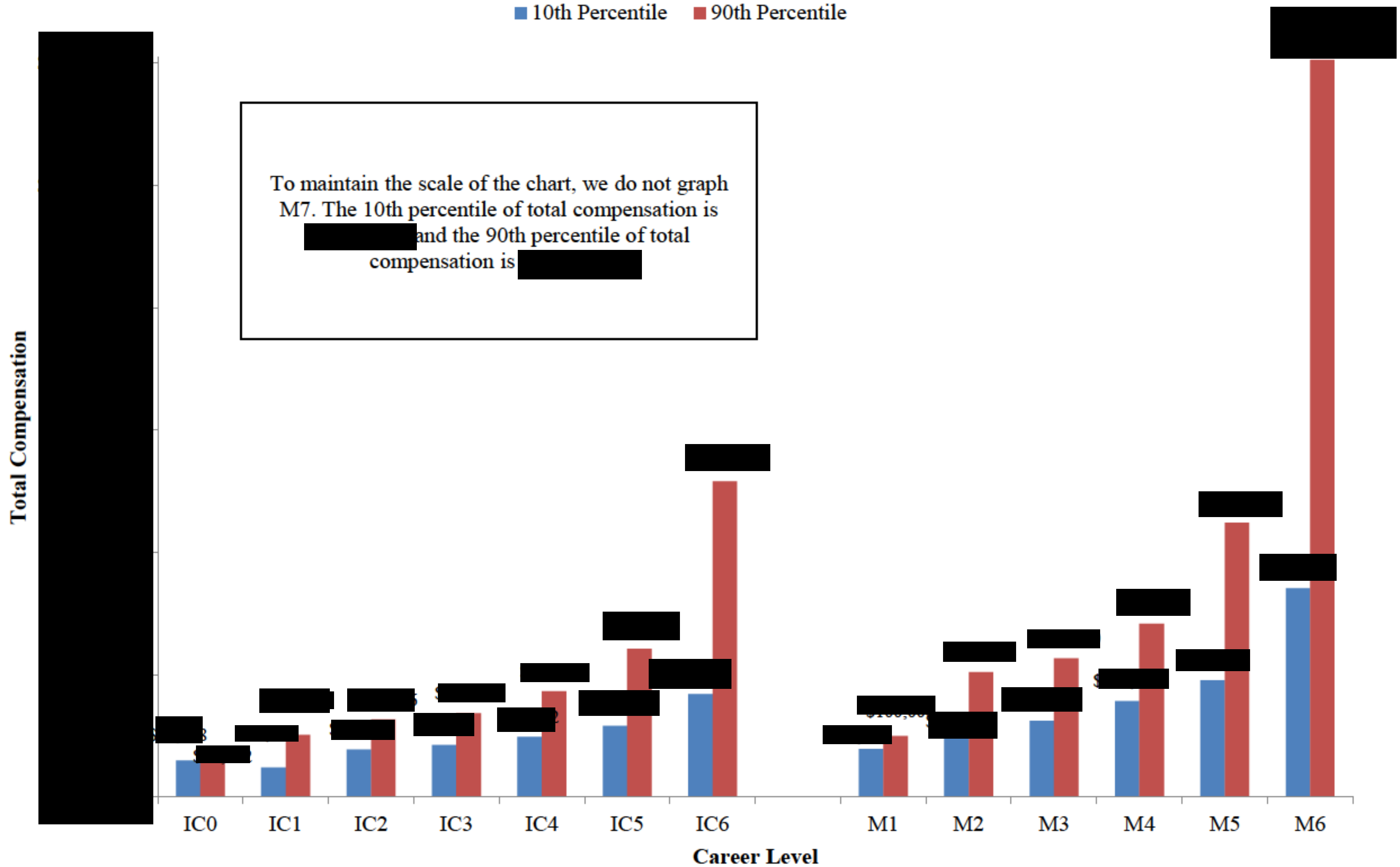
levels), again indicating that career levels in themselves span a broad range of employees whose pay may be differentiated by a host of factors related to the work they perform and their individual skills, abilities, and contribution.

The Distribution of Total Compensation in 2014 By Career Level

- Full-Time, Full-Year Employees -



Comparison of 10th to 90th Percentiles by Career Level Shows Wide Variation in Total Compensation in 2014



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44. Not only does the pay range increase with Career Level but the base pay ranges are also quite wide in each level, with the maximum pay set about 80% higher than the minimum; this remains true even within the same job family. The table below for one job family – Software Developers (ranging from Software Developer 1s at the IC1 level to Software Developer 6s at the IC6 level) – shows for each hierarchical level the minimum, 25th percentile, midpoint, 75th percentile, and maximum base pay salaries in FY14. The salary range is purposely set wide to allow individual managers flexibility to differentiate pay. As Oracle documents make clear, "[s]alary ranges are a tool to assist managers in making decisions about pay. They provide managers with a range of pay that is considered fair and competitive in the local labor market for a specific job. Oracle's ranges are intentionally broad to allow managers to differentiate between employees who are new to their roles and still learning, and those who are fully qualified, very experienced and top performers."[23] The ranges also [redacted] such that a [redacted] for example, could be earning more than a [redacted], depending on the specifics of what they are working on and the labor market for the skills involved.

Base Salary Ranges Set by Oracle for FY14 at HQCA[24]

Standard Job Titles	Career Level	Minimum	25th Percentile	Midpoint	75th Percentile	Maximum
Software Developer 1	IC1	[redacted]				
Software Developer 2	IC2					
Software Developer 3	IC3					
Software Developer 4	IC4					
Software Developer 5	IC5					
Software Developer – Architect	IC6					

[23] ORACLE_HQCA_0000364272_native.pptx, p. 5.
[24] ORACLE_HQCA_0000581471_Salary_Range_History.xlsx.

45. This provides Oracle managers with flexibility to differentiate employees within a given standard job title. Employee compensation depends on the job and role being considered, on the employee's personal "skills, knowledge, and experience," "comparisons to others in the organization who have similar skill sets for the same role," "performance," "previous compa-ratio" and "tenure in current position."[25] The setting of pay also depends on fluctuations in how much competitors are paying people with similar skills in the dynamic labor market within which technology firms compete for talent.[26] Software Developers are not the only job that exhibits wide ranges of base pay at Oracle – all jobs above entry level that contain many employees that share a standard job title exhibit a similar pattern.

[25] ORACLE_HQCA_0000364272_native.pptx, p. 11.

[26] See for example, iRec (ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx) vacancies 3031613 ("competing offer from Google"), 3052439 ("competing offer from VMWare"), 2961610 ("His experience is most relevant for the security service we are building as part of Oracle Management Cloud and will be competing against Splunk.)", 2750313 ("Usability engineer for Service, Exty, and other projects. Competitive offer with CX start up"), 2896003 "has 4 yrs of automation/testing experience in UI,API. She has M.S in Software Engg. and Java expertise (OCJP).She has a pending offer with SAP", 2973701 "Competing offer: Synopsis $143.36K (128K+12%bonus) and $20K sign-on bonus)", 1723974 (" 8+ years deep exp. in DW/ETL/data modeling, critical to build a CX reporting infrastructure. Infosys competing job offer"), 2755591 ("This is an outstanding candidate who wants to join the team and we are competing against others offers").

Within standard job titles, total compensation varies widely

46. At Oracle total compensation can be and often is far higher than base pay alone. There were 137 different standard job titles held by full-time and full-year employees in the three job functions in 2014 at Headquarters. The graph below summarizes the total compensation measures for the 15 most populous of these standard job titles in PRODEV.[27] The most populous was Software Developer 4, with 611 employees in 2014. Software Developer 4 employees' total pay ranged from [redacted] in 2014, and looking at the graph, one can see that the middle 80% received between [redacted] and [redacted] For Software Developer 5 (the next largest group, with 375 employees) the overall range in total pay for 2014 was $[redacted], and the middle 80% range was from $[redacted] Once bonuses and stock awards are added to base salary, there is even more scope for managers to make pay decisions that distinguish between employees that share the same standard job title.[28]

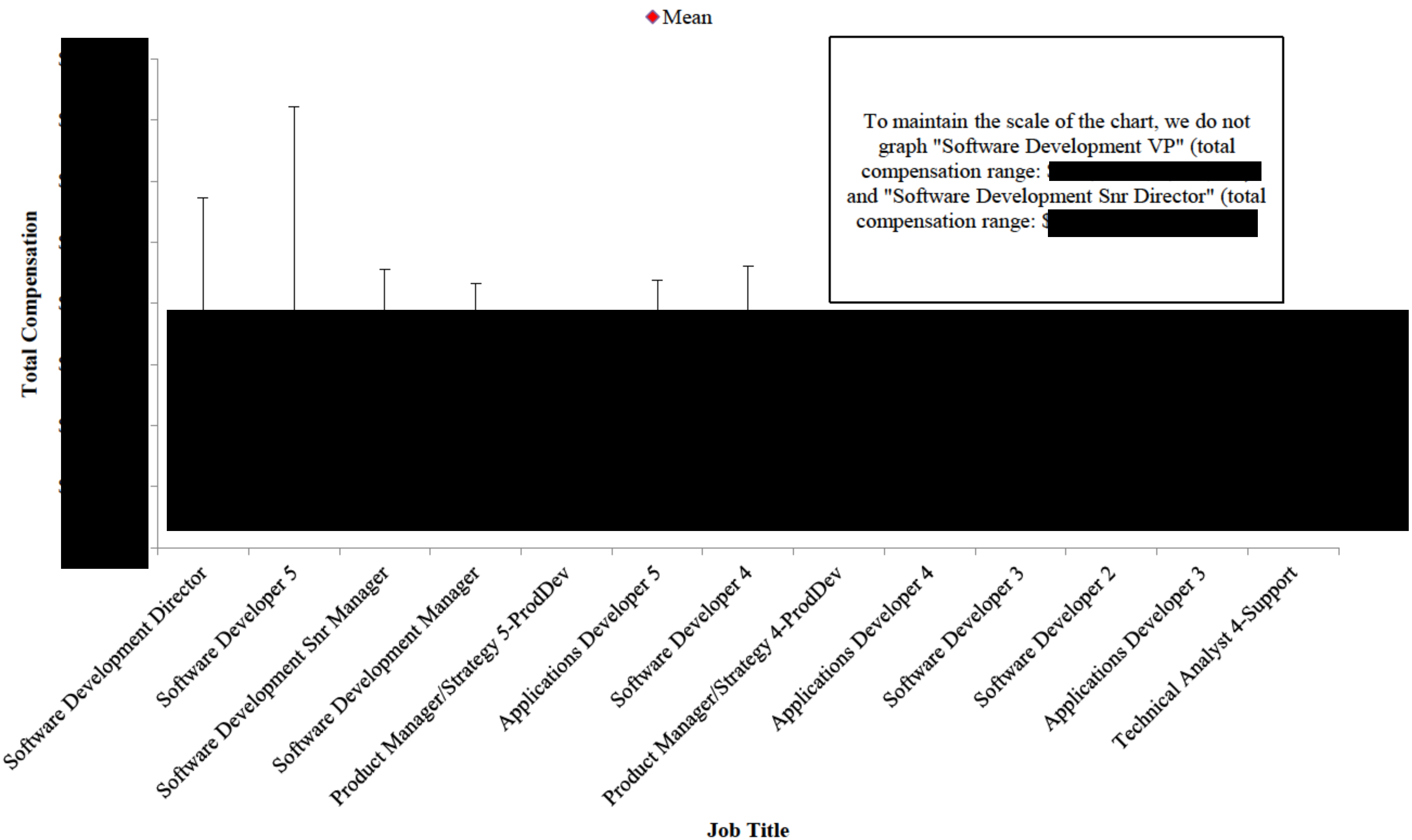
[27] I focus on PRODEV because according to the claims as defined by the SAC, that job function covers all three demographic groups at issue (women, Asians, and African Americans).

[28] Employees sharing a job title sometimes have different "discretionary titles." These do not appear to have much power to distinguish employees by the kind of work they are doing, because within a standard job title, the vast majority share the same discretionary title.

The Distribution of Total Compensation in 2014 By Job Title

- 15 Most Populated Job Titles Across PRODEV, INFTECH, and SUPP -

- Full-Time, Full-Year Employees -



Requisitions for specific positions at Oracle demonstrate how skills and required experience differ within standard job titles

47. The wide variation in pay ranges associated with different standard job titles suggests, based on economic principles, that not all employees within a set standard job title are performing similar work. An evaluation of the available data and documents bear this out in the context of Oracle specifically.

48. The thousands of job requisitions produced in this case provide a significant amount of information regarding how the skills and specific prior experiences sought differ between jobs within broader standard job titles. Employees who have skills that are in high demand in Silicon Valley will command higher compensation than those with more readily available, less in demand skills.[29]

> "Especially when technologies are new, hands-on implementation experience is an important mechanism through which engineers learn about working with new technologies—for example, in the early days of the Internet boom, the expertise required to design and build a professional e-commerce site was acquired by working at one of a few prominent Web companies. As IT workers move between firms, some of this technical knowhow is transferred to new employers. The literature on IT workers has established the importance of external labor markets for employers needing to acquire technical skills […]."[30]

Based on the material provided during discovery in this case, skill sets among employees in this group do appear to differ in substantial ways, even within a single standard job title.

49. Requisitions for non-entry level job openings for Oracle typically contain detailed descriptions of what is being sought for a successful applicant. For example, Requisition IRC1771772[31] was opened for a Software Developer 4 to work with both traditional On Premise and Software as a Service ("SaaS") Fusion Applications customers (emphasis added):

> "**Fusion Applications Lifecycle Management: The team's initiative is to provide a comprehensive solution for managing customer customization and data from a customer Test to Production environment, for both traditional On-Premise and the SaaS Fusion Applications customers.** The challenge resides in establishing a deep understanding of the wide

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[29] Miranda Declaration, paragraph 7. ORACLE_HQCA_0000607281.pdf. Economics literature confirms that IT companies are often willing to pay a premium for the knowledge new hires bring. See Tambe, Prasanna, and Lorin M. Hitt, (2013). "Job hopping, information technology spillovers, and productivity growth." *Management Science*, 60(2): 338-355.

[30] Tambe and Hitt (2013), p. 340.

[31] Taleo requisition (ORACLE_HQCA_0000070750_Requisition - Description and Qualification Data.xlsx).

range of software components (e.g. WebLogic server, RDBMS server, Identity Management products) that Fusion Applications is built on, and produce a performant and robust solution that hides unnecessary complexities while still providing the level of flexibility required by customers. […] Work is non-routine and very complex, involving the application of advanced technical/business skills in area of specialization. Leading contributor individually and as a team member, providing direction and mentoring to others. **BS or MS degree or equivalent experience relevant to functional area. 7 years of software engineering or related experience.** […] Qualifications we are looking for are: A Bachelor's Degree in the Computer Science or close-related Engineering major. Masters preferred. Excellent problem-solving and analytic abilities. **Fluency in the Java programming language. Experience in building enterprise applications on the J2EE platform. Knowledge of XML technologies. Knowledge of object-oriented design and implementation. Knowledge of one or more scripting languages (bash, perl, python, or ant). Knowledge of relational databases. Familiar with basic concepts such as tablespace and schemas. Experience with utilities such as RMAN or DataPump are a plus**."

50. The person hired to the specific job listed above, hired away from a senior software engineering position in a bank's hedge fund platform, has both a B.S. and M.S. in computer engineering, and an M.B.A.[32] Requisition 17000D7L also called for a Software Developer 4 but required "big data" skills (or the desire to learn more about big data efforts) and at least 5 years of experience. The position below requires knowledge of Hadoop, which I understand is a suite of technologies designed for large scale data storage, computing and processing (emphasis added):

The Oracle Audience Data Marketplace is the world's largest B2B aggregation of third party data, and combined with the Oracle Data Management Platform (Oracle DMP), the Oracle Data Cloud team enables marketers a comprehensive and unified data management platform to drive prospecting at scale, audience insights and cross-channel marketing actions. **As part of our core Data Engineering team, you will contribute to our backend engineering platform(s) and be on the cutting edge of modern big data analytics and data streaming. This platform is the central core for processing data at high volume, high throughput, and low latency.** You are someone comfortable with the idea of embracing challenges dealing with terabytes of data on a daily basis and petabytes of data at-rest. **You are or want to become knowledgeable about building large-scale data processing systems, data warehouses, and the latest trends in big data techniques and technologies.** […] Candidates should have: - 5+ years in Java, C/C++, Python or Scala and a proficiency OO design and ETL (Extract, Transform, and Load) procedures and solutions - 5+ years developing and operating software in a Linux/UNIX environment (incl. working with Perl, Python, bash, or your favorite scripting language) **- Knowledge of Hadoop related technologies (MapReduce, YARN, HDFS, Pig, Hive, HBASE, Zookeeper, Cassandra, Mongo, Spark, etc.) - Knowledge of building and tuning probabilistic data structures - Knowledge of real time streaming frameworks and solutions, such as Kinesis or Kafka - Knowledge building and operating big data production solutions at scale -** Experience in Scrum/Agile methodologies - B.S. in Computer Science or a related field […]"

[32] ORACLE_HQCA_0000085621.doc

51. The person hired into this position also had an M.S. in computer science, but further possessed certificates in online courses in data science and machine learning, and held 5 patents, working as a Principal Software Engineer at eBay before joining Oracle's big data group. These two positions share the same standard job title, but differences in the skills required, the availability of those skills in a competitive job market, and the innovativeness or profitability of the products worked on appear to drive compensation differences. In fact, the second position paid [redacted][33]

52. The background of another person hired as a Software Developer 4 in 2013 indicates that he functioned as a Senior I.T. Project Manager, not someone whose day-to-day requirements included coding. Their associated requisition even included a note about how very different and "unique" this person's role would be (emphasis added):[34]

> "**NOTE: the Job Title, Brief Posting Description, and Detailed Description in this iRecruitment app are somewhat misleading; this is a unique role that, while Development-related, is not directly involved in software coding or design. Corporate Architecture M&A Principal Manager: The Principal Manager will help the Oracle Corporate Architecture Group's M&A inbound analysis and integration team carry out Oracle's fast-paced corporate acquisition and integration strategy.** Specifically, the Principal Manager will act as a member of Oracle's M&A diligence virtual team, helping to coordinate the Corporate Architecture Group's work with virtual team members drawn from the company, as well as working to prioritize, plan, carry out, and track Corporate Architecture's M&A-related "due diligence" activities, including **the analysis of the third-party technology incorporated in the to-be-acquired products, integration planning work, and integration execution tracking**. While carrying out these responsibilities, the Principal Manager will interact with technical staff from Oracle Development, Oracle's Corporate Development (M&A) team, Oracle's M&A and IP attorneys, Oracle Support, Business Practices, as well as engineers and other staff from potential acquisition targets. This is an individual contributor role, at IC4 career level Oracle HQ location required."

53. A careful review of these position-specific postings indicates that the *combination* of standard job title and the particular nature of the work tasks specified better captures the type and level of work done

[33] These values have been converted to 2014 constant dollars.
[34] Person ID 892075880, iRec Vacancy IRC1981640 in IRec Data (ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx).

and the particular skills involved than would standard job title alone.[35] For example, the Software Developer 4 above was hired into a mergers and acquisitions group, which distinguishes them from someone in the same standard job title working on a Cloud Storage products. Similarly, one of the Software Developer 4s described above was in a big data organization in the company, but a QA Analyst 4 position in the big data area in same Career Level nonetheless calls for different skills and [redacted][36]

> New Big Data development effort needs a strong QA engineer to help get it off the ground. It's the best of both worlds: a startup feel, but with enterprise backing and stability. Responsible for developing, applying and maintaining quality standards for company products with adherence to both internal and external standards. **Develops and executes software test plans. Analyzes and writes test standards and procedures. Maintains documentation of test results.** Analyzes test results and recommends corrective actions. As a member of the technical/process QA division, you will design functional, integration and regression test plans, build and execute manual and automated tests and perform highly complex analysis for multiple products. Set cross-functional product testing standards. Analyze, evaluate and plan methods of approach and organize means to achieve solutions to complex problems. Work is non-routine and very complex, involving the application of advanced technical/business skills in area of specialization. Leading contributor individually and as a team member, providing direction and mentoring to others. **BS or MS degree or equivalent experience relevant to functional area. 7 years of software engineering or related experience.** Duties and tasks are varied and complex, so you will need to exercise independent judgment and initiative. The work includes writing and executing test cases and test plans, focused on system- and integration- level testing for correctness, performance, and usability. There will be a large automated test component to the position, so you will be expected to write, execute, and maintain automated tests as well as manual ones. We're looking for someone who has experience in a project lead role and/or who has supervised lower-level test engineers. **Need to be proficient in Unix and Java. Test automation experience, preferably with JUnit, TestNG, Selenium, or similar technologies, is required. Familiarity with Big Data technologies is a strong plus.**

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[35] Kate Waggoner May 1, 2019 deposition, 90:12-21. In particular, her discussion of how pay is set: "[…] it's not just within that job code, but there are differences by the product you are working on […]." 90:18-20. By way of analogy, consider the "standard" job title of assistant professor at a large research university. There are assistant professors in every department, from the humanities, to social sciences, to business, law and medicine. Most people are familiar with the fact that those assistant professors in the humanities earn less than those in say, economics, engineering, law or medicine. This is true, holding constant years of experience, number of publications, service contributions, the rank of their department, and so on. In order to test if there is gender bias in pay, one would not control for rank alone, but for department as well. If there is a correlation between gender and department, omitting department would bias the findings relative to female pay.

[36] Vacancy ID 2489751 in IRec Data (ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx), converted to 2014 constant dollars. Emphasis added.

54. The same variability is evident within other standard job titles as well. For Software Developer 3s, for example, the work is highly technical, based on the product or service around which the work is organized. The descriptions shown below indicate that these employees would not be suitable comparators in a pay analysis, given that some postings seek innovators with specialized knowledge and experience in SQL to prototype new software while others focus on ensuring that products are released to customers "bug-free."

> **Software Developer 3**
>
> *Organization Name*: **Database Research and Software Advanced Development, Oracle Labs**[37]
>
> *Department Description*: The database research and advanced software development group in Oracle Labs is working on **incubating new technologies for Oracle software, and transferring leading edge research into products across a broad range of the Oracle technology stack. We are looking for experienced software engineers with MS/PhD in Computer Science** to join the Database Research and Advanced Software Development team. This is a great opportunity to **innovate and contribute to building next generation system** where the database is optimized to run on highly scalable, low power hardware architecture. This will enable analytic processing over several terabyte datastore in sub second.
>
> *Required Skills*: Programming of database internals using C/C++ programming language to drive SQL processes. Experience with in-memory, columnar and SQL internals Experience writing code on top of low arm processors Experience with SQL query optimization, query execution and data access will be very desirable **Previous experience in an R & D organization prototyping new products and technology for commercial software Master's and PhD in Computer Science highly desired**

> **Software Developer 3**
>
> *Organization Name*: **Fusion Middleware** [38]
>
> *Department Description*: Oracle Fusion Middleware is the foundation for thousands of software applications developed around the world. We are creating new components and capabilities tailored to give Fusion Applications a competitive edge in the applications marketplace. Our Fusion Application components are extensions to Oracle's J2EE Application Development Framework (ADF) and are created using Java and XML. We take advantage of the latest Web technologies including AJAX, Flash, and Java Server Faces (JSF). We offer the richest Web UI experience possible and provide a huge development productivity edge over our competitors by greatly simplifying the application development process. The Oracle Fusion Middleware Team is looking

[37] IRec data. (ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx) Vacancy ID 1535737. Emphasis added.

[38] IRec data. (ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx) Vacancy ID 1689521. Emphasis added.

> for Information Technology Specialists and Quality Assurance Engineers interested in building the next generation of world class application development tools. **We are looking for highly motivated individuals who will ensure our products are delivered on time with zero defects. If you have experience coordinating release schedules, implementing product builds, creating product installs, and testing mission critical software releases** then you need to get us your resume today. As a member of the Fusion Middleware Release and Operations Team **you will learn how to integrate a variety of Oracle technologies** including ADF/JSF, BPEL/SOA, WebLogic Server, WebCenter/Portals, Document Management/UCM, Internet Directory etc. If you're a problem solver and you're looking for a new set of challenges in an environment that rewards innovation then we want to talk to you.
>
> *Required Skills*: **BS or MS degree or equivalent experience relevant to functional area. 4 years of software engineering or related experience**. Job Responsibilities: 1. Develop automated tools to efficiently and **reliably build and test** Oracle Fusion Middleware product releases 2. **Implement installation scripts and procedures** for Fusion Middleware components 3. Create **installation scripts** for Fusion Middleware database objects 4. **Coordinate internal uptake of new versions of Oracle technologies** including RDBMS, ADF/JSF, BPEL/SOA, Internet Directory, etc. 5. **Create and test product updates / patches** for critical customer issues 6. Support uptake of Fusion Middleware releases by Oracle internal development teams 7. Setup and maintain databases for development, QA, install testing, etc. 8. Create and maintain WebLogic Service templates for various releases. Job Experience:1. 2+ years of experience in product release management 2. 2+ years of experience using a scripting language like Perl, Python, Borne/C/Korn Shell Programming 3. DBA experience using Oracle RDBMS 4. Experience using source control systems 5. Knowledge of WebLogic Server (WLS) a plus

The person hired for the Middleware position started at $[redacted] and described himself as a "Build and Release Engineer" holding a Bachelor of Engineering in Computers.[39] The Oracle Labs hire, whose starting pay was $[redacted], held a Ph.D. in Computer science and sought a position in "research on exascale query processing and cloud computing."[40] Even though they share a standard job title, the content of the work they do and the skills they draw upon are quite different, in ways that impact their pay.

<u>A statistical cluster analysis indicates that controlling only for standard job title and not more detailed aspects of work does not group employees doing substantially similar work</u>

55. In order to further explore how job content varies within a standard job title, Oracle's new hire requisitions were analyzed to understand whether there are systematic textually identifiable differences in

[39] ORACLE_HQCA_0000084860.doc. Starting pay converted to $2014.
[40] ORACLE_HQCA_0000084213.pdf. Starting pay converted to $2014.

job requirements even holding job title constant.[41] In Attachment E, I present this research in more detail, but several studies have used clustering algorithms to extract separate subsets of skill requirements from the text of undifferentiated job requisitions, with a particular emphasis on identifying the specific skills required for different types of IT jobs that share the same job category on job posting sites.[42] Much of this research stems from a need to identify high demand skills in the face of rapid change in the types of skills required by IT jobs. Economists also have a long history of utilizing coded text data in their analyses, including converting detailed paper hardcopy job descriptions into standardized occupations and industries that can be analyzed quantitatively.. Following techniques used in this research area (and described in more detail in the Attachment), I use these methods to analyze the 521 detailed text job requisitions for the largest standard job title in the data, Software Developer 4. Ultimately the algorithm clusters similar requisitions into groups that are most similar based on the specific terms contained in the descriptions. The analysis applied to the Software Developer 4 requisitions resulted in the creation of 24 unique clusters.

56. I present "word clouds" that visually depict the importance of each word, where importance is measured using word frequency within and across documents calculated by the clustering technique.[43] Less frequent words may appear larger if the algorithm determines they are more important. The word clouds for all 24 clusters of requisitions for Software Developer 4s are in the Appendix but I will discuss two clusters here as examples. Each word cloud below presents the 50 most important words per cluster, with the most important terms being presented in large blue or purple font, and the less important terms being presented in small red font. When visually comparing the word clouds, it is evident that there are distinct differences in the importance of terms that appear in each of the clusters.

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[41] The requisition data contains information relating to job listings and included generic company information, as well as detailed text that described the specific job requirements. The generic text was not analyzed, as there is no variation to study. Rather, the job specific detailed text was analyzed for this analysis.

[42] Woweczko, Izabella A. (2015) Skills and Vacancy Analysis with Data Mining Techniques, *Informatics*, 2: 31-49; Litecky, Chuck, et al. (January/February 2010), "Mining for Computing Jobs," *IEEE Software*.

[43] For the purpose of presenting terms or words in a word cloud, important terms are identified by the algorithmic process as those with the highest proportion in a cluster minus their proportion across all clusters.

57. The word cloud below is based on the 10 requisitions in Cluster 13, which has an average starting salary of $[redacted]. The term with the greatest weight that appears in Cluster 13 is "test," which suggests that this cluster of requisitions relates to testing applications that are developed by others. Closer manual inspection of the text in the qualifications section of these requisitions supports this finding. As just one example, a portion of the responsibilities section Closer manual inspection of the text in the qualifications section of the requisitions supports this finding. As just one example, a portion of the responsibilities section of requisition IRC2797620 in Cluster 13 states:

> "As fusion apps system testing team, we are responsible for fusion apps SAAS setups OVM, high availability, enterprise manager, enterprise deployment, and lifecycle testing, which includes • design, implement, and execute test cases based on design specifications • develop automation framework in java for web 2.0 applications • develop programs in java to automate test cases • execute, debug, and fix automated test suites • report bugs and track for a resolution • work with global development teams to build testing solutions and troubleshoot issues in order to deliver product in high quality."[44]

58. The average starting salary of Cluster 2 is higher, at $[redacted]. The chart above shows that the incidence of terms for Cluster 2 is different than those that appear in Cluster 13. The highest weighted term in Cluster 2 is "exadata," with "database" and "storage" also being common terms. The prominent

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[44] IRec data. (ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx).

terms that appear in Cluster 2 indicate that this group of requisitions is associated with developing Oracle's Exadata database machine. For example, an excerpt of requisition IRC2189577 in Cluster 2 states:

> "As a member of the sustaining engineering database team, specializing in the future technology of engineered system, you will articulate, manage, integrate and test critical security and database fixes for Exadata engineered systems. You will work at the forefront of defining the future direction of releases, by being responsible for articulating all necessary security and other critical fixes from across the Exadata stack which includes Linux, storage, networking and database components, and finally, integrating, testing and filtering out the critical and important content by working in close collaboration with various technical teams across the organization and Linux community."

59. The cluster analysis is consistent with the idea that controlling only for standard job title and not more detailed aspects of work does not group employees doing substantially similar work from a labor economics perspective. As a result, if women or Asians happen to be distributed across these clusters differently than white men – for example, women were 20.0% of new hires in Cluster 13 and 7.7% of new hires in Cluster 2 – then not accounting for within-job title differences in skills and responsibilities will lead to omitted variable bias. The inference is that standard job title alone does not similarly situate employees.

60. Because the level of position-specific detail varies significantly across requisitions, the clustering technique – while instructive – cannot be applied uniformly across all of the data. For example, Oracle Labs is a research and development organization of the company, where cutting edge work is performed according to requisition descriptions.[45] Some of the requisitions contain no detail on Oracle Labs, and clustering techniques would not be able to distinguish these postings from others in Oracle Labs that described it in much more detail:

> "**The Mission of Oracle Labs is straightforward: Identify, explore, and transfer new technologies that have the potential to substantially improve Oracle's business. Oracle's commitment to R&D is a driving factor in the development of technologies that have kept Oracle at the forefront of the computer industry. Although many of Oracle's leading-edge technologies originate in its product development organizations, Oracle Labs is the sole organization at Oracle that is devoted exclusively to research.** The acquisition of Sun Microsystems, along with dozens of other acquired companies, brought a wide array of technologies to Oracle's portfolio. Oracle executives recognized that in Sun Microsystems Laboratories, Sun brought the combined company the benefits of an independent research organization - now renamed Oracle Labs. Expertise in building and maintaining compilers and high performance runtime systems."

Nonetheless, the clusters confirm what reading the requisition text suggests, which is the content of work is not fully or accurately captured by standard job titles.

61. Moreover, if men and women or Asians and Whites are distributed differently on average across the kinds of work being done within a standard job title, using only that title as a control in a regression model leads to omitted variable bias, because the work of Software Developer 4s (for example) can differ tremendously and these differences may correlate to gender and/or race. Again, "discrimination" can only be *inferred* based on the magnitude and statistical significance of a variable placed into the regression model to identify a protected trait like gender or race. But if the model is mis-specified, and other variables are poorly constructed, then the conclusions drawn from the sign and statistical significance of the gender or race variable are unreliable.

[45] See, for example, Vacancy ID 2481627 (ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx).

IMPLICATIONS OF THE RANGE OF EMPLOYEES AND WORK ROLES FOR THE STATISTICAL ANALYSIS

62. Basic economic principles state the high likelihood that someone being paid $48,000 is doing different work than someone being paid $600,000 regardless of the fact that they share a job function. For example, any manager even vaguely attentive to cost-effectiveness issues and bottom-line profitability will not pay someone $600,000 to do work that can be procured for $48,000. Conversely, someone who could command $600,000 for his or her work is unlikely to remain at an employer who pays only $48,000. The analytical question is determining what factors an analyst has to take into account in order to construct groups for analysis who ultimately are similarly situated by the analysis from a labor economics perspective, by which I mean that their skills and responsibilities are sufficiently similar once all appropriate variables are examined and taken into account.

Not all models are equally reliable for statistical inference

63. A regression model is a method for averaging over a dataset to understand the relationships between variables. In order to assess whether this summarizing exercise is useful or not for understanding the data, it is important to examine the underlying data and not just the regression model results.

64. For example, there are thousands of persons who have been hired over the course of the data provided in this case. The largest number of these hires is to the standard job title Software Developer 4. Two things in the data are notable about these hires. First, starting pay can differ substantially, even though they are hired into the same "standard job title." The job descriptions from the requisitions discussed above indicate reasons this may be the case, such as the extent to which the job requires innovative skills in newly developing technologies.

65. Second, if you plot the age of these hires versus the pay they receive, there is virtually no relationship. In typical jobs at many companies and industries one would expect a positive upward sloping relationship, such that those at higher ages earn more due presumably to their greater labor market

experience.[46] But you do not see that pattern in the Oracle data – for example, for Software Developer 4s who are newly hired from the external labor market – indicating that some of these hires at young ages appear to be earning high pay based not on years of work experience but instead on some particular skill or ability they have. One might also expect roughly similar ages among new hires in a single standard job title, if that job title were closely related to the nature and value of the work these hires were brought on to do. However, new hires to Oracle, even limited to Software Developer 4 positions, range in age from 25 to 62. The fact that both 25 and 62 year old workers are hired into Software Developer 4 positions indicates two possible things – (1) that employees are hired into these roles at a certain level within a job family based on the skills they possess (rather than just the years they have worked), and (2) as noted above, the Software Developer 4 standard job title is not accurately or narrowly measuring work content.

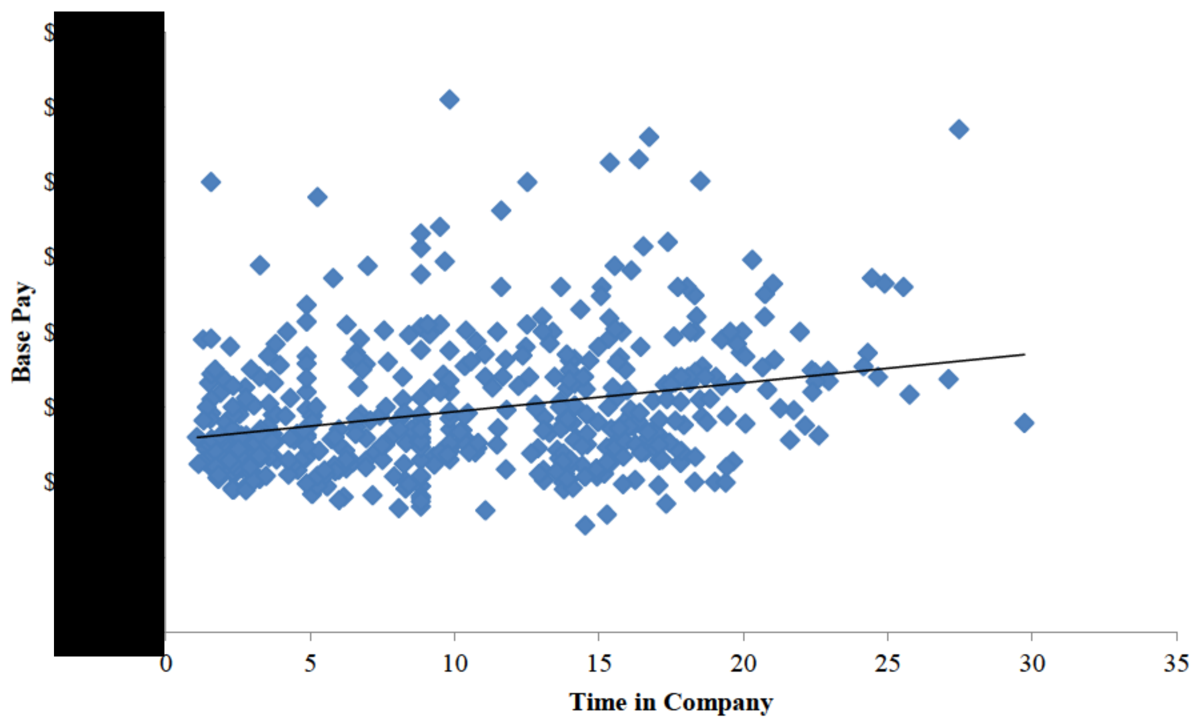
66. The latter implication is important to interpretation of a measured pay difference between protected and non-protected employees. If for example men who apply are more likely to possess "hot skills" than female applicants, simply due to the characteristic of the labor market or who happens to apply to Oracle, using standard job title alone without some measure of the kind of work they do or product they work on, will instead inappropriately attribute some of that impact of having or not having "hot skills" to gender.

67. Modeling experience correctly for the Oracle employees in the job functions that OFCCP has sought to study is no simple task. To briefly review what a regression model does, consider the relationship between salary and company tenure: in many jobs, the longer an employee is at a company, the more they earn. This could be because the company uses a seniority system with lockstep pay increases over time, or it could be that as employees gain valuable on-the-job skills and experience, their pay increases as the value of their work increases.

[46] This has a longstanding and prominent research area in labor economics for decades. See for example, Becker, Gary S. "Investment in human capital: A theoretical analysis." *Journal of Political Economy* 70.5, Part 2 (1962): 9-49; Mincer, Jacob. "On-the-job training: Costs, returns, and some implications." *Journal of Political Economy* 70.5, Part 2 (1962): 50-79; Ehrenberg, Ronald G., & Smith, Robert S. (2015). *Modern Labor Economics: Theory and Public Policy*. Twelfth Edition.

68. The scatterplot below depicts the relationship between base salary and tenure for a random sample of full-time Oracle employees in the PRODEV job function. The vertical axis is base pay, the horizontal axis is time at the company, and each dot represents an employee's combination of pay and tenure. As the scatterplot and its fit or trendline shows, there is a very slight positive relationship on average between tenure and salary for these employees.[47] In a company in which pay increased in lockstep with tenure, this upward sloping relationship would be more pronounced with observations tending to cluster at low tenure, low pay and at higher tenure, higher pay.

There is a Slight Positive Relationship Between Company Tenure and Base Salary for PRODEV Employees
- Full Time, Full Year Employees in 2014 -
- Random Sample of 500 PRODEV Employees -



[47] The trendline is a regression line where the dependent variable is earnings and the independent variable is tenure. In this example I use a simple linear relationship between earnings and tenure for illustrative purposes only. When modeling pay more fully, the appropriate method is generally to use the natural log of pay, and to incorporate the ability to capture a non-linear pattern between earnings and tenure.

69. Looking at the trendline, at zero years of tenure (new hires) the line "predicts" pay is about $[redacted].[48] At 20 years of tenure, the (regression) line predicts pay is about $[redacted][9] In effect, the line depicts average pay for the employees who share a tenure level.[50] If one were to draw a line up from the horizontal axis at about 10 years of tenure to where it intersects the trendline, it shows that employees with 10 years of tenure are predicted to earn about $[redacted] on average. Now, for the employee dots near the trendline, that prediction is fairly accurate. There are a number of employee dots with 10 years of tenure which are far from the trendline, both much higher and much lower pay than predicted, meaning that the trendline does not accurately predict their pay. For example, the highest paid employee with 10 years of tenure earns almost $[redacted], and the lowest paid employee with 10 years of tenure earns about $[redacted] The trendline predicts pay, and tenure might even be a statistically significant predictor of pay, but the prediction is quite inaccurate for a number of employees.[51]

70. The large prediction errors for employees, also known as the "residuals," between actual pay and predicted pay based on this simple two-variable model suggest that the model is inadequate. Textbooks

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[48] This is a simple linear trendline, for illustrative purposes.

[49] I use the word "predict" not necessarily in any causal sense, but simply that the model, when applied to the data used will "fit" each combination of pay and tenure average in a particular way. I used the term "fitted values" interchangeably with "predicted."

[50] "The key idea behind regression analysis is the statistical dependence of one variable, the dependent variable, on one or more other variables, the explanatory variables. The objective of such analysis is to estimate and/or predict the mean or average value of the dependent variables on the basis of the known or fixed values of the explanatory variables." Gujarati, Damodar N. (1988) *Basic Econometrics*, Second Edition. New York: McGraw-Hill, Inc., pp. 23-24. For a more thorough discussion of regression, there are many econometric textbooks that describe the methodology in great detail. See, for example, Greene, William (1993) *Econometric Analysis*, 2nd Edition, NY: Macmillan Publishing Company.

[51] R-squared is a quantitative measure of how well the regression model fits the data. A model that explains none of the variation in the dependent variable has an R-squared of 0; a model which perfectly predicts the variation in the dependent variable has an R-squared of 1. (Gujarati (1988), p. 67). Here, the R-squared obtained by regressing pay on tenure is 0.08, indicating that just 8% of the variation in pay is explained by tenure at Oracle. Whether a particular R-squared is high or low depends on the data being analyzed. In time series data, R-squared tends to be quite high. An R-squared of 0.9 in a time series might be considered low. In Census data or in other one-time cross-section surveys collected across a broad swath of the population, an R-squared of 0.3 might be considered reasonably high. Data collected in a single company provides a great deal of detail about employees, unlike widely accessible databases like the Census which collects data on non-workers, pilots, teachers, janitors and entertainers, among others. One therefore expects much higher R-squared results in single company data.

recommend examining the residuals as a way to diagnose potential problems with the model.[52] There might be additional variables that need to be included to explain pay, such as years and types of work experience before joining Oracle, or standard job title. It could also be the case that the model is flawed because it is combining very different kinds of employees into a single analysis without distinguishing them. For example, there may be a subset of employees who work in "cutting-edge research" areas in which tenure is of less importance than possessing a set of relatively rare specialized skills.[53] Another subset of employees might be working on legacy products that are being maintained but not substantially redesigned, in which case years at Oracle might be a highly relevant factor for pay.

71. The two graphs below show how tenure and pay are related for Software Developer 4s in 2014. The first graph for developers in the Oracle Labs organization, which focuses on cutting edge research.[54] No employee has more than 5 years of tenure at Oracle, and the longer someone has been at Oracle, the less they earn.

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[52] Analysis of residuals is common in econometrics. The regression model is estimated on data containing the actual data for each observation. The regression coefficients and an individual's values for each of the control variables are used to estimate a predicted value for each observation. The difference between the actual value and the predicted value is called the residual. The computer programs that estimate regression models choose the coefficients that minimize the sum of the squared residuals, i.e., the distances between the actual and predicted values. See Gujarati (1988) *Basic Econometrics*, or any basic econometrics textbook.

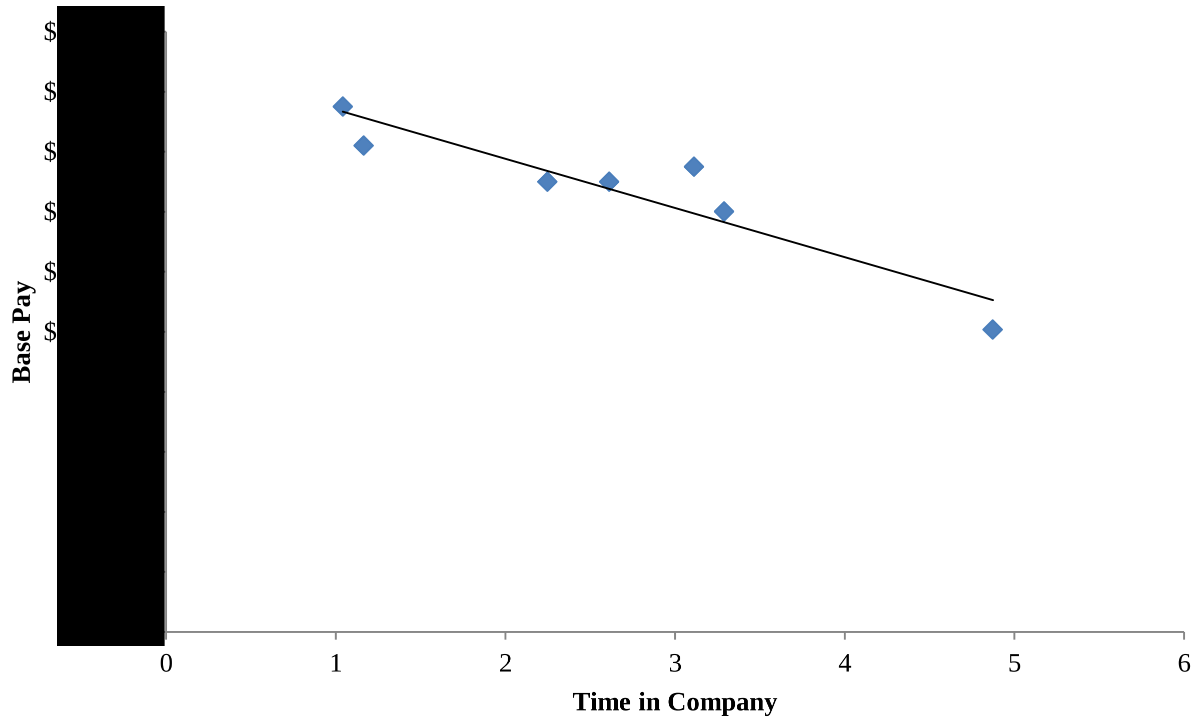
[53] "Because not all products and services have the same value to Oracle, the value of the skills, duties, and responsibilities necessary to develop, enhance, or service Oracle's wide array of products and services also differs and changes over time. For example, (and there are plenty more, twenty years ago, employees skilled in Siebel technologies were highly sought after in the marketplace. Today, by contrast, there is high demand for (and comparatively limited supply of) employees with experience specifically in cloud-based technologies and artificial intelligence. As technology continually changes and develops, the competition and market demand for employees skilled in the latest technologies also changes, meaning the value to Oracle of various skills, duties and knowledge also fluctuates over time." Miranda Declaration, paragraph 7. ORACLE_HQCA_0000607281.pdf)

[54] According to Oracle's web site, "Oracle Labs researchers look for novel approaches and methodologies, often taking on projects with high risk or uncertainty, or that are difficult to tackle within a product-development organization. Oracle Labs research is focused on real-world outcomes: our researchers aim to develop technologies that will someday play a significant role in the evolution of technology and society." (https://labs.oracle.com/pls/apex/f?p=LABS:ABOUT:0, accessed on June 27, 2019.)

There is a Negative Relationship Between Company Tenure and Base Salary for Software Developer 4s at Oracle Labs

- Full-Time, Full-Year Employees in 2014 -

- Organization: BG41-Oracle Labs-RAPID-ORCL USA -



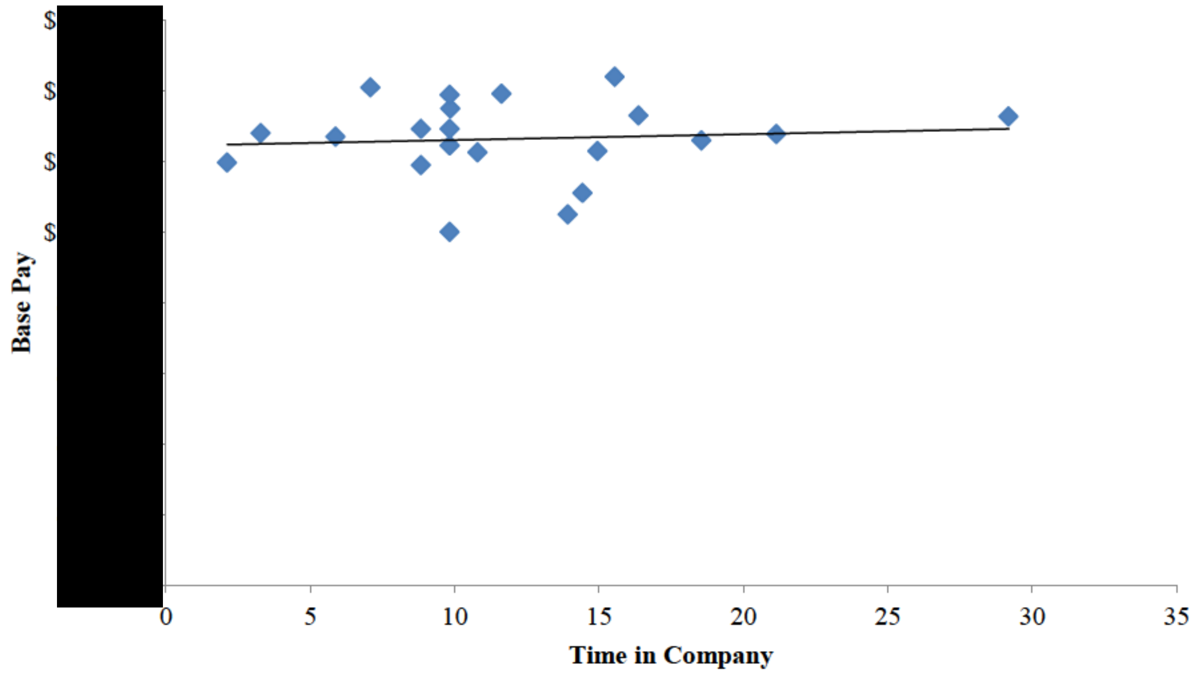
72. The next graph is for the Software Developer 4s working on the Application Developer Framework for Fusion Applications, which according to the Oracle web site has been around in some form since the early 2000s.[55] Employees in this organization have worked at Oracle for as long as 30 years. Among these employees, the relationship between tenure and pay is small but positive.

[55] See https://www.oracle.com/technetwork/developer-tools/jdev/jdev-history-099970.html. Accessed on June 27, 2019.

There is a Slight Positive Relationship Between Company Tenure and Base Pay for Software Developer 4s Working on Application Developer Framework for Fusion Applications

- Full-Time, Full-Year Employees in 2014 -

- Organization: 0EF1-ADF for FA-Cloud-ORCL US



73. The first graph I presented for pay and tenure aggregated all PRODEV employees into one graph with one best fit line to predict their pay based on tenure. The variation (or residual) between actual and predicted pay is much less in the graphs that take standard job title and organization into account. It is good econometric practice to assess a model's usefulness by examining residuals visually and not simply to rely on whether coefficients are statistically significant or the R-squared is high. [56]

74. Graphs like these inform my opinion that the analyses presented by OFCCP were not performed correctly, in that they leave out a number of important pay-related factors and aggregate over employees

[56] "[…] [E]xamination of the residuals is a good visual diagnostic to detect autocorrelation or heteroscedasticity. But these residuals can also be examined, especially in cross-section data, for model specification errors, such as omission of an important variable or incorrect functional form." Gujarati (1988), p. 407. "R-squared is sensitive to the range of variation of the dependent variable, so that comparisons of R-squareds must be undertaken with care…R-squared is also sensitive to the range of variation of the independent variable, basically because a wider range of the independent variables will cause a wider range of the dependent variable and so affected R-squared as described above." Kennedy, Peter. (2008) *A guide to econometrics*. Malden, MA: Blackwell, p. 27.

who are far too diverse for the model they use. By failing to take products and services worked on – and the skills required to perform that specific work – into account, the OFCCP model essentially aggregates all of the employees in a given job function for analysis, and averages all of these tenure patterns into a single number with respect to tenure. This number does not then reflect a causal relationship between tenure and pay, but an unknown mixture of both causal forces and aggregation-caused outcomes. Instead, the regression model is simply summarizing the average fitted relationship between pay and tenure across employees in many different parts of the company, some of which reward long tenure and some which do not, mostly likely because the kinds of skills they demand and how those skills are acquired differ in substantive ways.[57]

75. This concern applies to other variables in the model. The regression model's results for gender or race are also an average, just as tenure was above. Although the regression model summarizes the relationship of pay and gender into a single number, some women receive less than men and some much more. The same is true for race. The scatterplots depict so much variation in outcomes across individuals relative to what the OFCCP regression line predicts that I conclude that the OFCCP model is not adequately modeling compensation at Oracle and thus is unreliable for drawing conclusions about total compensation and gender or race at Oracle.

<u>If important variables are left out of the model that are correlated with the variable of interest in the model, the regression results are tainted by omitted variable bias</u>

76. In real [redacted]es that should be included in a regression model. For example, in the simple best fit or trendline example above, there is no control for relevant work experience prior to Oracle. The measured effect of tenure is thus muddied because there may be employees who are new to Oracle but who have decades of relevant experience elsewhere that are not in the model.

[57] "Although regression analysis deals with the dependence of one variable on other variables, it does not necessarily imply causation. In the words of Kendall and Stuart: 'A statistical relationship, however strong and suggestive, can never establish a causal connexion: our ideas of causation must come from outside statistics, ultimately from some theory or other.'" Gujarati (1988*) Basic Econometrics*, p. 18.

77. In the context of using regression methods to study a gender or race discrimination pay claim, there is a particular problem that the statistician must deal with. If there is a variable that does in fact relate to pay and is left out of the model – i.e., it is "omitted" – then the question is how this affects the magnitudes of the other coefficients in the model. It turns out that many explanatory variables are correlated to each other, such that omitting a variable from a regression, or including it when it was previously omitted will change the value of the coefficients on other variables. For example, if women had more work experience than men on average, and you omitted work experience, the measured effect on pay of being female would be biased by that omission. In other words, the coefficient on female will measure both the impact of being female as well as the fact that some of the impact of female is actually due to their greater amount of work experience. Where the true effect should be spread over two variables, it is included only in one of those variables, distorting the measure from that one variable and of course attributing nothing to the omitted variable. This is what is called "omitted variable bias." This is a persistent issue in multiple regression analysis in the real world, where it can be difficult to know what factors matter, and difficult to obtain accurate measures for variables you know are important.

78. In this case the OFCCP attempts to use regression methods to compare men and women or Asians, African-Americans and Whites who they claim are performing substantially similar work, and to then test to see if women or Asians are paid differently than men or Whites. They control for standard job title, but as shown above, even within a given standard job title, the range of pay (and of skills and abilities) is considerable. If Oracle's "standard job titles" are overly broad, such that they include many types and levels of work, use of these job titles with no further refinement can lead to misleading and biased conclusions regarding pay for women and minorities.

<u>Analyzing residuals is a useful way to examine how varied the data is and thus how well the regression model predicts pay</u>

79. As noted above, a regression analysis produces a set of averaged outcomes for any data set it is performed on. Yet the average may do a poor job of describing the specific individuals in the analysis.

We can use the regression to inspect the nature of the variation "under the hood" of the averaged regression results, however. In order to examine the variation around the averaged regression outcome, we can use the commonly derived set of average impact regression coefficients together with each employee's individual values for the model's variables. Because the regression coefficients estimated on the entire set of employees considered are common, they represent the average impact across all these employees, and thus there is one set of regression coefficients that is applied to each employee in the data to compute each individual employee's predicted or "regression-expected" pay. We compute the pay the model predicts for each employee, and compare that predicted pay to their actual pay. If the model is well specified, meaning we have captured most or all important factors that impact pay and we have measured them correctly, the model should predict within some reasonable range what an employee actually earned. If we have left out variables, or measured them poorly, we will not get a good set of predictions, and there could be wide discrepancies for substantial numbers of employees between the actual and predicted pay. The issue is whether those discrepancies are systematic, and the model has omitted an important factor. This "in-sample prediction," or analysis of residuals, is a common way to assess the quality of a regression model.

80. There are statistical techniques to test whether an individual's actual pay and predicted pay are statistically significantly different. But it is also the analyst's responsibility from an economic perspective to assess the actual width, not just the "statistical width" of the confidence interval. All confidence intervals based on the normal distribution will have 95% of the values in the distribution within two standard deviations of the mean. Thus every distribution shares the same "statistical width" when reduced to statements of the observations that are within two standard deviations of the mean. However, some distributions are tall and narrow, meaning that these 95% of all observations are relatively tightly bunched, and other distributions are wide and flat, meaning that the observations that are within the 95% confidence interval are widely dispersed. A prediction that has a confidence interval of plus or minus 10% of the value of the mean is *economically* different than a prediction which has a confidence interval of plus or minus 40% of the mean. Both statements have the identical 95% of all

possibilities within the stated interval, but the quantitative range these intervals cover is quite different. For example, a predicted value of $125,000 plus or minus 10% ranges from $112,500 to $137,500. A predicted value of $125,000 plus or minus 40% ranges from $75,000 to $175,000.

81. When analyzing these residuals, some women or minorities will in fact have been paid less than a regression model predicts based on their non-gender, non-race characteristics such as estimated prior experience and standard job title (as will some male and white employees).. Some women or minorities will be paid about what the model predicts, and some will earn more than the model predicts based on their individual characteristics. This is not surprising in any regression model. Again it must be emphasized that the issue is by how much the predictions vary when compared to actual pay. An average always *can* be estimated; that in and of itself does not mean it is necessarily the best or even a good summary statistic to describe the data. A sink with separate hot and cold taps will produce warm water on average, but neither tap is accurately described as providing warm water. In a regression context, this means that the determination of what the important factors to hold constant other than gender or race are a crucial component to the interpretability of a coefficient. A pay regression is only an average and does not in and of itself answer the question of whether, from a statistical perspective, the circumstances of pay outcomes of female employees at Oracle are amenable to common analytical treatment.

<u>Oracle's complexity makes model assessment that much more important</u>

82. As I described above, Oracle is a large Fortune 100 company that offers a wide array of complex technological products produced by software developers, hardware developers, tech writers, project managers and other specialized employees. Base salaries for full time, full year employees range from [redacted], and once bonuses and stocks are included, total compensation ranges from [redacted] Even within a standard job title, educational requirements vary depending on the project from those needing a college degree through others requiring a Master's or a Ph.D. The requisite knowledge base differs as well. Some of the position-specific requisitions for Software Developer 4 describe working on building statistics modules for an analytics platform using their Master's in Statistics

and programming in C and C++,[58] while others indicate the need for a B.A., M.A. or Ph.D. in computer science to perform work creating "enterprise applications used by customers to design and execute cross channel marketing campaigns."[59] Nothing in the materials I have reviewed suggests that these skills sets are interchangeable. Yet a simple variable for the standard job title Software Developer 4 would imply these employees *are* fungible.If the model is truly holding skills and responsibilities constant in order to compare similarly situated employees, it should include variables to capture those skills. If the way pay is set and administered is different for college hires than for those employees joining through a posted requisition for a specific position, then aggregating over the two hiring paths is not appropriate. Again, a model is always to some extent a simplification, a representation of a more complicated reality. Whether it is a useful model depends on the strength of its simplifying assumptions about what is important to include in the analysis.

<u>Scatterplots show that the OFCCP model does not fit the data well</u>

83. As noted, a regression coefficient is an *average* effect, a single number that summarizes the average relationship between two variables (such as compensation and gender) holding other factors constant (such as tenure). The question is how well that single number or average summarizes the many data points being averaged. In this section, I use the OFCCP's data and variables to gauge how well the relationship between pay and race or gender is summarized into a single number. One way to examine this variability is to study employees' actual earnings relative to what the OFCCP model predicts for each person. The statistical software itself essentially automatically predicts pay for everyone in the data as part of its calculations that generate the regression results. It is a simple matter to modify the OFCCP computer code to retain and view each employee's predicted pay.

84. I made one other adjustment to the OFCCP model, to remove the gender and race variables from the model that predicts pay. The idea here is to predict pay based only on job and employee characteristics *other than gender or race:* What would an employee earn regardless of gender and race

[58] Requisition Vacancy IRC1505775. (ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx)
[59] Requisition Vacancy IRC2499832. (ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx)

based on their characteristics? Thus, I re-estimated the OFCCP's regression models each year, dropping gender and race as control variables, and then examined each person's actual and predicted pay.[60]

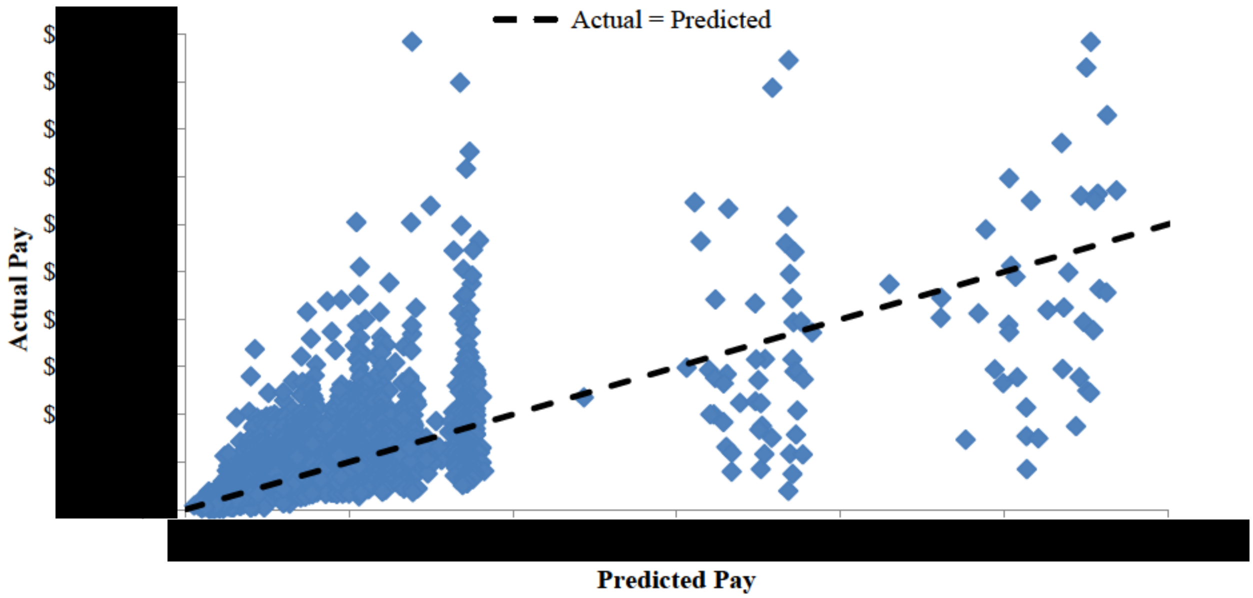
85. The graph below plots actual total compensation for each employee on the vertical axis and what their predicted compensation would be based on the non-gender, non-race variables in the OFCCP analysis on the horizontal axis. I have restricted this to employees whose actual pay is under [redacted] because otherwise much of the data points are compressed into the lower left corner. Each dot in the graph indicates a person-year in the data. The dashed line indicates where actual pay equals predicted pay. Dots above the dashed line indicate employees who are paid more than the OFCCP model predicts; dots below the line indicate employees who are paid less than his model predicts. By design, because regression models estimate the average effect, roughly half of all the points should be scattered randomly above the line and half below.

[60] I here use OFCCP's method of calculating total compensation – though I later explain in detail why such a method is wrong – because the objective here is to examine how well OFCCP's own approach fits the data regarding actual Oracle employees.

The OFCCP's Regression Model Cannot Explain Wide Pay Differences in Employees it Considers Similar: Actual vs. Predicted Total Compensation (Medicare Wages)

- Prediction Based on OFCCP Model, Without a Gender Control -

- 2013- 2018, INFTECH, PRODEV, and SUPP Job Functions -



Not shown: 21 observations whose actual pay exceeded $5 million.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

86. The first thing to leap out of the scatterplot is that many observations are clustered in the bottom left of the graph, even after restricting the population to those earnings under [redacted] The reason for this is there are quite a few observations whose actual pay is vastly higher than their predicted pay.[61] The OFCCP regression model cannot explain wide pay differences in employees it considers similar. For example, take the point along the horizontal axis at [redacted] which is where predicted pay equals [redacted] If one were to draw a straight line vertically from that point upwards, it would intersect with a dot for an employee below the dashed line indicating someone whose actual pay was below the predicted amount of [redacted]. If one were to continue that same line up from $[redacted] and intersect it with an employee dot above the dashed line, that is someone whose actual pay was higher than the predicted [redacted] Both of those dots represent employees who based on their observable

[61] For example, one employee was predicted to earn $[redacted] actually earned $[redacted] Another was predicted to earn $[redacted] but actually earned $[redacted]

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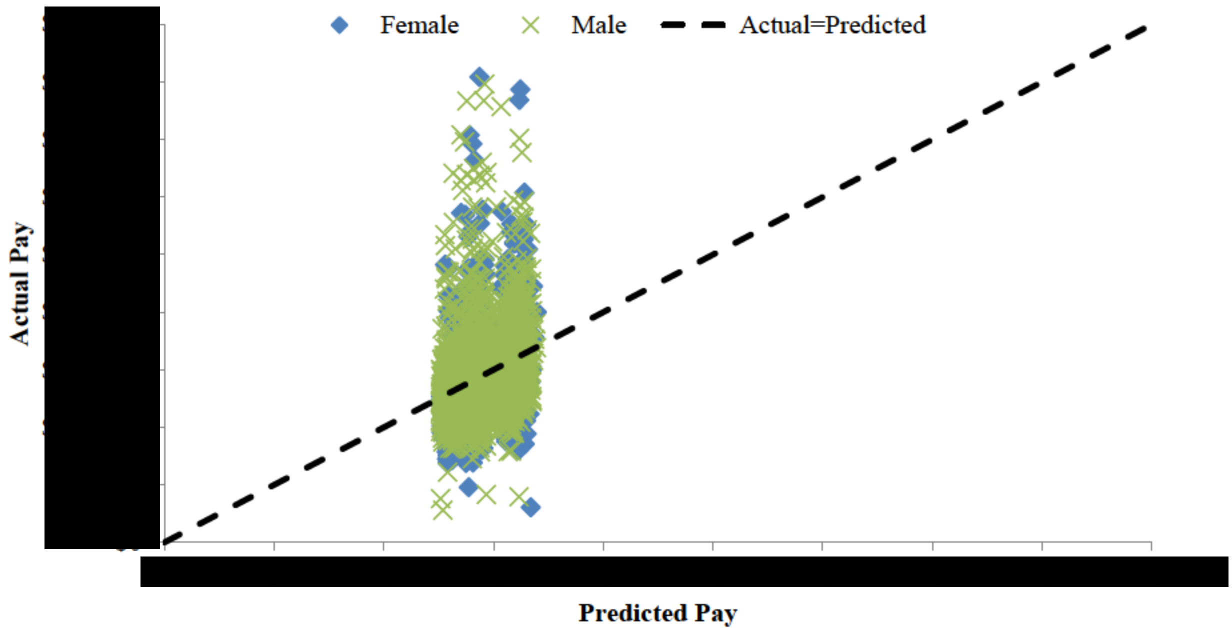
characteristics, were predicted by the OFCCP model to be paid $[redacted] but one is paid more than the expected $[redacted] and the other employee is paid less.

87. There are 13 observations whose predicted pay is between [redacted]0. Their actual pay, however, ranges from $[redacted]. This wide variation in actual pay between employees that the model considers roughly similar is unexplained by the regression model, because the model makes the same average prediction for all of them. There are several explanations for why the model is that far off explaining pay at Oracle. First, the OFCCP mis-measured total compensation by including portions earned by exercising stock options from previous years. Second, the control variables used in the model do not similarly situate employees and hence do a poor job at explaining pay generally. Third, the single regression model is applied to an employee population that is far too diverse.

The scatterplot below shows the same information as the graph above but it is restricted to full-time Software Developer 4s in order to drill down on the largest standard job title in the data. It shows women as blue diamonds and men as green hatches. All full time Software Developer 4s are predicted by the OFCCP model to earn between $[redacted] Their actual pay ranges from [redacted] to over [redacted] The highest earning Software Developer 4 according to the OFCCP data is a woman who, in 2016, exercised stock options she received years earlier, between 2000 and 2007. The OFCCP measurement of total compensation does not reflect work she performed in 2016 but rather her decision to cash in stock options. The second lowest earning female Software Developer 4 earned just under [redacted] due to her having been on unpaid leave from [redacted] through [redacted] Because the OFCCP model does not take leaves of absence into account, their model interprets her as being underpaid relative to her prediction. The lowest earning Software Developer 4 earned just over [redacted] for reasons that are unclear in the data, as his annual base pay at Oracle was [redacted] at the end of 2013 and Regular Earnings (recorded in the same dataset where Medicare wages are found) were over [redacted] for 2013.

.[62] The OFCCP measurement of total compensation does not account for all the wages she was paid in the year.

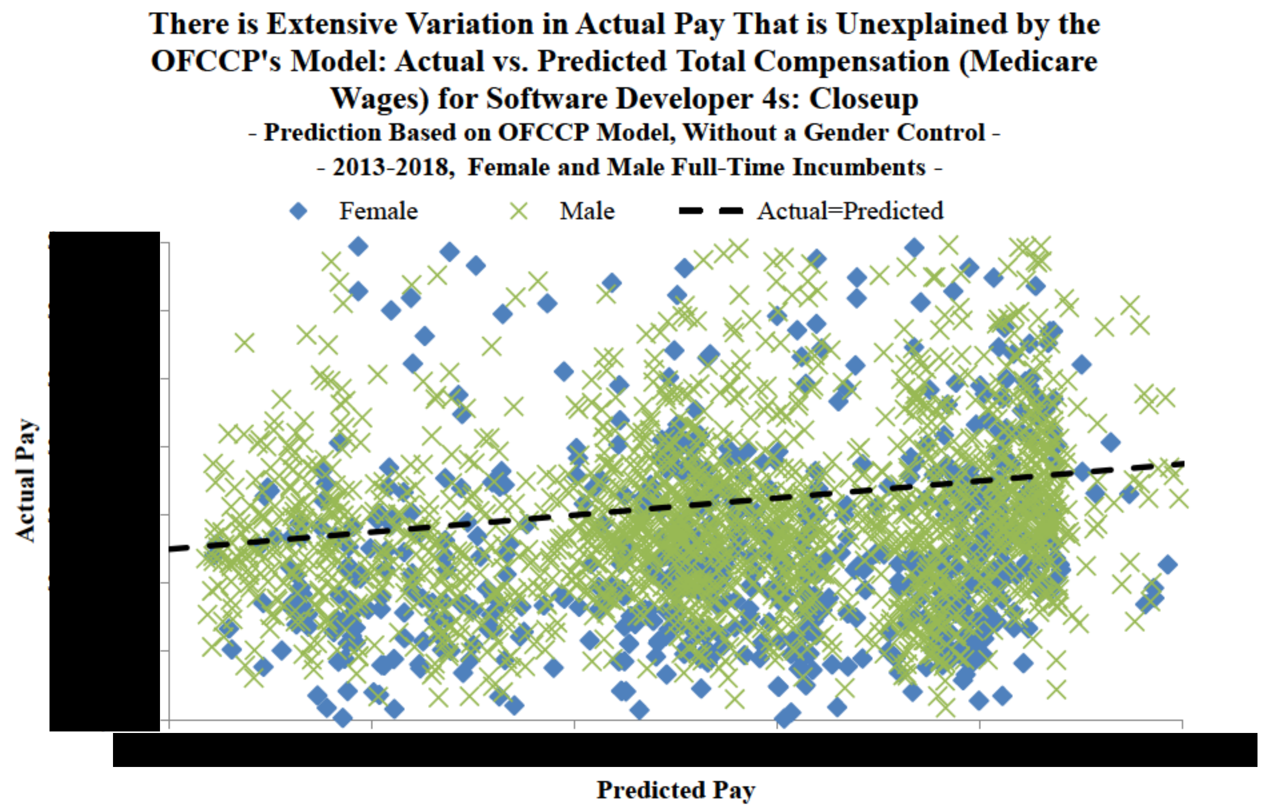
There is Extensive Variation in Actual Pay That is Unexplained by the OFCCP's Model: Actual vs. Predicted Total Compensation (Medicare Wages) for Software Developer 4s
- Prediction Based on OFCCP Model, Without a Gender Control -
- 2013-2018, Female and Male Full-Time Incumbents -



Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

88. The chart above shows how narrow the predicted pay band is ([redacted] relative to actual pay [redacted]. Even zooming in to the part of the chart where actual pay is between $[redacted] as shown in the chart below, the extensive variation in actual pay that is unexplained by the OFCCP model's prediction is evident.

[62] Person ID 893560722.



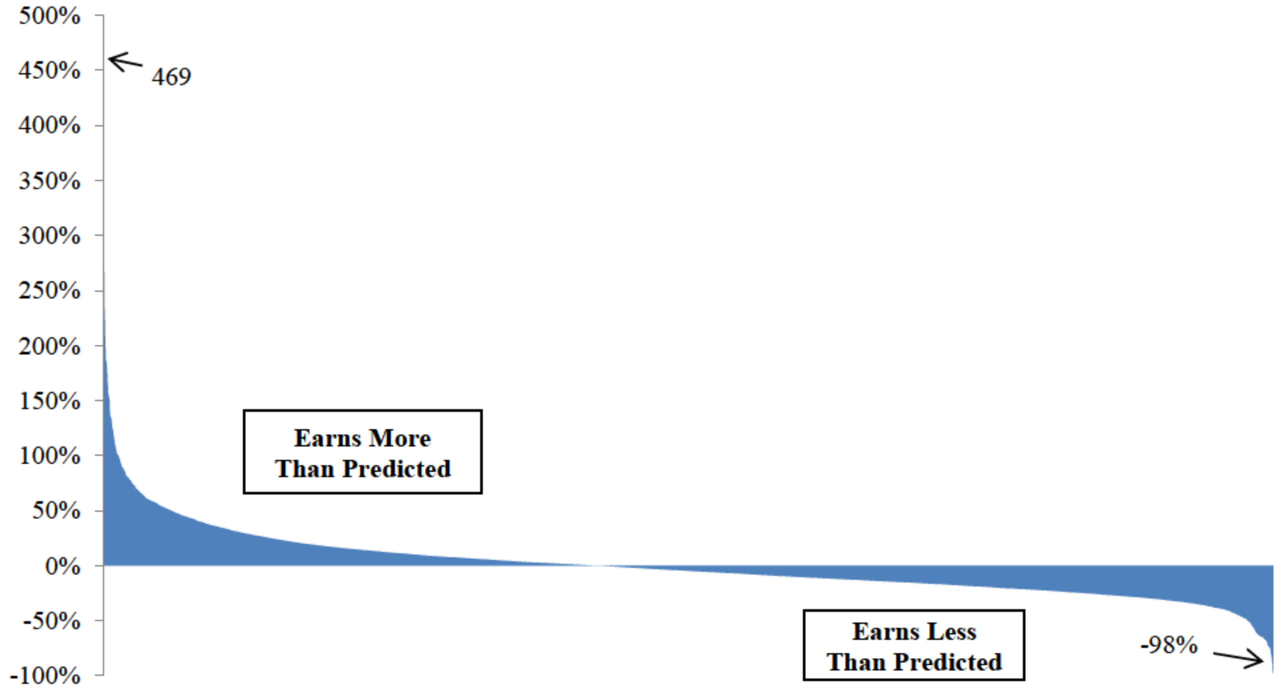
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

89. The OFCCP model cannot explain why some female Software Developer 4s earn so much more than predicted and some earn so much less. Employee 105257 (an Asian woman) was predicted to earn [redacted] but actually earned [redacted] in the "Transaction/Data/Space" organization. She has been at Oracle for 18.6 years, of which 14.3 have been as a Software Developer 4. Employee 116276 (also an Asian woman) was predicted by the model to earn about the same amount ([redacted] but she actually earned [redacted] in the "Public Cloud Platform Development" organization. She too worked for Oracle for 18.3 years but has only been a Software Developer 4 for 0.9 years. The OFCCP's model would attribute the gap between her actual and predicted pay as evidence of discrimination against women, but that model does not take organization or time in standard job title into account, and it cannot explain why the other woman earned so much more than predicted.

90. The next graph shows the same information for female employees but portrays it somewhat differently. As before, an employee whose actual pay is greater than her predicted pay is plotted above the horizontal axis and an employee whose actual pay is less than her predicted pay is plotted below the axis. The height of the bar measures for each female employee, the percentage by which actual pay differs from predicted pay.[63] Employee outcomes are sorted from highest to lowest. If most or all women were adversely affected by Oracle's pay policies and practices, they would largely appear below the horizontal zero axis – i.e., their percentages would be negative when comparing actual to predicted "should have been paid" pay. The graph shows that, even using the OFCCP model, 43% of women are not systematically adversely situated relative to men; the point at which the bars flip from positive to negative is near the middle of the graph, not over toward the left. That the height of the bars ranges from positive 469% to negative 98% shows that a one-size-fits-all regression model is likely inappropriate. A single regression coefficient on gender is a summary measure that masks a great deal of variation in what the OFCCP claims supports its contention that there is a pattern or practice of pay discrimination against women.

[63] This is calculated as (exp(residual)-1)*100.

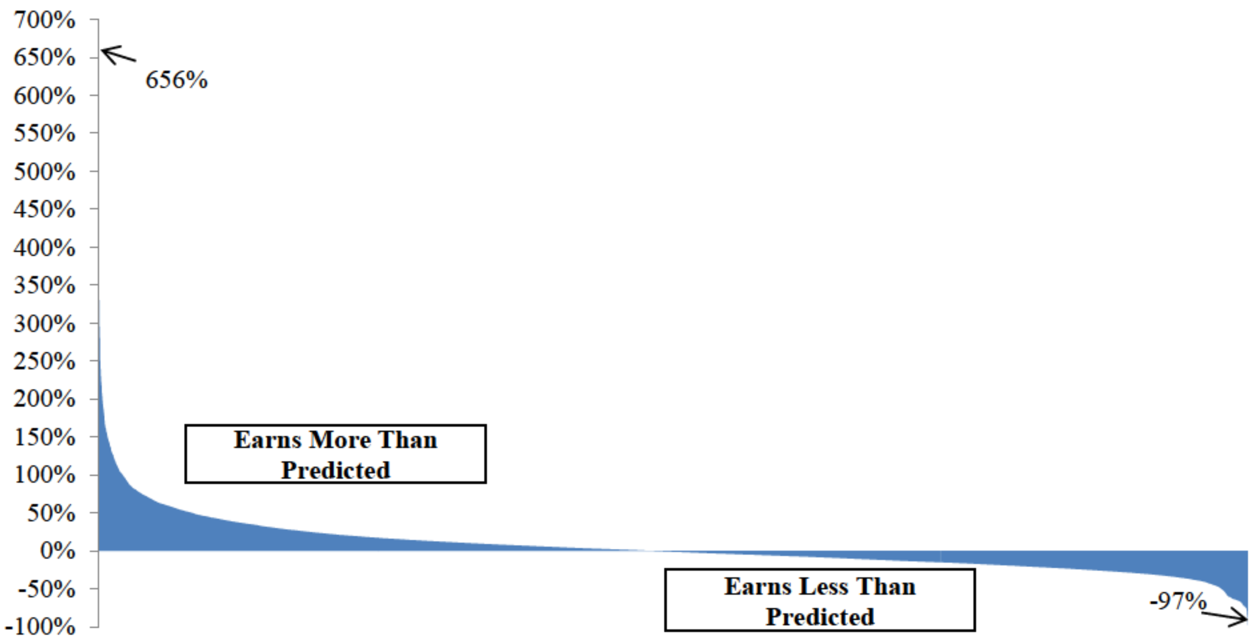
There is Wide Variation in the Percent Difference Between Actual and Predicted Total Compensation (Medicare Wages) for Women
- Prediction Based on OFCCP Model, Without a Gender Control -
-2013 - 2018, Female Incumbents in INFTECH, PRODEV, and SUPP Job Functions -



Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

91. The graph for Asians is quite similar, with the gap between actual and predicted pay ranging between positive 656% and negative 97%. Almost 48% of Asians earn more than the OFCCP model predicts. The OFCCP uses its model to argue that all Asians in PRODEV are underpaid and owed damages but looking under the hood, so to speak, the model is not a solid basis upon which to draw such a conclusion.

There is Wide Variation in the Percent Difference Between Actual and Predicted Total Compensation (Medicare Wages) for Asians
- Prediction Based on OFCCP Model, Without a Race Control -
- 2013-2018, Asian Incumbents in PRODEV Job Function -

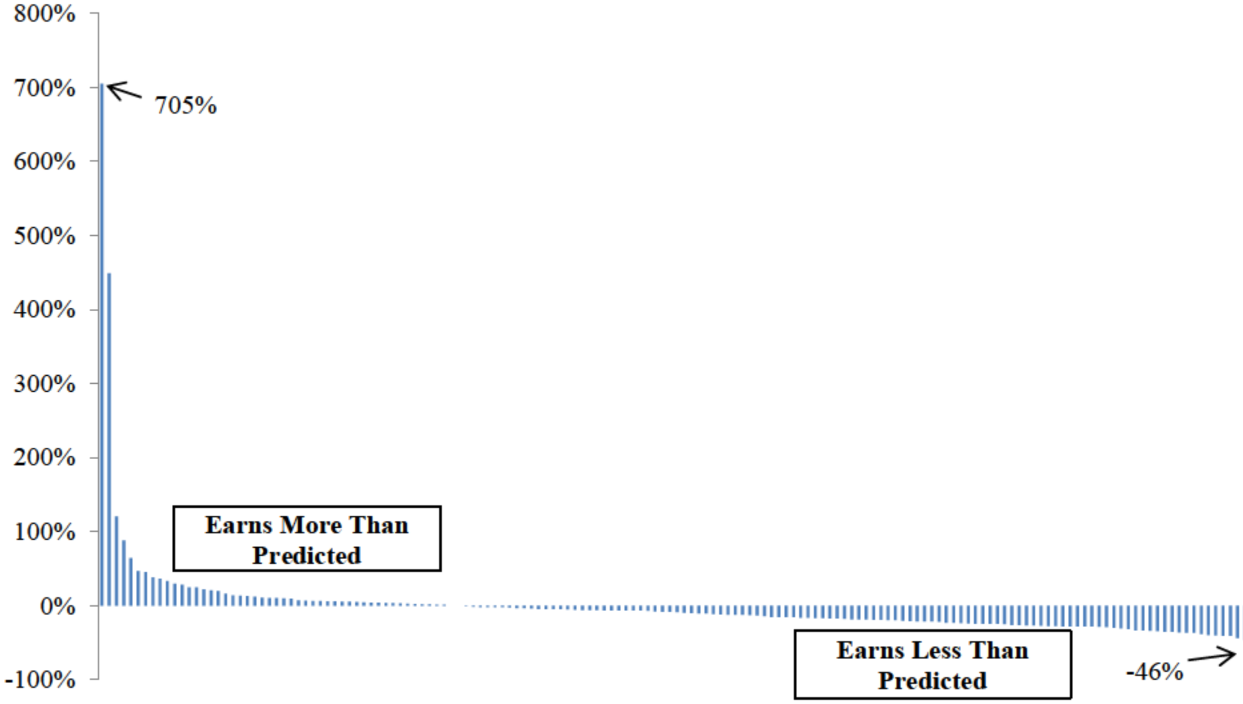


Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

92. A very similar pattern is evident for African-Americans, with the gap between actual and predicted pay ranging between positive 705% and negative 46%. The OFCCP estimates damages for African-Americans assuming all are underpaid but this graph shows how that is not the case even according to their own model.

There is Wide Variation in the Percent Difference Between Actual and Predicted Total Compensation (Medicare Wages) for African Americans
- Prediction Based on OFCCP Model, Without a Race Control -

-2013 - 2018, African American Incumbents in PRODEV Job Function -



Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

93. The OFCCP model is flawed, both in how it measures total compensation, and in what variables it includes as relevant control factors, as I further discuss below. The statistical issue in this case is whether Asians doing similar work to Whites are paid less, after controlling for other factors that impact and explain pay. A regression model answers this question by predicting pay based on an individual's job and personal characteristics (as reflected in the variables the analyst chooses) and then comparing that prediction to actual pay. This approach hinges on having the correct control variables, because otherwise it is not comparing "apples to apples." What the charts above show is that relative to the average benchmark set by the regression model, women and Asians can be paid well above what the OFCCP model predicts or well below that amount. The OFCCP does not address or even discuss *why* pay

diverges so much expected for employees supposedly doing similar work, or why the predictions their model generates are so far off from actual pay for so many employees.

<u>The OFCCP theories of discrimination treat Oracle as a monolithic entity and their models are aggregated to reflect that, but their analyses show a wide variety of outcomes across Oracle that directly conflict with that conception of the company</u>

94. In its March 11, 2016 Notice of Violation ("NOV"), the OFCCP claimed that Oracle discriminated against women, African Americans and Asians with respect to their pay. They used regression techniques to model gender and race pay differences in 2014 base pay after taking into account gender (race), work experience at Oracle, work experience prior to Oracle, full-time/part-time status, exempt status, and standard job title.[64] This is the same basic model the OFCCP uses in the subsequent SAC, although in the SAC the OFCCP applied the model on 2013 through 2016 data and used total compensation rather than base pay as the dependent variable.[65]

95. However, the OFCCP did not find issues at Oracle HQCA as a whole when analyzing data prior to issuing the NOV, but rather in three job functions for women, one job function for Asians, and one job function for African-Americans. If Oracle can be said to have a single set of pay practices, it should apply across all its job functions, and yet the OFCCP only claimed statistically significant disparities in three of the sixteen job functions they analyzed. I have not seen evidence that the process used to hire at Oracle over the time period covered by the OFCCP's allegations differed as between the three job functions they allege have pay issues and those they do not.

96. In the NOV, the OFCCP analyzed a database containing a 2014 snapshot of Oracle employees and their pay across 16 job functions at Oracle HQCA.[66] I used their program and data to run regressions

[64] Though the NOV states in Attachment A that global career level and job specialty were also accounted for, these factors are included in standard job title and so do not independently enter the model. DOL000001395-000001406.
[65] SAC, paragraph 13. For African Americans, however, the claim was still made about base pay and not total compensation. (SAC, paragraph 16)
[66] DOL000001395-000001406.

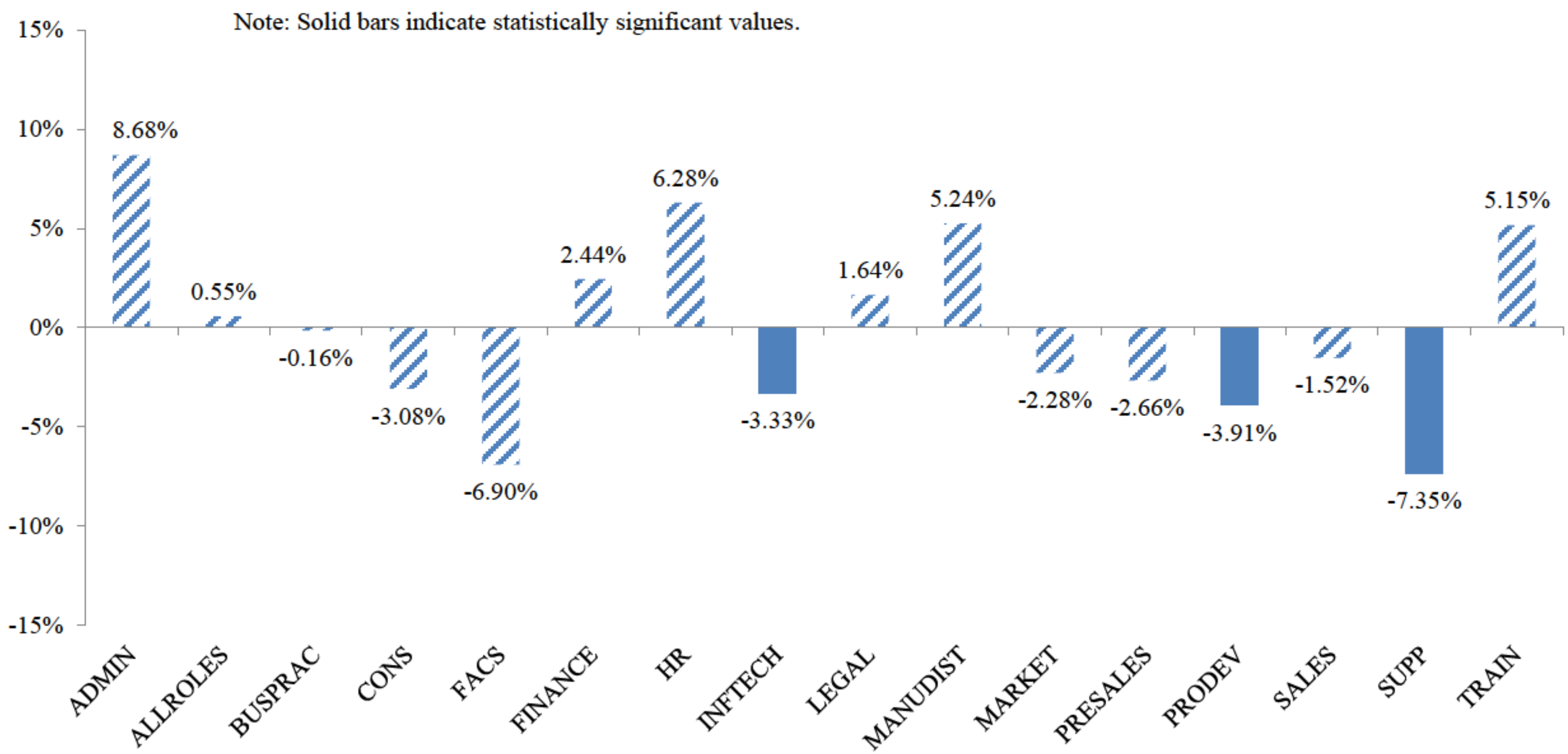
for all the job functions in the data.[67] The charts below show the coefficient on female and on Asian and African American found by running the OFCCP regression analysis. When the OFCCP applied the same regression model for all job functions, it did not find any statistically significant adverse pay differences for females other than in the PRODEV, INFTECH and SUPPORT functions and for Asians and African Americans, only in PRODEV.

97. The OFCCP does not makes claims across the board, and its NOV model generated pay differences adverse to the protected groups in only a subset of job functions. These findings are inconsistent with a claim that Oracle as a whole discriminates against these groups. But OFCCP nonetheless aggregated their regression models at the job function level.

[67] I was provided with OFCCP's backup programs and output with redacted sections and was able to replicate similarly to their findings for PRODEV, INFTECH, and SUPPORT. The OFCCP controlled for the following factors: standard job title (those with less than 5 employees are grouped together), full-time/part-time status, exempt status, global career level, job specialty, estimated prior work experience, and company. Note that grouping jobs with less than 5 employees together could group together very different employees with fundamentally different skills and responsibilities.

The OFCCP's NOV Analysis Shows No Systematic Pattern of Statistically Significant Results for Women vs. Men

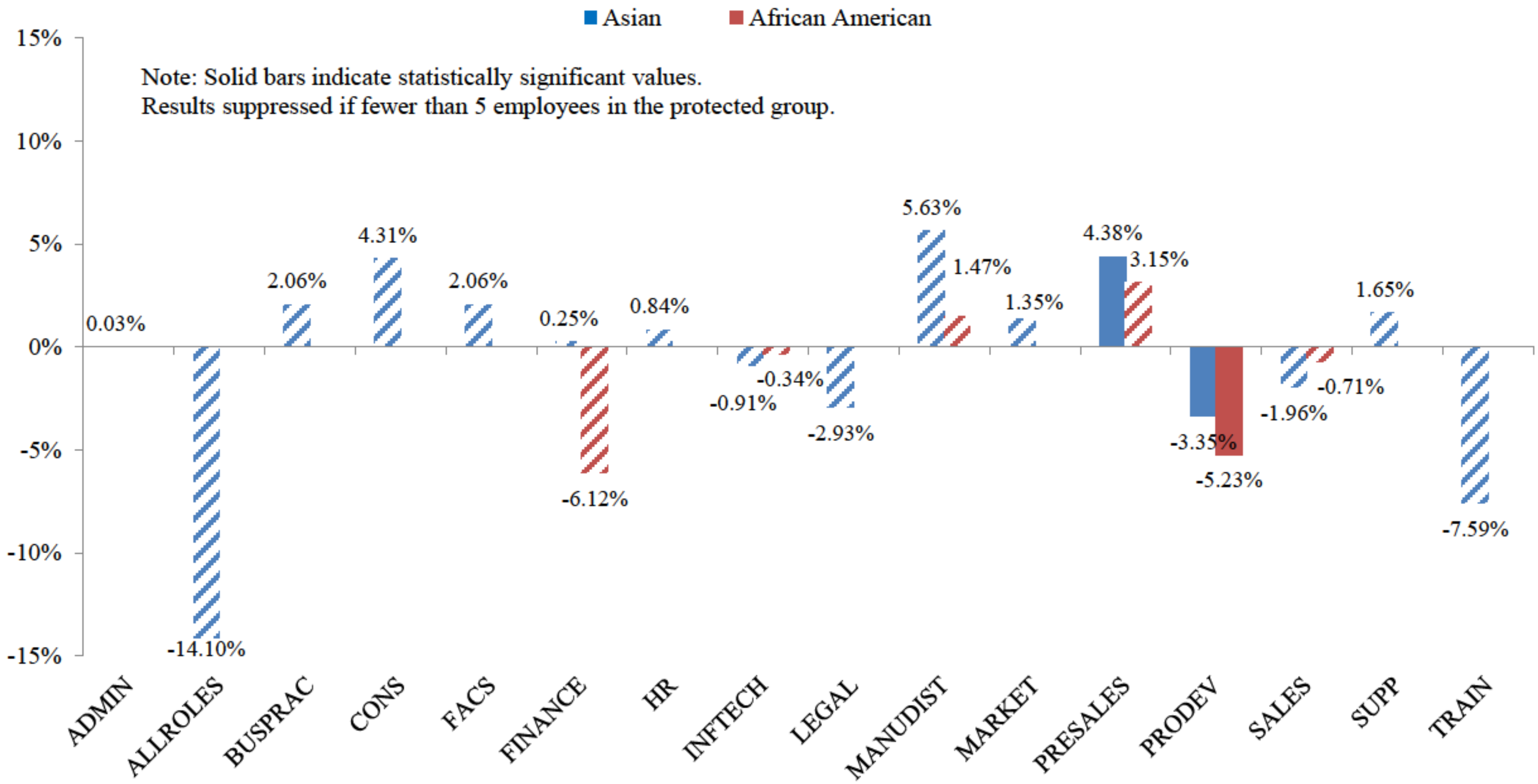
- OFCCP Presented the Three Statistically Significant Results and Ignored Thirteen Job Functions With Insignificant Results -



Model controls for female, standard job title (ones with less than 5 employees are grouped together), part-time/full-time, exempt status, time in company, and estimated prior experience (age minus 18).

The OFCCP's NOV Analysis Shows No Systematic Pattern of Statistically Significant Results for Asians and African Americans

- OFCCP Presented the One Statistically Significant Negative Result and Ignored Fifteen Job Functions With Insignificant Results -



Model controls for race, standard job title (ones with less than 5 employees are grouped together), part-time/full-time, exempt status, time in company, and estimated previous experience (age minus 18).

98. If pay outcomes at Oracle were due to some common, uniform practice used by all Oracle managers, there should be no manager-related patterns in the unexplained portion of pay (i.e., the difference between actual and predicted pay in the OFCCP model). One can examine this hypothesis by using the OFCCP model (without gender or race controls) to calculate the difference between actual pay and predicted pay using their model. Once this commonly applied model is run, we look at whether there are patterns in those residuals that suggest different supervisors make different decisions regarding pay for women and non-white employees, or whether no such patterns exist.

99. The pie chart below categorizes second-level managers[68] of women in all three job functions in 2014 according to the sign and significance of unexplained pay differences that come directly from the OFCCP model. I restrict the analysis to managers of at least ten employees and two women for convenience, but there is no issue with small sample sizes: the power of the statistical tests depends on the OFCCP model and data, not the number of employees being supervised.[69]

[68] The charts are based on managers two levels above the employee. Charts for third, fourth, and fifth level managers are in Attachment D.

[69] The same charts cannot be generated for African American employees because of the small sample size and our restriction to supervisors with at least 10 employees and 2 of the protected group.

Supervisors Two Levels Above Employee: Total Compensation (Medicare Wages) for Women

- Prediction Based on OFCCP Model, Without a Gender Control -

- 2014, PRODEV, INFTECH, and SUPP Job Functions -

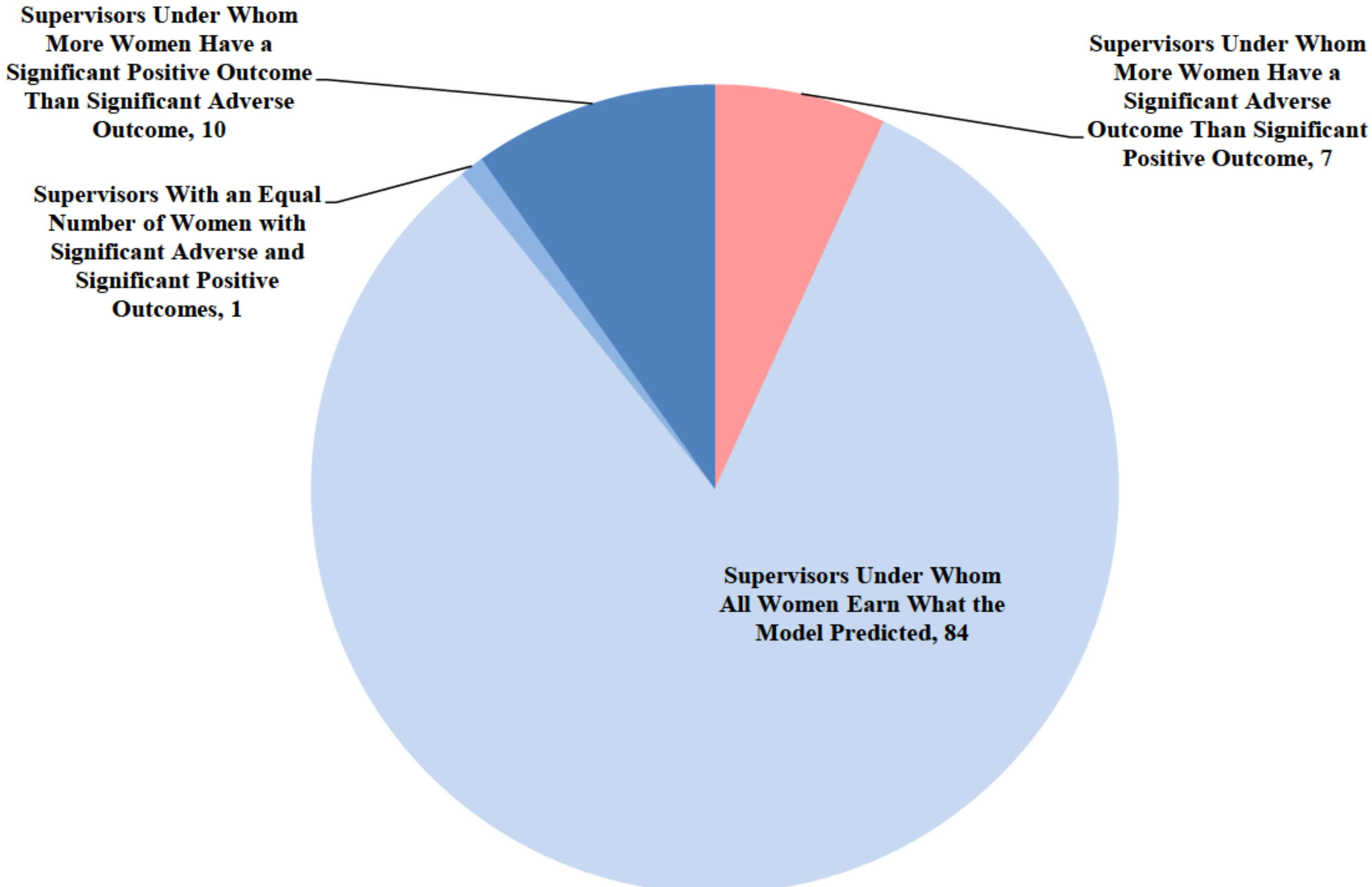


Chart is limited to supervisors with at least 10 employees and 2 women, accounting for 42.0% of women employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

100. The results show that for most managers, women earn about what the OFCCP model predicts they would make absent alleged discrimination (i.e., the difference between actual pay and the pay predicted by the OFCCP's aggregated model is not statistically significant). This is shown in the light blue slice of the pie chart above. The small, somewhat darker blue indicates managers under whom there are equal numbers of women who earn statistically significantly more than predicted and who earn statistically significantly less than predicted. The darkest blue slice represents managers under whom more women earn statistically significantly above the model's prediction than there are earning statistically significantly below predicted. The red slice indicates the share of managers under whom more women earn statistically significantly less than predicted than earn statistically significantly more. These results are generated using the OFCCP model with its flaws included – but even in that model, it is apparent that the pay experiences of women working under different managers varies considerably. This is inconsistent with a hypothesis of pay decisions being administered in a common, adverse, and centralized manner.

101. The pie chart above shows the distribution of managers according to the pay outcomes of the women they supervise. When the pie chart is instead redrawn to show the distribution of women under supervisors for whom more women in fact earn more or less than the OFCCP model predicts, it is clear that only a small minority of women work under supervisors where a greater number women are paid statistically significantly less than the OFCCP model predicts than are paid statistically significantly more than predicted under that same supervisor.

Employees by Supervisors Two Levels Above: Total Compensation (Medicare Wages) for Women

- Prediction Based on OFCCP Model, Without a Gender Control -

- 2014, PRODEV, INFTECH, and SUPP Job Functions-

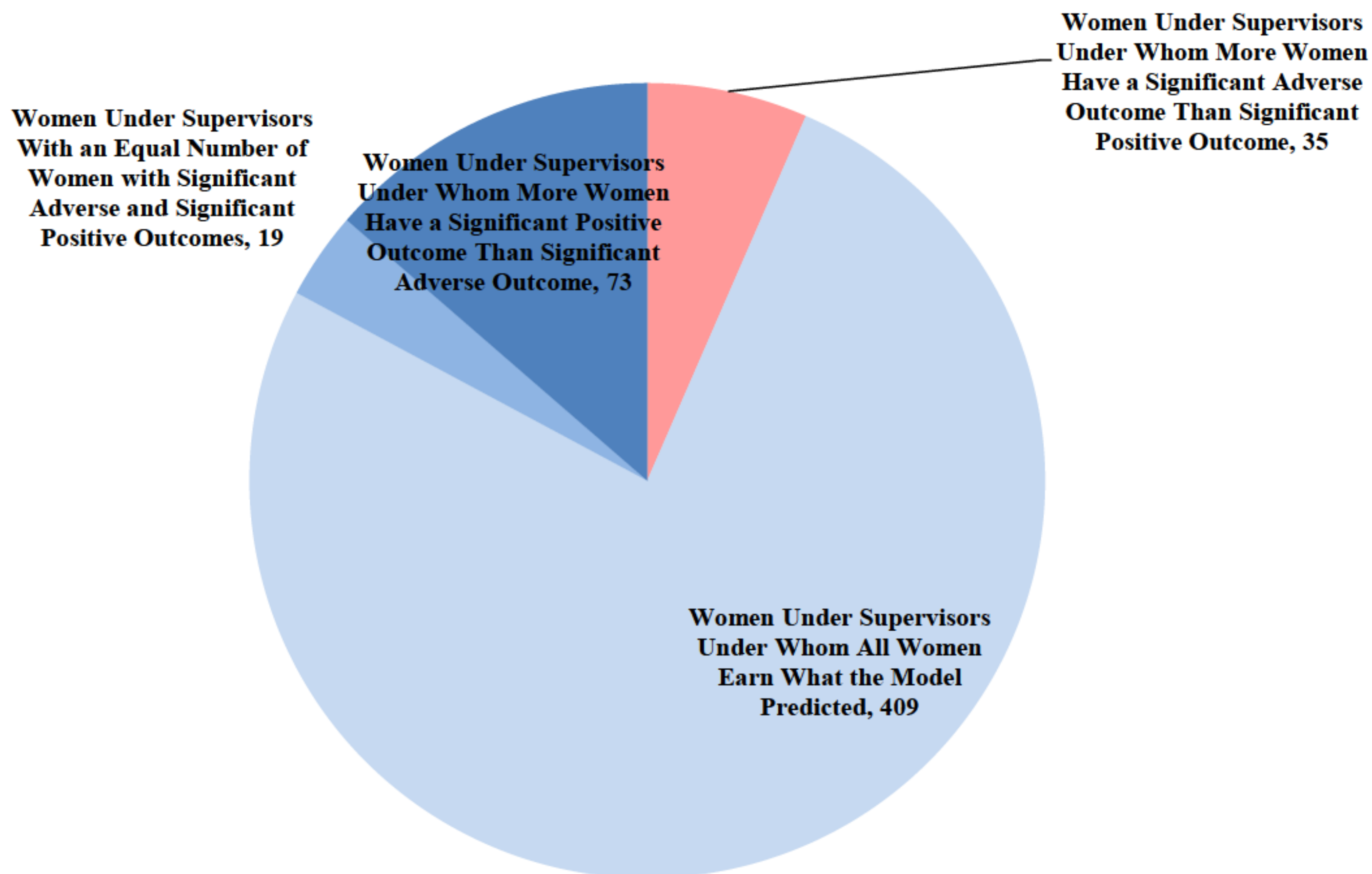


Chart is limited to supervisors with at least 10 employees and 2 women, accounting for 42.0% of women employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

102. The results for Asians also indicate a role for managerial decision making that the OFCCP model does not account for. Again, most supervisors of Asian employees in PRODEV have more Asians earning what the model predicts or earning statistically significantly more than that. Similarly, the majority of Asians work in supervisory units where more Asians tend to earn statistically significantly more than the OFCCP model predicts than earn statistically significantly less.

Supervisors Two Levels Above Employee: Total Compensation (Medicare Wages) for Asians

- Prediction Based on OFCCP Model, Without a Race Control -

- PRODEV Job Function, 2014 -

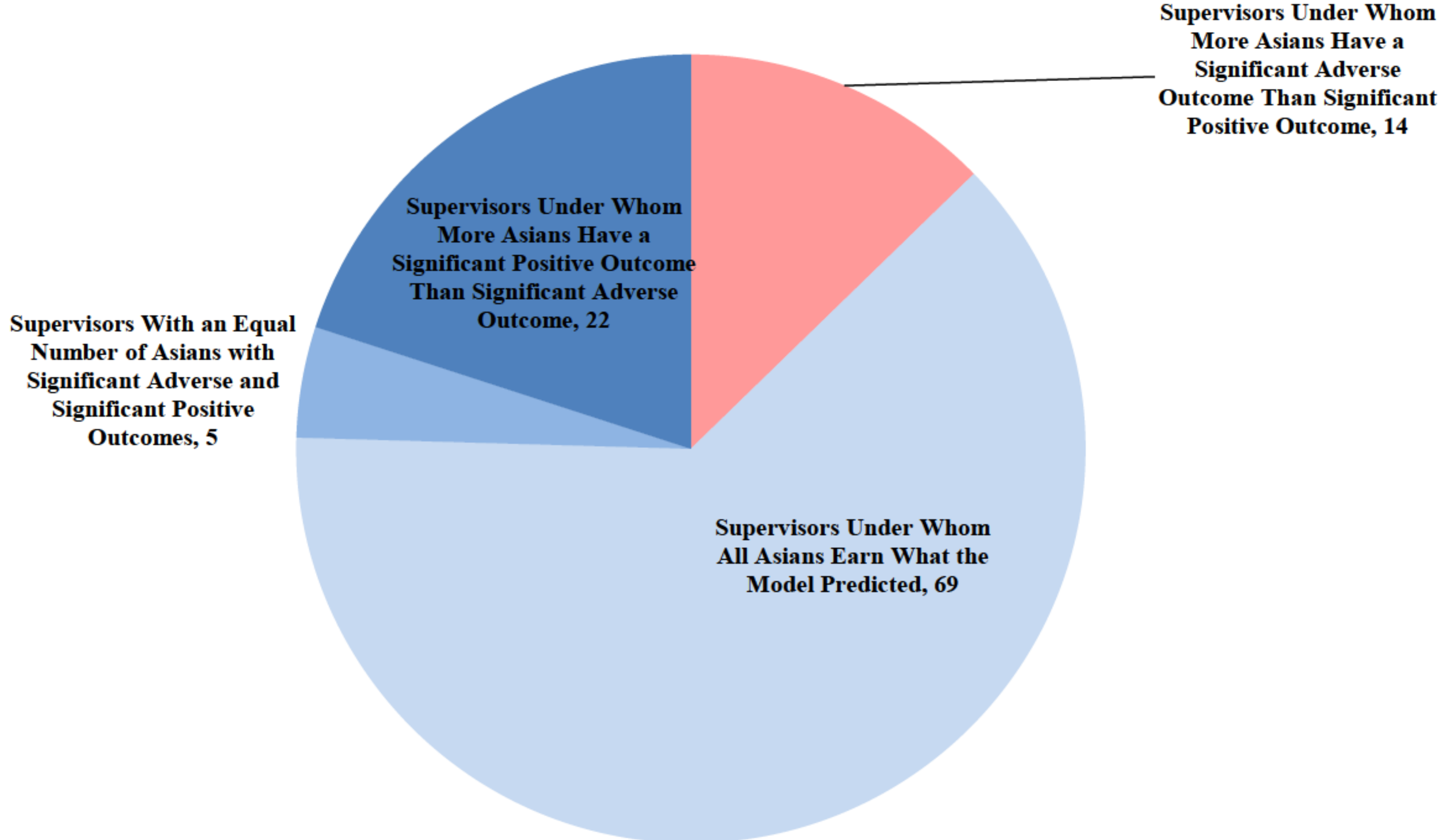


Chart is limited to supervisors with at least 10 employees and 2 Asians, accounting for 52.2% of Asian employees. Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Employees Under Supervisors Two Levels Above: Total Compensation (Medicare Wages) for Asians

- Prediction Based on OFCCP Model, Without a Race Control -

- PRODEV Job Function, 2014 -

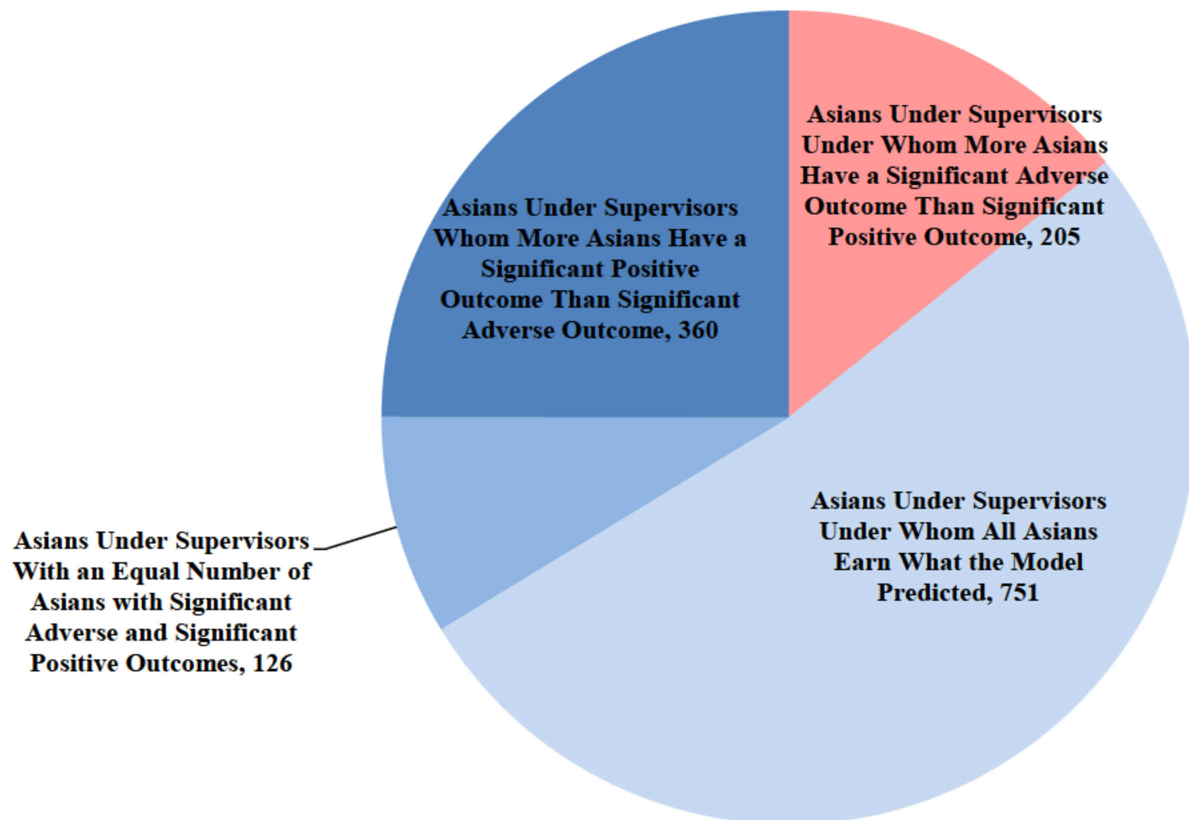


Chart is limited to supervisors with at least 10 employees and 2 Asians, accounting for 52.2% of Asian employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

103. The OFCCP claims three of sixteen job functions discriminate against women and/or Asians, but propose that this is accomplished with *companywide* policies regarding starting pay and pay raises and career development thereafter. Their discussion of that claim does not explain why only three job functions would be purportedly affected by companywide policies. One way to make sense of their argument is to claim managers in those job functions behave differently than the others.[70] That, however, leaves open the question of whether managers inside those job functions at issue also behave in varied ways, but their model fails to incorporate any managerial effect.

104. I turn next to a discussion of what the OFCCP did in their regression models, and why what they did is incorrect and highly misleading.

<u>THE OFCCP ANALYSIS IS SERIOUSLY FLAWED AND DOES NOT SUPPORT THEIR CLAIMS WHEN THE REGRESSION APPROACH IS MORE REFINED</u>

<u>The OFCCP did not measure total compensation correctly</u>

105. The OFCCP's NOV analysis is flawed in that it analyzes base salary rather than total compensation.[71] However, the total compensation measure adopted by the OFCCP in its SAC analysis is also incorrect. In its total compensation models, the OFCCP uses a measure from employee W-2 data called Medicare wages. But Medicare wages are simply the taxable earnings of an employee in that year.

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[70] This approach does not account for supervisory chains that cross job functions. For example, [redacted] an Asian male (Person ID 200179), was a manager in INFTECH until December 2011 when he transferred into PRODEV. [redacted] also an Asian male (Person ID 887465652), worked in INFTECH and was directly managed by [redacted] from April 2010 to February 2015. [redacted] also then transferred into PRODEV and continued to directly report to [redacted] for another year. (ORACLE_HQCA_0000070738_Emp_Personal_Experience_Qualification_Assign_Details.xlsx) According to the OFCCP hypothesis, [redacted] would not have been discriminated against by his manager while he was in INFTECH, but would have been upon moving into PRODEV under the same manager.

[71] It is total compensation that matters, and not simply base pay or even bonuses or stocks considered in isolation. From the Global Compensation Training Manual: "When recruiting you should consider the value of the "total reward" rather than salary alone, both tangible and intangible: Value of base salary, annual target variable (ATV)/bonus, Benefits (retirement plan, medical, life and disability insurance, car/car allowance, etc.), Oracle experience, training, career development, long term opportunities, location etc." (ORACLE_HQCA_0000000407_Global Compensation Training - 2011 Managing Pay Final (Native).PPTX)

The problem with this measure of total compensation is that the employees can receive significant amounts of stock in any given year, but due to awards vesting over time (four years typically for each award) the dollar value of an award given in a year will not appear in the year of the award, and hence not on that year's W-2. Instead, what will appear is taxable dollars from the exercise and sale of *previously received* options or the sale of *previously received* RSUs that occurred in that year. Thus, an employee can receive a share award in a given year, and not realize any dollars of taxable income related to that award until years later.[72] Taxable pay is also affected by the decisions employees make about 401k contributions[73], and by variations in the share exercise behavior of employees. If the purpose of the regression analysis is to examine earnings attributed to a particular year, one should not use the W-2 data. Total compensation for work performed in a year should instead be measured as base pay plus bonuses earned and stock awarded *in that year*. The data that was produced by Oracle permits this computation, but the OFCCP failed to use it correctly.

106. For example, Oracle employee [redacted] was a fulltime Senior Vice President for the entirety of 2014. His Medicare EE taxable entry was [redacted], and this is what OFCCP used as his total compensation for that year. The same data set shows his 2014 Regular Earnings were [redacted] and that [redacted]

[72] Oracle's 2018 Stock Plan describes tax consequences of various decisions by the employee regarding their stock options, which is very similar to previous years' plans: "If you exercise your options and hold the shares […], you will include in income as compensation an amount equal to the excess of the fair market value of the shares on the exercise date over the option exercise price. The included amount will be treated as ordinary income and, if you are an employee, will be subject to income tax and FICA (Social Security and Medicare) withholding by Oracle […]. If you exercise your options in a cashless sell-all transaction […], you will include in income an amount equal to the excess of the selling price of the underlying shares over the option exercise price. The included amount will be treated as ordinary income and, if you are an employee, will be subject to income tax and FICA (Social Security and Medicare) withholding by Oracle. […] If you are an employee, the income recognized upon exercise will be included on your Form W-2 for the year in which the option is exercised […]." RSUs are also treated as ordinary income when they vest. (Oracle_HQCA_0000416526_2000 LTIP 02 01 2018.pdf, p. 19-20, edited for readability.)

[73] According to the Employee Handbook, employees can contribute up to 40% of their cash compensation (salary, bonus and commission) on a pre-tax basis. (Oracle U.S. Employee Handbook, ORACLE_HQCA_0000000464)

[74] ORACLE_HQCA_0000070722_AllEarnings2.xlsx

[75] ORACLE_HQCA_0000581403_Stock_Data_Product_Statement_Combined.xlsx

[redacted] That he decided to exercise those options in 2014 does not mean that they represent his compensation for the work he did *in that same year*. His Medicare EE Taxable pay includes the delayed compensation he earned in other years but happened to cash in this particular year, presumably because he deemed it advantageous financially to do so. Counting his [redacted] While this is a particularly vivid example, there are thousands of cases similar to this, where the OFCCP failed to properly measure total compensation for work performed in the year they were supposedly examining pay.

107. The example above shows how the OFCCP's measure can overestimate actual total compensation for employees in a given year. The OFCCP measure of "total compensation" also can severely underestimate actual total annual compensation. Employee [redacted] worked full time, all year as a Software Developer 2 in 2013. His base pay in the data was [redacted]; his Regular Earnings were [redacted] and his Medicare EE Taxable pay was [redacted]. He earned [redacted] and was awarded [redacted]. Correctly calculated, this employee's total compensation in 2013 was [redacted] To correctly measure total compensation associated with work in a given year, the OFCCP should have used base pay plus bonuses earned and stock awarded within that year.[76]

<u>The factors the OFCCP adopted as control variables in their Notice of Violation and Second Amended Complaint regression models do not similarly situate employees with respect to their characteristics and the nature of the work they are doing</u>

<u>The OFCCP used flawed measures of tenure and experience in their Notice of Violation analysis, which they then repeated in their Second Amended Complaint analysis</u>

108. The OFCCP included a proxy intended to measure prior work experience, as well as tenure at Oracle America, Inc., in the analyses supporting their claims in the NOV and in the SAC. Prior

[76] See US Manager's Orientation presentation dated December 6, 2016 (ORACLE_HQCA_0000042091_MASTER US Manager Orientation 1201 (Native).PPTX) which describes the components of compensation and divides it into base pay, short-term incentives (bonuses), and long-term incentives (stock options and restricted stock units).

experience was measured as age minus 18 minus years at Oracle America, Inc.[77] Time worked at Oracle affiliates in other countries (like Oracle India), and time worked at companies that were later acquired by Oracle, are thus counted as prior experience rather than as Oracle experience. This error was easily avoided using the data provided in the case. The data contain, and OFCCP could have used, an employee's "continuous service" hire date to measure total Oracle tenure, which includes any time spent in other Oracle affiliates or at a firm that was acquired.

109. "Human capital" is the knowledge and skill an employee gains through education and labor market experience. Economists distinguish between "general" human capital, or skills and abilities that an employee would bring to any firm, and "specific" human capital, i.e., the detailed knowledge more valuable to a particular company than to other companies. [78] The OFCCP analysis confuses the two by grouping years worked at directly relevant entities (non-U.S. Oracle affiliates and acquisition targets) in with all other potential work experience rather than counting it as Oracle-specific relevant experience along with time at Oracle America, Inc. A person working on Oracle products and services at its India affiliate is more likely to have direct relevant experience to Oracle products and services in the United States. Similarly, someone whose company is acquired by Oracle is more likely to have direct relevant experience to the work they perform once they are at Oracle.

110. The OFCCP method for estimating prior experience is over-inclusive, in that it counts as general experience years which should be counted as "tenure at Oracle," and also in that it counts all years since age 18 prior to joining Oracle America, Inc. as prior work experience without accounting for periods of unemployment or other non-work periods. Again, prior experience is measured in OFCCP models as age minus U.S. Oracle tenure minus 18 years. Someone who took a year off before applying to Oracle, such as Employee ID 892041040 who was hired in February 2013, is credited by the OFCCP as having the

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[77] More typically, years at college are not included in these kinds of measures and so I use age minus total Oracle tenure minus 22.

[78] Becker, Gary S. *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press, 2009.

same amount of prior experience as someone of the same age hired in 2013 who did not take a year off.[79] Because women are more likely to have breaks in their work histories, "potential" work experience tends to over-estimate prior experience for women more than for men.[80] This in turn leads to biased regression models because the model credits many women with more prior work experience than they in fact have, and so over-predicts expected pay.

111. These crude techniques for estimating experience also do not account for the relevance of that experience. A Software Developer's summer cashier job in a bookstore, for example, does not convey anything useful to a technology company assessing their programming skills. This is not an abstract concern. Employee 891368075 was hired as a User Experience Developer 3. The OFCCP's method for defining prior experience treats her year working at Walt Disney World Inc. as a cast member at Epcot, trainer, and campus representative the same as her years of work at Microsoft as a Program Manager in the Office User Experience Team.[81]

<u>The OFCCP did not take leaves of absence into account</u>

112. The OFCCP tenure measures are also incorrect because they do not take leaves of absence into account. An employee who had a heart attack and missed seven months of work, for example, has less tenure than an employee hired the same day who worked continuously over the same time frame. This matters when it comes to compensation, because all else constant, more time spent engaged doing work is generally correlated with increased productivity and pay, as is well-established in the labor economics literature.[82] This is of particular interest in the gender context because women tend to take more leave

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[79] The manager comments for Vacancy ID 1945800 note that "[redacted]

[80] Mincer, Jacob, and Solomon Polachek (1978). An Exchange: The Theory of Human Capital and the Earnings of Women: Women's Earnings Reexamined. *The Journal of Human Resources* 13(1):118-134. Killingsworth, Mark R., and James J. Heckman. (1986) "Female labor supply: A survey." *Handbook of Labor Economics* 1: 103-204.

[81] Person ID 891368075, whose resume appears in ORACLE_HQCA_0000083390.pdf. This person also does not list any work experience between October 2007 and May 2009, but the OFCCP method of counting experience would not account for this.

[82] See Ehrenberg, Ronald G., & Smith, Robert S. (2015). *Modern Labor Economics: Theory and Public Policy*. Twelfth Edition. Pearson, pp. 390-391 on how as a general principle earnings tend to increase

than men.[83] Incorrect tenure measures for women are a well-documented issue in estimating pay regression models.[84] Essentially, the regression model systematically over-predicts pay for those who take time off from work because it assumes they have more time on the job than they actually do. In other words, the gap between actual pay and predicted pay is exaggerated because the model does not measure work experience properly. The omission of leaves of absence biases the prior experience estimates for all leave takers; but because women take more leave than men on average – both in general and at Oracle in particular – this means that the effect is more problematic for women than men.[85] Also, from a practical perspective, bonuses at Oracle may also be adjusted to take time worked that year into account – so the failure to account for leave is problematic for analyzing bonuses as well.[86]

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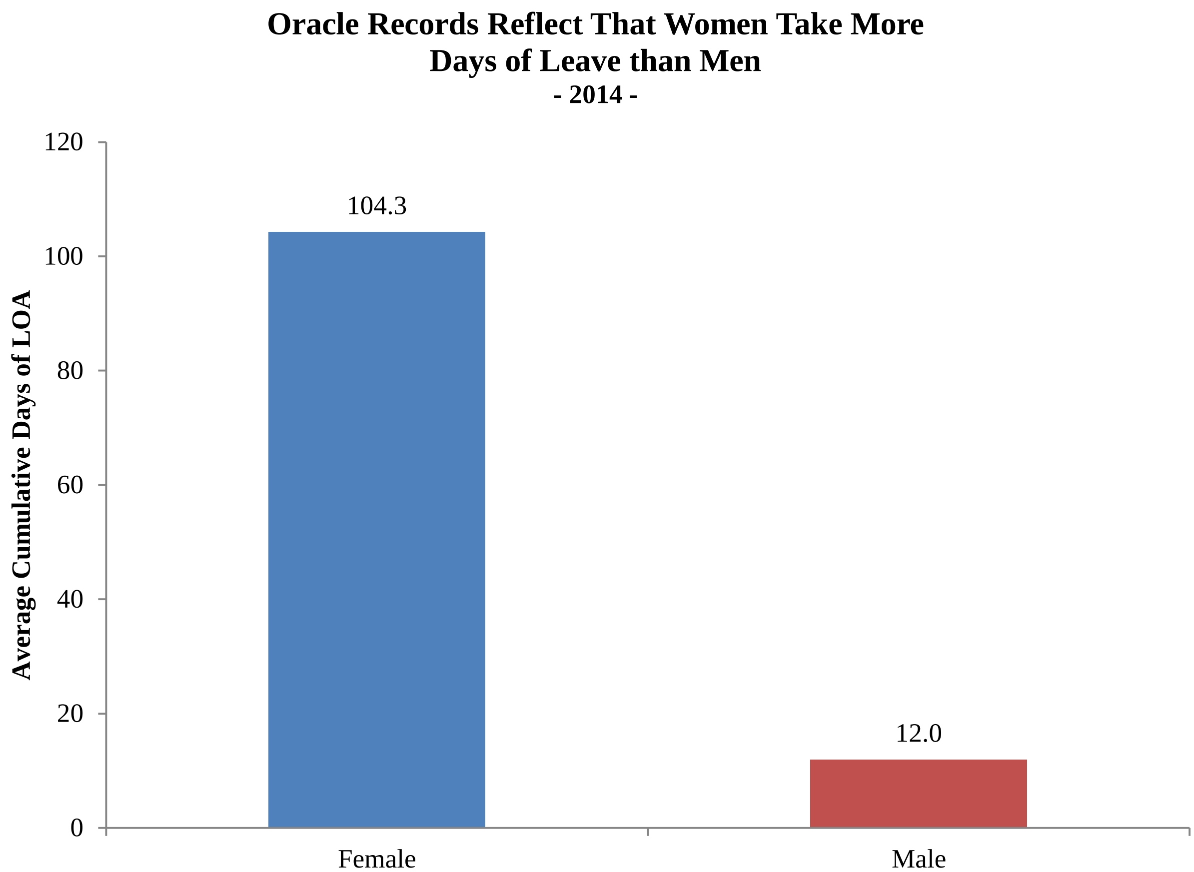
with job tenure because of on-the-job training and experience. This general principle not hold true in every specific instance, however, and it is not true of all jobs at Oracle. As noted in this report, there are jobs for which the pay premium from additional tenure is very different from other jobs.

[83] Mincer, Jacob, and Polachek, Solomon (1974). "Family investments in human capital: Earnings of women." *Journal of Political Economy*, 82(2, Part 2): S76-S108. Spivey, Christy (2005). "Time off at what price? The effects of career interruptions on earnings." *ILR Review*, 59(1): 119-140. Waldfogel, Jane (1998). "Understanding the" family gap" in pay for women with children." *Journal of Economic Perspectives*, 12(1): 137-156.

[84] Mincer, Jacob, and Polachek, Solomon (1978). "An Exchange: The Theory of Human Capital and the Earnings of Women: Women's Earnings Reexamined." *The Journal of Human Resources* 13(1):118-134. Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz (2010). "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors." *American Economic Journal: Applied Economics,*2(3): 228-55. Goldin, Claudia. (2014) "A grand gender convergence: Its last chapter." *The American Economic Review* 104, no. 4: 1091-1119. Blau, Francine D., and Lawrence M. Kahn. (2017) "The gender wage gap: Extent, trends, and explanations." *Journal of Economic Literature* 55, no. 3: 789-865. Killingsworth, Mark R., and James J. Heckman. (1986) "Female labor supply: A survey." *Handbook of Labor Economics* 1: 103-204.

[85] For a study of how loss of experience affects men who temporarily leave the labor force, see Angrist, Joshua D., Stacey H. Chen, and Jae Song. (2011) "Long-Term Consequences of Vietnam-Era Conscription: New Estimates Using Social Security Data." *American Economic Review*, 101 (3): 334-38.

[86] At Oracle, bonuses can be prorated for work during the year. "Furthermore, bonuses may be prorated to reflect time not worked in a bonus period (due to leave of absence, transfer, new hire, part-time, or change of status from hourly to salaried.) Oracle U.S. Employees Handbook, p. 42. (ORACLE_HQCA_0000000464.pdf)



113. For acquisitions and transfers from non-US Oracle affiliates, the leave data is incomplete because the available data indicates their original hire date at the predecessor company but does not record their leave histories at that company. This can be controlled for at least in part by including variables that indicate an employee came to Oracle through a lateral transfer from an affiliate or were an experienced external hire.

<u>The OFCCP did not control for time in standard job title, a factor which impacts pay within a job, and which is used by Oracle managers in promotion decisions</u>

114. OFCCP did not control for tenure in the current standard job title. But the research literature in labor economics is quite clear about the importance of job-specific skills in explaining pay and

promotion.[87] Time in standard job title also appears in the information managers compile to justify a pay raise or promotion.[88] In contrast, the OFCCP model considers someone new to a position to be as skilled as someone who has worked in the position for years, as long as both were hired at Oracle in the same year.

<u>The OFCCP does not control for the products or services employees work on, and instead simply aggregates together employees working on very different products requiring different skills and abilities</u>

115. Labor economists have shown that pay is a function of productivity, and the more the employee contributes to the bottom line, the more they tend to be paid.[89] All else constant, an employee working on a highly profitable product or an innovative new product with high profit potential will be paid more than an employee working on a low profit margin product.[90] The employee on a highly profitable product or a

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[87] Becker, Gary S. (2009) *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press. This phenomenon is also studied in the job matching literature, examining how well workers match to jobs. See, for example, Jovanovic, Boyan. (1979) " Job Matching and the Theory of Turnover." *The Journal of Political Economy*, Vol. 87, No. 5: 972-990.

[88] ORACLE_HQCA_0000022967 IC Promotion Template.pdf. The PRODEV templates also track industry experience. ORACLE_HQCA_0000022954 PD Promotion Template.pdf. ORACLE_HQCA_0000023006 PD Manag Promotion Template.pdf.

[89] In labor economics, wages in the short run are influenced by wages in the market, the demand for the company's product and the structure of the market they compete in. See for example, Cahuc, Pierre and Andre Zylberberg (2001) *Labor Economics*, Cambridge: The MIT Press, p. 175. Firms also often link pay to group or company profits when work by necessity is organized in teams and individual output is difficult to observe (as is the case with software developers whose productivity is not measured simply by number of lines of code, for example, because quality of code is prized over quantity). Ehrenberg, Ronald G., and Robert S. Smith (2015) *Modern Labor Economics: Theory and Public Policy*. Twelfth Edition. Pearson Education Inc., pp. 60-70, p. 374. Lazear, Edward, P. (2000) "Performance Pay and Productivity." *American Economic Review*, 90 (5): 1346-1361. These factors are readily apparent in managers' business justifications for raises and promotions as well. "If [redacted] were to leave the [redacted] team, we will not be able to meet the current release schedule for [redacted] and this will have a significant impact not only on our Fusion Middleware customers, but our Oracle Enterprise Repository customers into the foreseeable future. While these products contribute roughly [redacted] in license revenue for Oracle by themselves, they are key differentiators to a growing segment of our middleware customers. Further, [redacted] is cited as a key differentiator against [redacted] offerings. We need to continue to invest and accelerate the applicability of this product in the context of application integration to further our differentiation against our [redacted] competitor." (ORACLE_HQCA_0000423688_CF_81005385_478564052.xlsx)

[90] Kate Waggoner was asked in her deposition what product had to do with salary setting. "Product, if I'm thinking like software developers, the product they are developing, if it's a really old legacy product or a cutting edge new product, and there's not a lot of talent out there that know how to do this, they would command a higher position in the range versus somebody who's working on J.D. Edwards that's existed forever." Waggoner May 1, 2019 deposition 91:4-10.

strategic product considered key to future growth is also more likely to be recruited by a competitor, thereby driving up their pay at Oracle.[91]

116. It is my understanding that "organization" recorded for each employee in the data is correlated, at least in a general way, with products and services worked on. This is reflected in the declaration of Steven Miranda and letters between the attorneys in the present matter, as well as in the requisitions discussed above.[92]

117. In the incumbent pay models, I control for both standard job title and organization.[93] While an organization may encompass more than one product or service, the variable is a useful proxy for the

[91] This is evident from the managerial justifications for salary increases and promotions called "Dive and Save" interventions. For example, pay raises for several employees on a team were described as necessary because "One of our [redacted] groups, the [redacted]ecently lost 3 of their 8 people. Several companies in the area are heavily recruiting from our [redacted] database teams. Top developers who joined in the last few years are especially vulnerable [sic]." (See ORACLE_HQCA_0000423720_CF_81077593_478616283.xls; ORACLE_HQCA_0000423721_CF_81077832_478616360.xls; ORACLE_HQCA_0000423722_CF_81077871_478616398.xls; ORACLE_HQCA_0000423723_CF_81077970_478616422.xls; ORACLE_HQCA_0000423724_CF_81078057_478616432.xls)

[92] The "Organization_Name" field contains alphanumeric codes that reflect the cost centers in which each employee works. Cost centers are developed, altered, or deleted in partnership between finance, the business, and HR. These groups work together to organize jobs by product or service, and use the resultant cost centers for purposes of tracking budget, allocating pools of money that can be used for salary increases or bonuses, and tracking other financial outcomes. Not every product or service team at Oracle has its own "Organization_Name," however. (Letter to Laura C. Bremer from Jinnifer Pitcher, June 29, 2018, Re: OFCCP v. Oracle, Inc., et al., Case No. 2017-OFC-00006 Response to June 8, 2018 Letter Re: Data Questions)

[93] Organizations indicate cost centers. "Oracle organizes its business, teams, and employees through a financial and accounting hierarchy. This financial and accounting hierarchy mirrors the managerial hierarchy at a high level but often diverges from the managerial hierarchy at a more granular level. That divergence occurs because managers may oversee more than one product team, as that term is defined for the purposes of the financial and accounting hierarchy. Conversely, what is a single product team for financial and accounting purposes may have multiple managers. **At the most granular level of the financial and accounting hierarchy, "cost center" (sometimes called "organizations") are used for purposes of tracking budget and other financial outcomes. A cost center can encompass a single product or service team, but not every product or service team** has its own cost center." Miranda Declaration, paragraph 8, (ORACLE_HQCA_0000607281).

See also: The "Organization_Name" field contains alphanumeric codes that reflect the cost centers in which each employee works. Cost centers are developed, altered, or deleted in partnership between finance, the business, and HR. These groups work together to organize jobs by product or service, and use the resultant cost centers for purposes of tracking budget, allocating pools of money that can be used for salary increases or bonuses, and tracking other financial outcomes. Not every product or service team at

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103.85

importance of the content of the work being performed. According to the data, HQCA employees in the relevant job functions worked in 1,039 organizations during the 2013-18 time frame.

The OFCCP does not control for patent awards, a sign of innovation and expertise

118. Companies like Oracle rely on patented technology to build their business in innovative directions and reap the rewards, which can be in the billions of dollars. The race to prove ownership is intense, and the legal battles frequently spill into public view.[94] A company will not know in advance which patented product will be most successful, so it is in their interest to patent as much as possible. Consequently, Oracle has a patent application bonus system in place, which awards up to [redacted] to a person or team that proposes a patent and passes the internal review by the Patent Review Committee and an outside patent attorney interview.[95] Oracle also maintains an internal web page for employees interested in the patent process that keeps track of patents and serves as "a training resource for prospective inventors. Access to issued and pending Oracle patents can provide prospective inventors with information about the state of the art and what ideas have already been patented at Oracle, either by looking at what their colleagues have patented or by using the engine's semantic search features."[96] The subject of the patent must be new or a significant technical improvement over other solutions and have a significant contribution to the business; the person or team applying for the patent must be able to explain how it is built or how it functions.[97] In the three HQCA job functions in the data, over [redacted] of employees earned one or more patent bonuses.[98] This varies across the company, with [redacted] of IC 6 level employees in PRODEV having ever earned such a bonus. Patent-level work is potentially of enormous value to the

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Oracle has its own "Organization_Name," however. (Letter to Laura C. Bremer from Jinnifer Pitcher, June 29, 2018, Re: OFCCP v. Oracle, Inc., et al., Case No. 2017-OFC-00006 Response to June 8, 2018 Letter Re: Data Questions)

[94] For example: "Apple and Samsung End Smartphone Patent Wars," *New York Times*, June 27, 2018; "Google loses Android battle and could owe Oracle billions of dollars," money.cnn.com, March 28, 2018.

[95] ORACLE_HQCA_0000414372_patent Primer 07-07-2014.pptx, July 8, 2014.

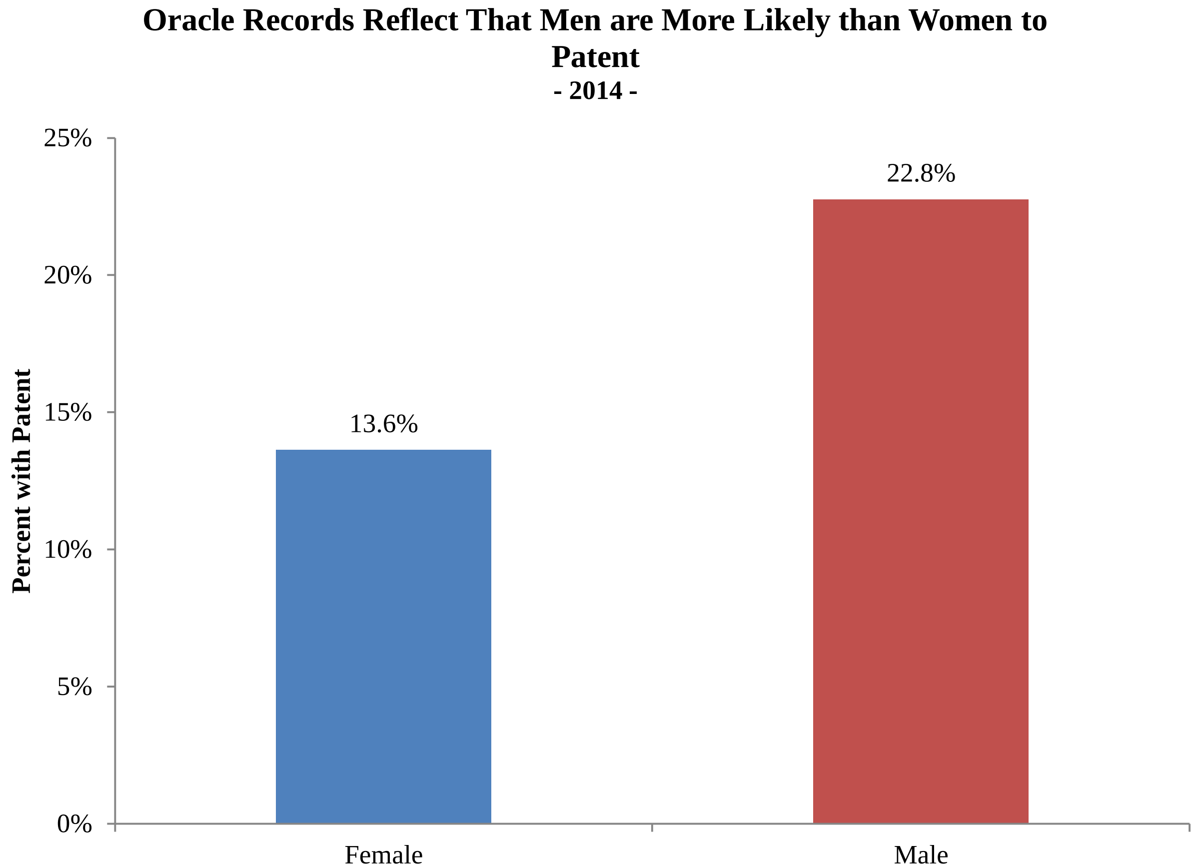
[96] ORACLE_HQCA_0000417308-0000417309.tif

[97] ORACLE_HQCA_0000414372_patent Primer 07-07-2014.pptx, July 8, 2014.

[98] Counting each full-year employee in 2013-2014 once, 19.8% of employees have ever been awarded a patent bonus. Extending the time period to 2013-2018, 19.3% of employees have ever been awarded a patent bonus.

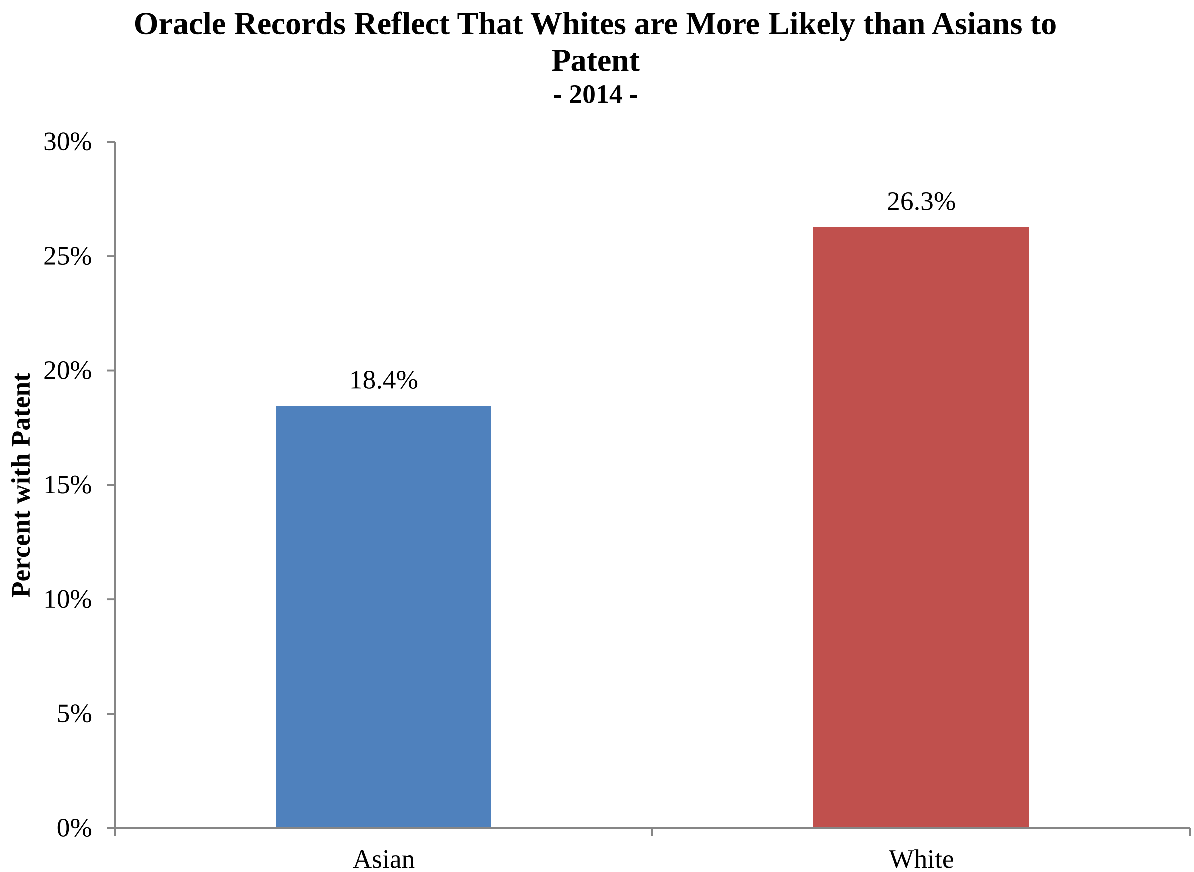
company, and will generally correlate with high levels of skill and innovative ability not otherwise captured by measures of experience that OFCCP used (like age or years since hire at Oracle).[99]

119. The failure to control for exceptional innovation and expertise (proxied by generating patent-able work) will bias results in the OFCCP model, because the patent bonus data indicate that men and women at Oracle file for patents at different rates, as do Asian and white employees. This is not just because some employees got a patent bonus that boosts their total compensation, but because the fact that they were associated with a patent indicates they are particularly high productivity employees, holding constant their other characteristics.[100]



[99] Patents also serve as an objective measure of individual or group productivity, which can be especially useful in white collar positions where productivity is not otherwise directly observable. Ehrenberg and Smith (2015), *Modern Labor Economics* pp. 373-376.

[100] "[…] if it's a really old legacy product or a cutting edge new product, and there's not a lot of talent out there that know how to do this, they would command a higher position in the range versus somebody who's working on J.D. Edwards that's existed forever." Waggoner May 1, 2019 deposition 91:5-10.



<u>The OFCCP claims visa holders are paid less but does not test this</u>

120. The OFCCP has expressed concern that Oracle prefers to hire employees on work visas as a source of less expensive labor. “This strong preference for a workforce that is dependent on Oracle for authorization to work in the United States contributes to Oracle’s suppression of Asian employees’ wages.”[101] But the OFCCP did nothing to account for H-1B work visa status in their SAC model.

[101] SAC, paragraph 39.

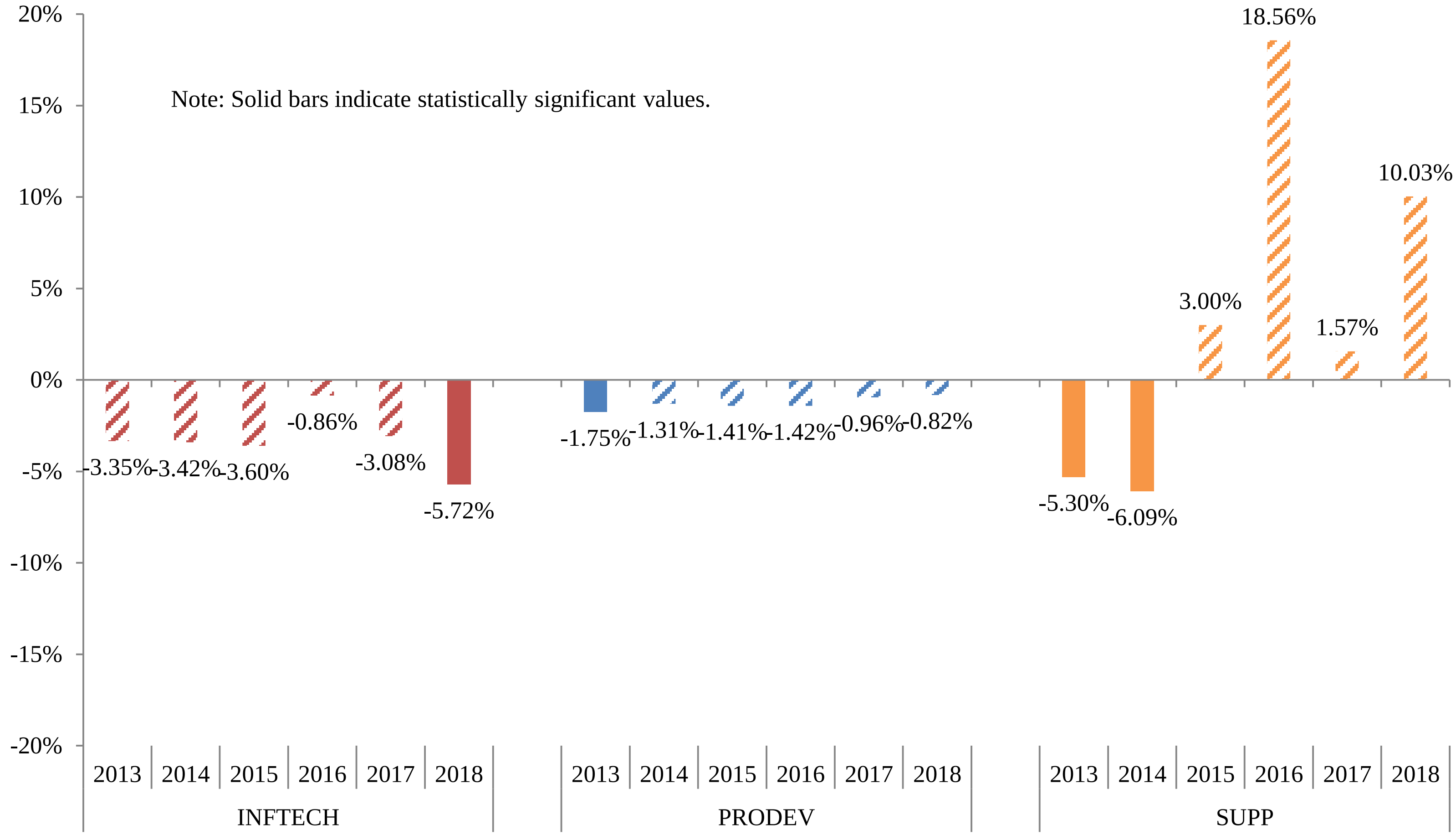
EXAMINED MORE CAREFULLY, THE DATA SHOWS NO PATTERN OF STATISTICALLY SIGNIFICANT PAY DIFFERENCES FOR WOMEN, ASIANS, OR AFRICAN-AMERICANS

121. In this section, I present modified regression models examining total compensation at Oracle that address some of the issues discussed above. Specifically, I present the results of modified regression analyses that add controls for total Oracle tenure (based on continuous service date that includes time worked at non U.S. Oracle affiliates or acquired firms), cumulative time spent on leave of absence, time in standard job title, organization, whether the employee ever has a patent bonus, whether there was a leave of absence in the current year, and whether they arrived at Oracle as an experienced hire or through an acquisition. These regression analyses still group employees together by high-level job function, which mirrors OFCCP's approach. Even aggregated in that way, the analyses show that there is no evidence of systematic adverse pay outcomes for women, Asians, and African Americans at Oracle.

These results do not show any patterns of statistically significant pay differences across years or job function

122. The chart below depicts the coefficients on female by job function and year. The bar furthest to the right, for example, indicates that women on average earned 10.03% more than men, all else constant, but that this disparity could have occurred by chance at conventional levels of statistical significance (i.e., the coefficient is not statistically significantly different from zero). Striped bars indicate the coefficient is not statistically significantly different from zero according to the factors included in the model. Solid bars indicate statistical significance, such that total compensation is on average different between men and women or between protected race categories relative to white employees.

Modified Regression Analysis of Total Compensation Shows No Systematic Pattern of Statistically Significant Results for Women vs. Men Across Years or Job Functions

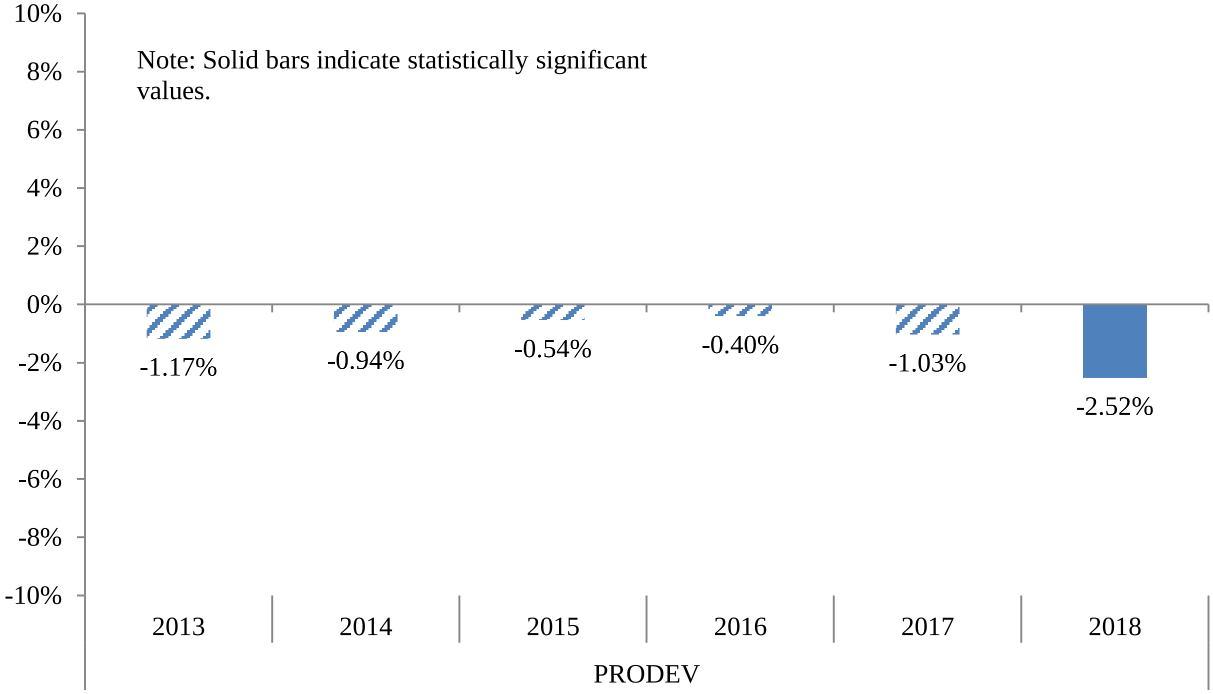


Model controls for female, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

123. The results show that there is only one year (and not the same year) showing a negative and statistically significant pay disparity on average in total compensation between women and men in each of the PRODEV and INFTECH job functions. There are two statistically significant adverse results on average in the SUPPORT function in 2013 and 2014, but from 2015 onwards, the coefficients are all positive (although not statistically significant). Overall, these results do not demonstrate a pattern that would support a hypothesis of systematic and wide-scale pay discrimination against women at Oracle HQCA.

124. The same regression model was used to estimate pay disparities between Asians and Whites in PRODEV (the only job function the OFCCP makes claims about for Asians). The chart below shows only one year of statistically significant adverse result on average for Asians in PRODEV, in 2018. There is no evidence of a systematic adverse pay disparity on average between Asians and Whites at Oracle HQCA.

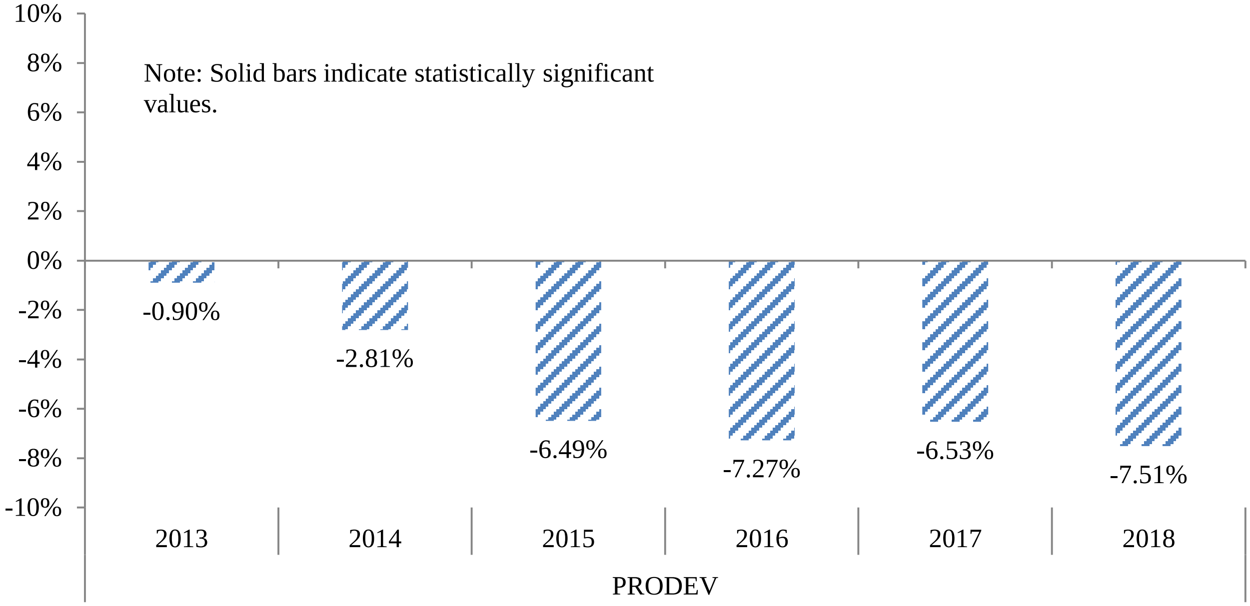
Modified Regression Analysis of Total Compensation Shows No Systematic Pattern of Statistically Significant Results for Asians vs. Whites Across Years Within PRODEV



Model controls for Asian, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

125. The OFCCP also makes claims about pay disparity for African Americans in PRODEV. The chart below shows that total compensation for African-Americans is never statistically significantly different from that of Whites at Oracle HQCA.

Modified Regression Analysis of Total Compensation Shows No Statistically Significant Results for African Americans vs. Whites in Any Year Within PRODEV



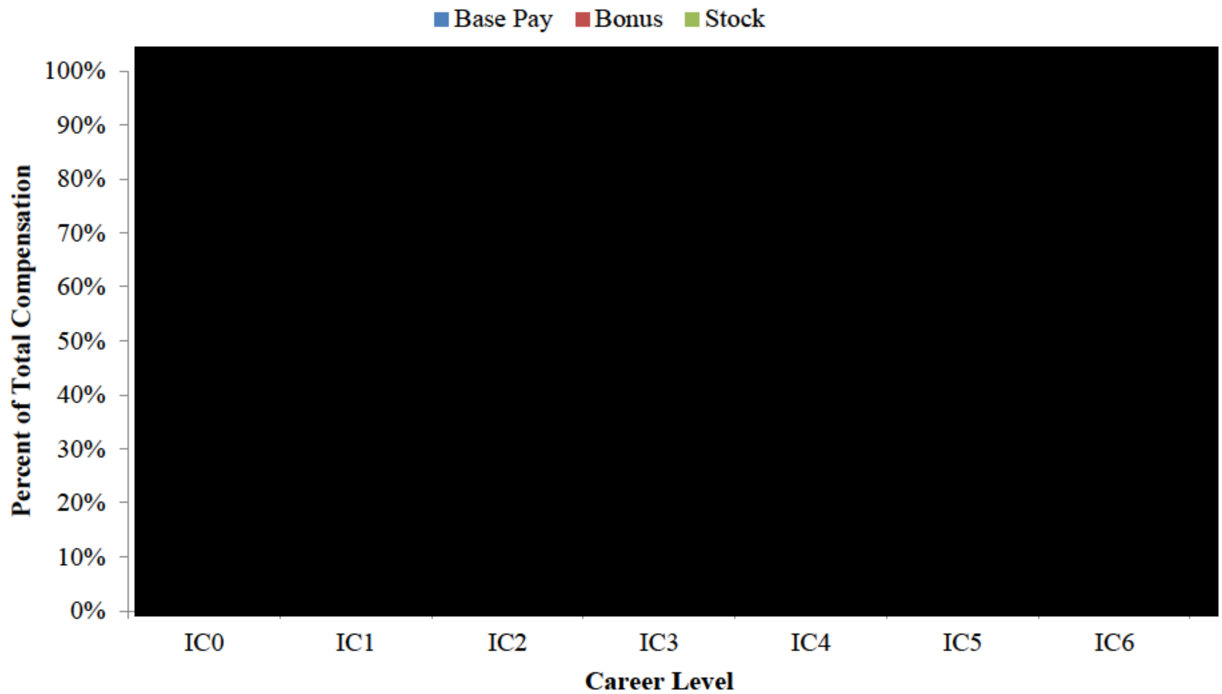
Model controls for African American, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

<u>These results do not show any pattern when examining managers separately from individual contributors</u>

126. As the charts below show, [redacted] tend to receive a greater share of their total compensation in bonuses and stock awards than [redacted]. Given that there are different emphases on the type of compensation awarded by Career Level, it is instructive to estimate the compensation regression models separately for IC Career levels and M Career Levels.

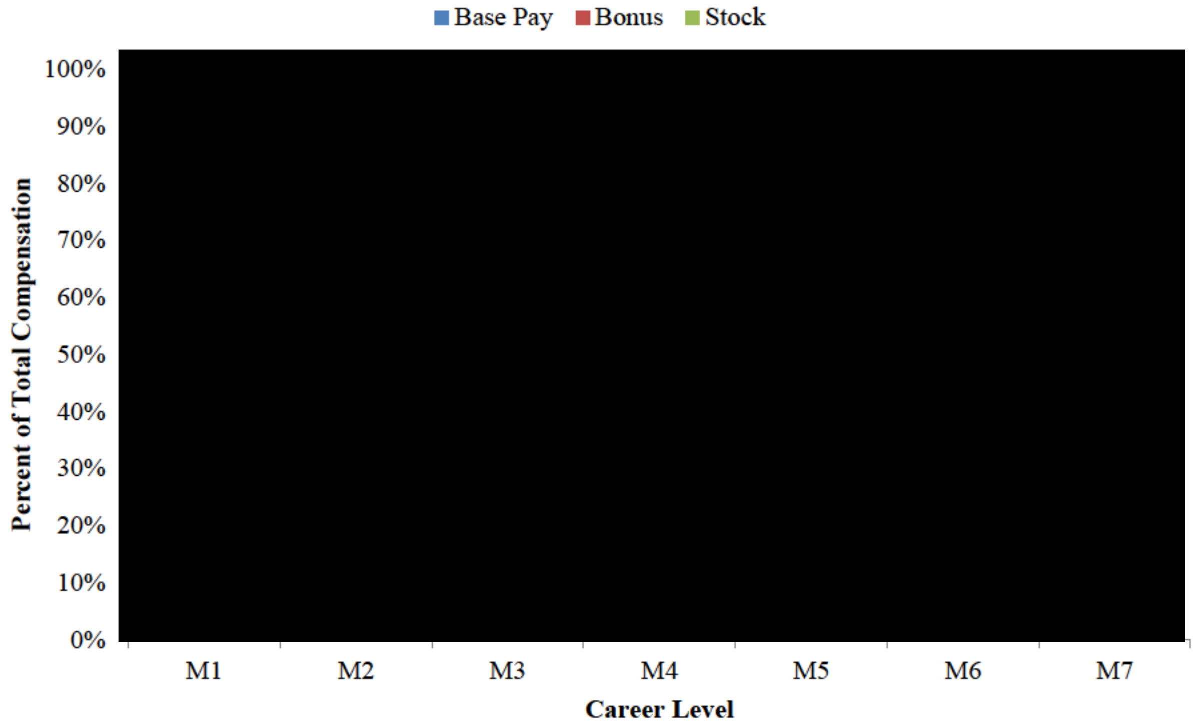
In the Individual Contributor Career Levels, Total Compensation is Comprised [redacted]

- 2013-2018, Full Time Full Year Employees, Individual Contributors By Career Level -



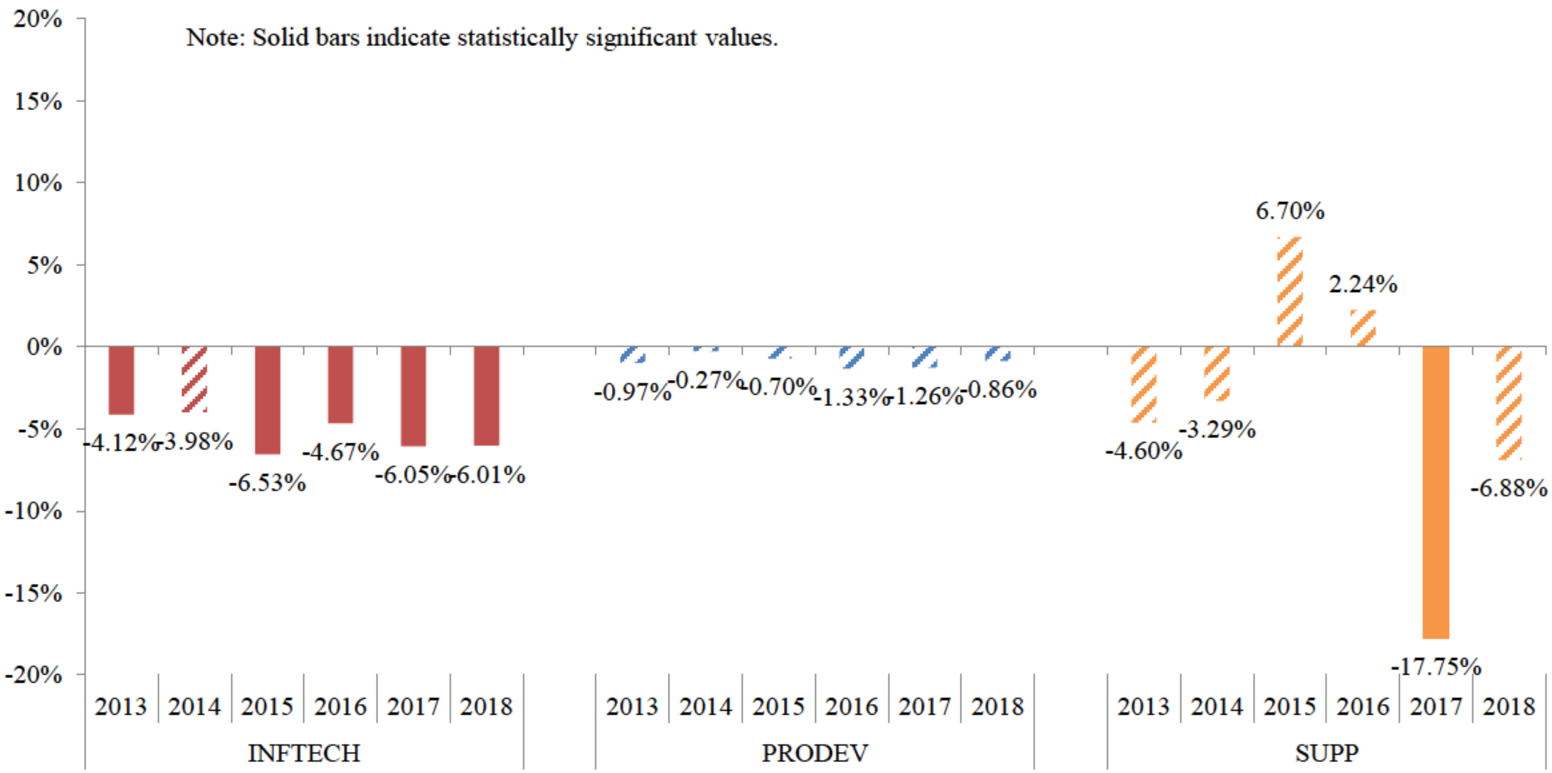
At Higher Manager Career Levels, [redacted] of Total Compensation

- 2013-2018, Full Time Full Year Employees, Managers By Career Level -



127. In PRODEV, which comprises 85% of employees covered by the OFCCP's allegations, there are no statistically significant differences in total compensation. In SUPPORT, women earn more or less than men depending on the year, with just one year showing a statistically significant adverse outcome for women. The statistical results for ICs in INFTECH stand in contrast to both PRODEV and SUPPORT when the same regression model is applied. The majority of the annual differences are negative and statistically significant. This is likely an indication that a meaningfully different regression model applies to INFTECH as compared to the other two job functions. Taking the findings of all job functions together does not support an inference of a consistent pattern of discrimination against women.

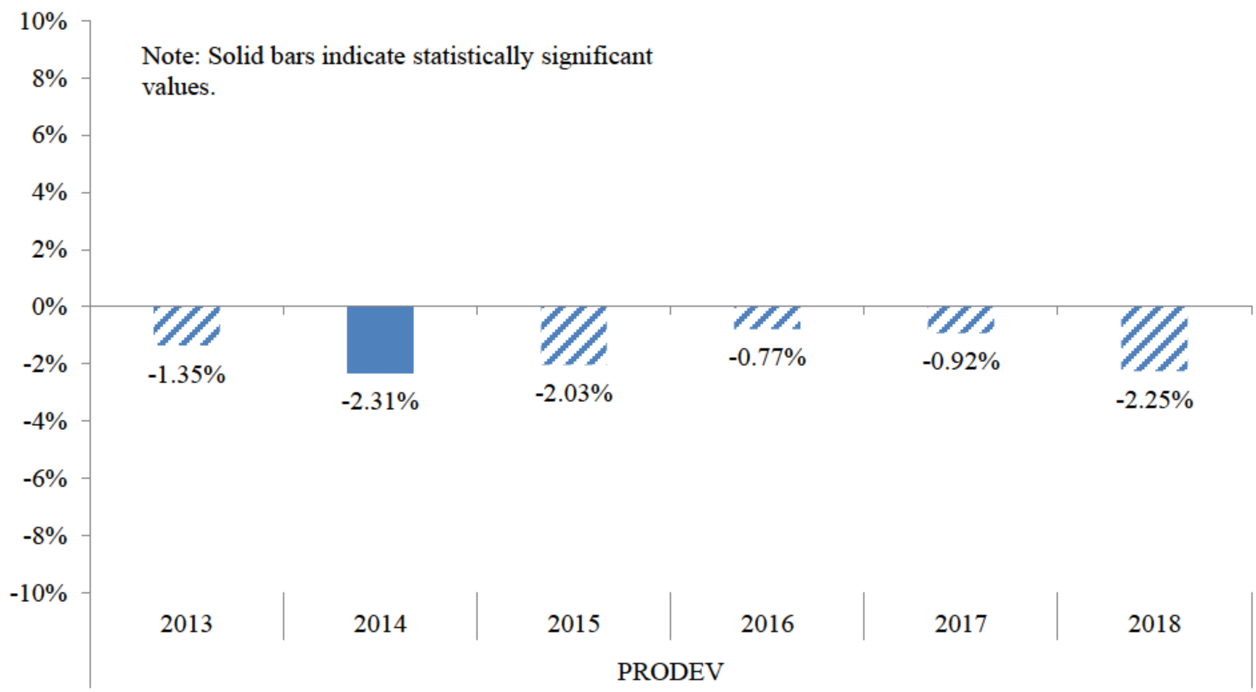
Modified Regression Analysis of Total Compensation Shows No Systematic Pattern of Statistically Significant Results for Women vs. Men in IC Career Levels Across Years or Job Functions



Model controls for female, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

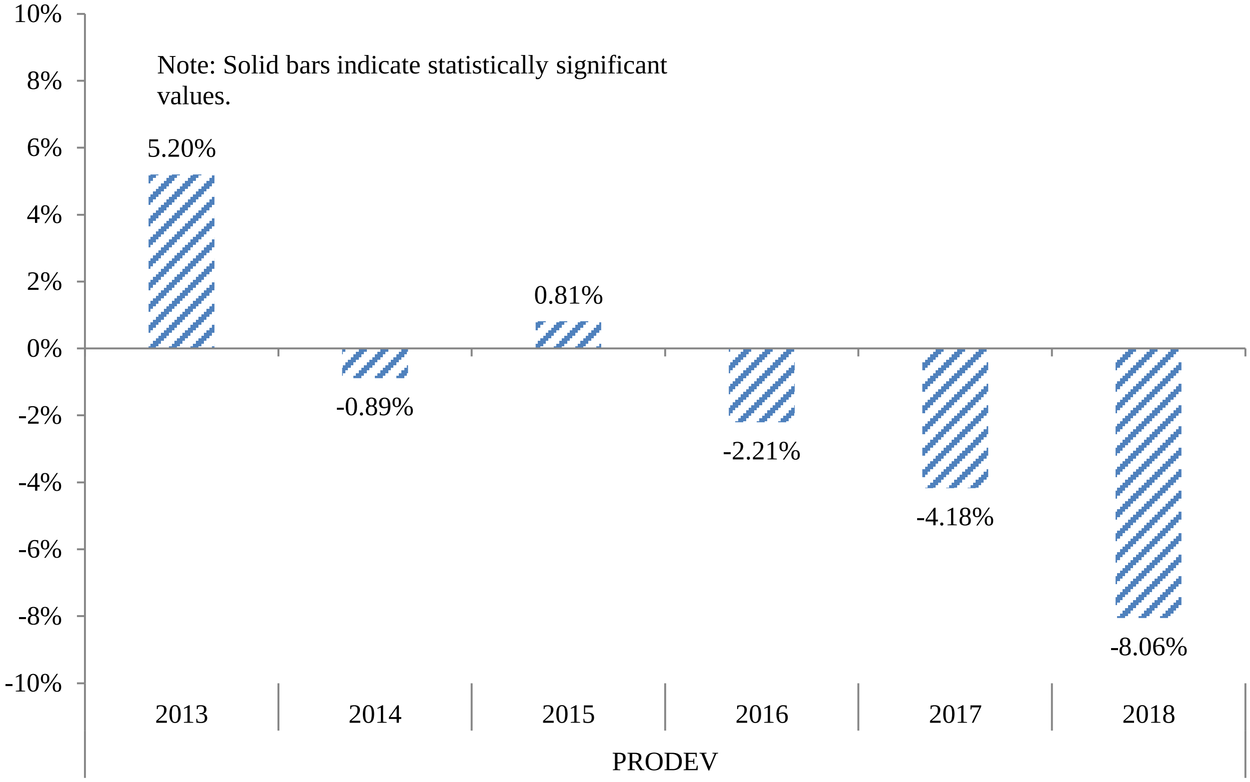
128. The same regression model was used to analyze pay disparities between Asians, African Americans and Whites in the IC track of the PRODEV job function. There is a statistically significant difference in total compensation between Asians and Whites in only one of the six years in the data. The results for African-Americans do not show any statistically significant disparity on average compared to Whites in any year. As was true for women, the data for race as a whole do not support a hypothesis that Asian or African American IC career path in PRODEV employees are systematically adversely affected by pay discrimination.

Modified Regression Analysis of Total Compensation Shows No Systematic Pattern of Statistically Significant Results for Asians vs. Whites in IC Career Levels Across Years Within PRODEV



Model controls for Asian, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

Modified Regression Analysis of Total Compensation Shows No Statistically Significant Results for African Americans vs. Whites in IC Career Levels in Any Year Within PRODEV

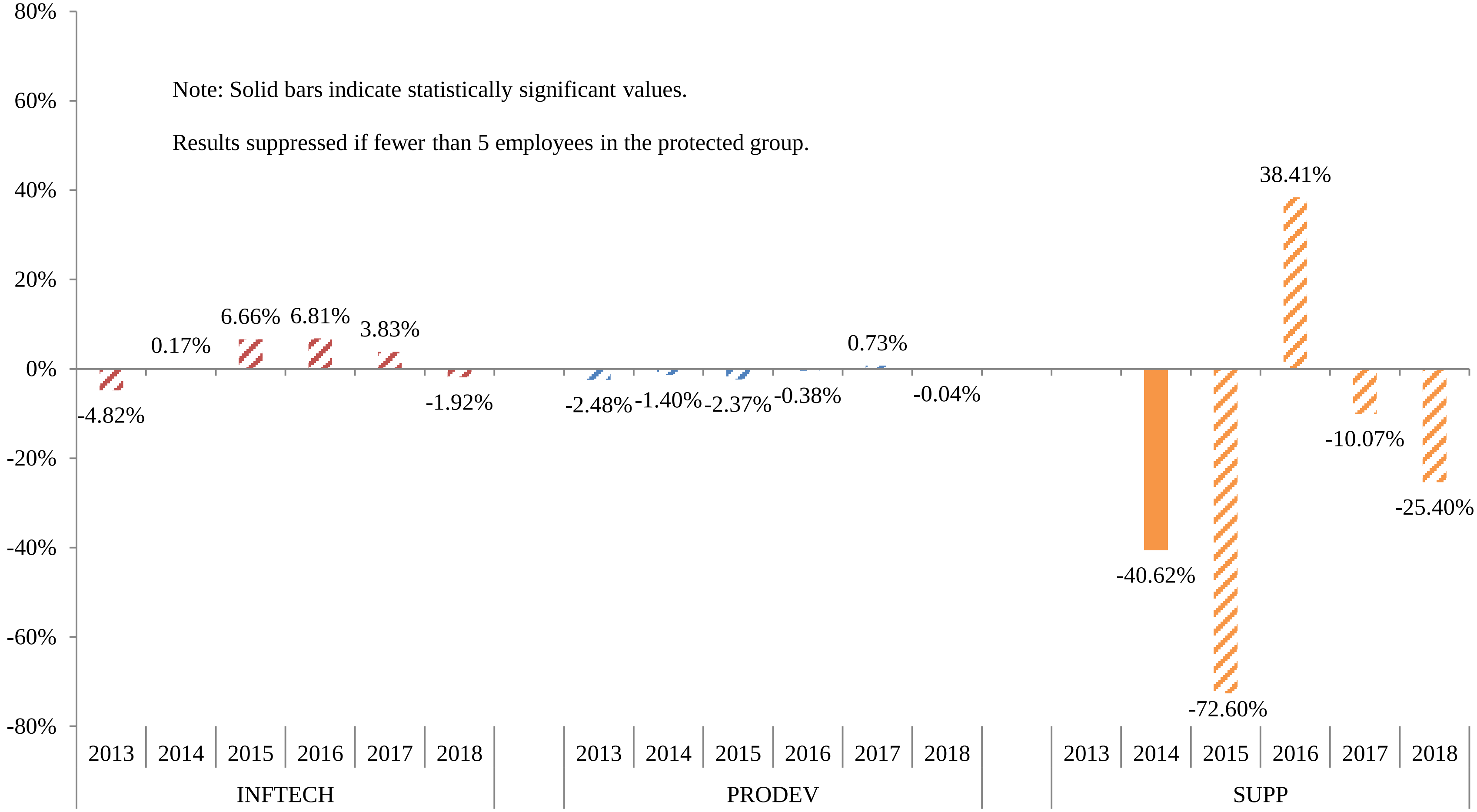


Model controls for African American, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in job, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

129. When the regression model is estimated by job function, employees in the Managerial Career Levels, the results show a mix of positive and negative by gender and race coefficients which are statistically insignificant.[102] The one statistically significant coefficient is negative, for women in the SUPPORT job function in 2014, but in INFTECH in the same year, the coefficient is positive. Among Asians compared to Whites, there is also a mix of positive and negative results on average, none of which are statistically significant. I conclude that the data for IC and Manager employees do not support a hypothesis that women and Asian managers are being discriminated against in pay at Oracle.

[102] There are fewer than 5 African American managers and so these results are not shown.

Modified Regression Analysis of Total Compensation Shows No Systematic Pattern of Statistically Significant Results for Women vs. Men in M Career Levels Across Years or Job Functions



Model controls for female, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

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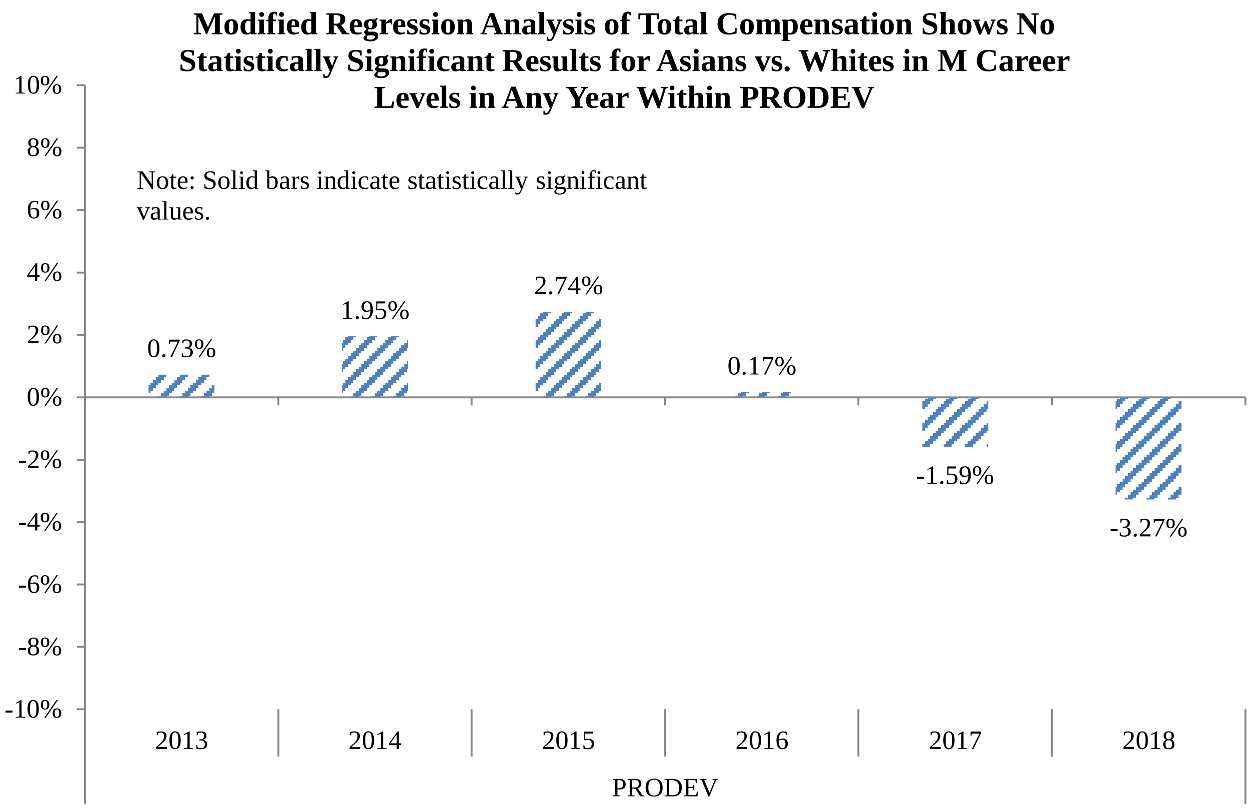


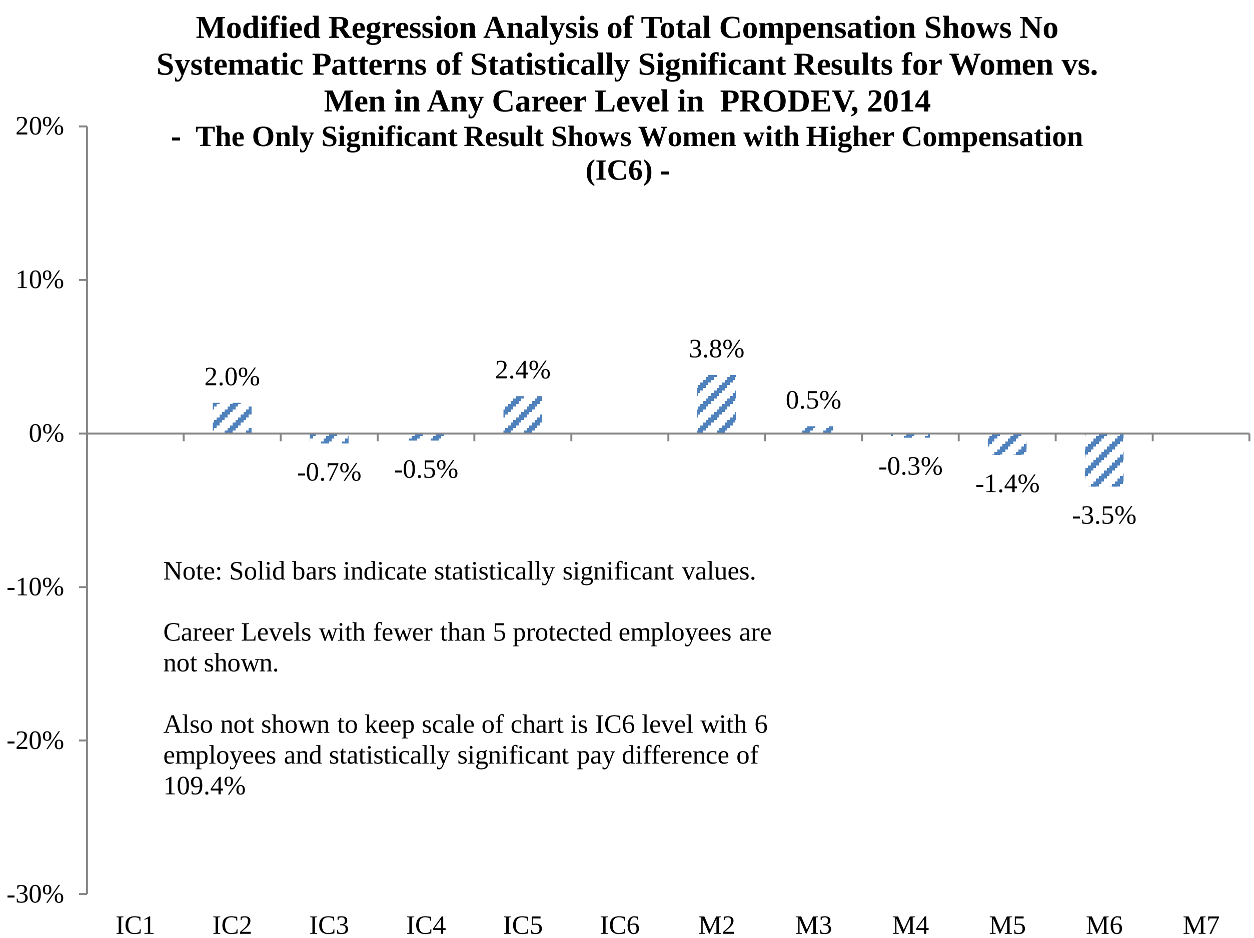
Model controls for Asian, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

These results do not show any pattern by Career Level

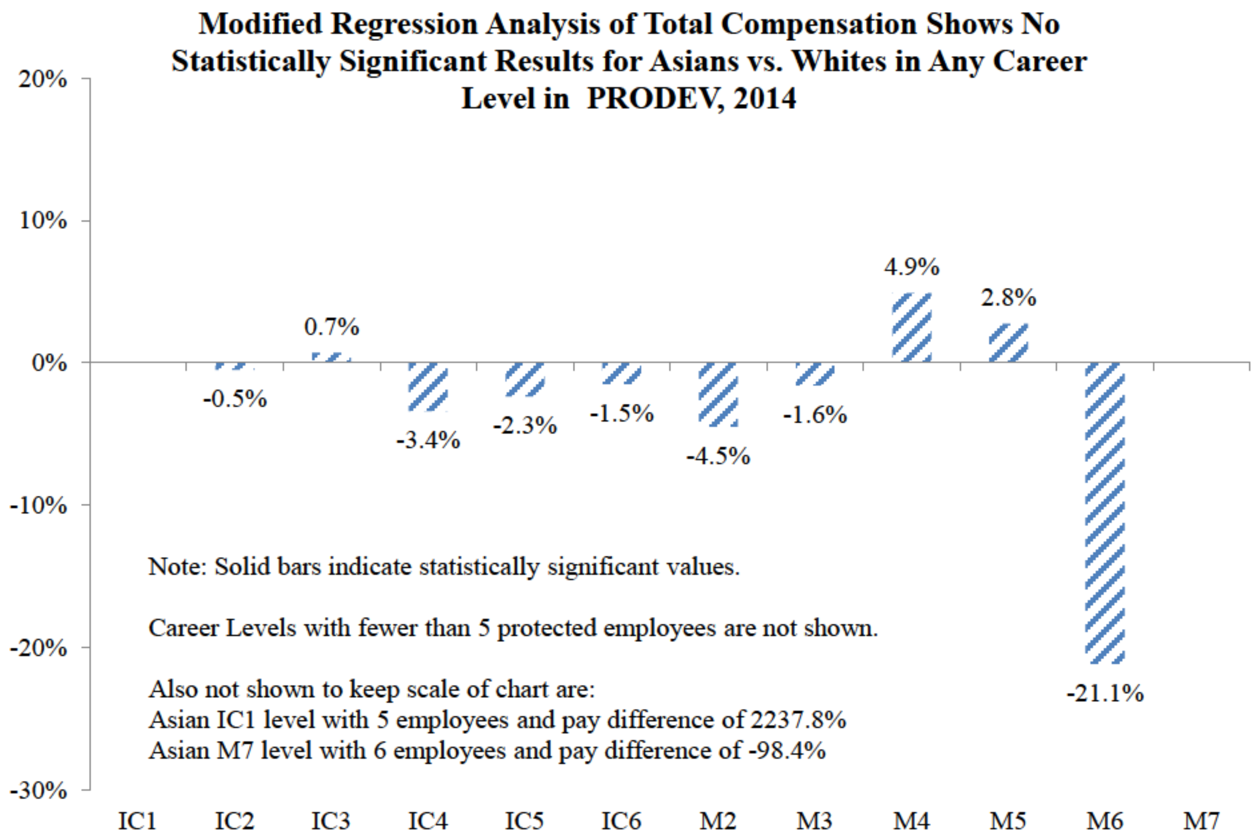
130. The OFCCP claims that pay differences widen with tenure.[103] In the PRODEV job function, there are enough employees to support a regression analysis by Career Level in 2014.[104] Among women, there is one positive statistically significant coefficient (in IC6[105]) and four other levels have a positive result. Asians also have a mix of positive and negative coefficients that are not statistically significant and

[103] SAC, paragraphs 26-28.
[104] If a Career Level has fewer than 5 protected group employees, the result is not shown.
[105] In order to maintain the scale of the graph, this result that women are paid 109.4% more is not depicted in the chart.

African Americans have negative but not statistically significant coefficients. These results show that there is no statistically significant pay disparity at lower career levels that widen at higher levels.



Model controls for female, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.



Model controls for Asian, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

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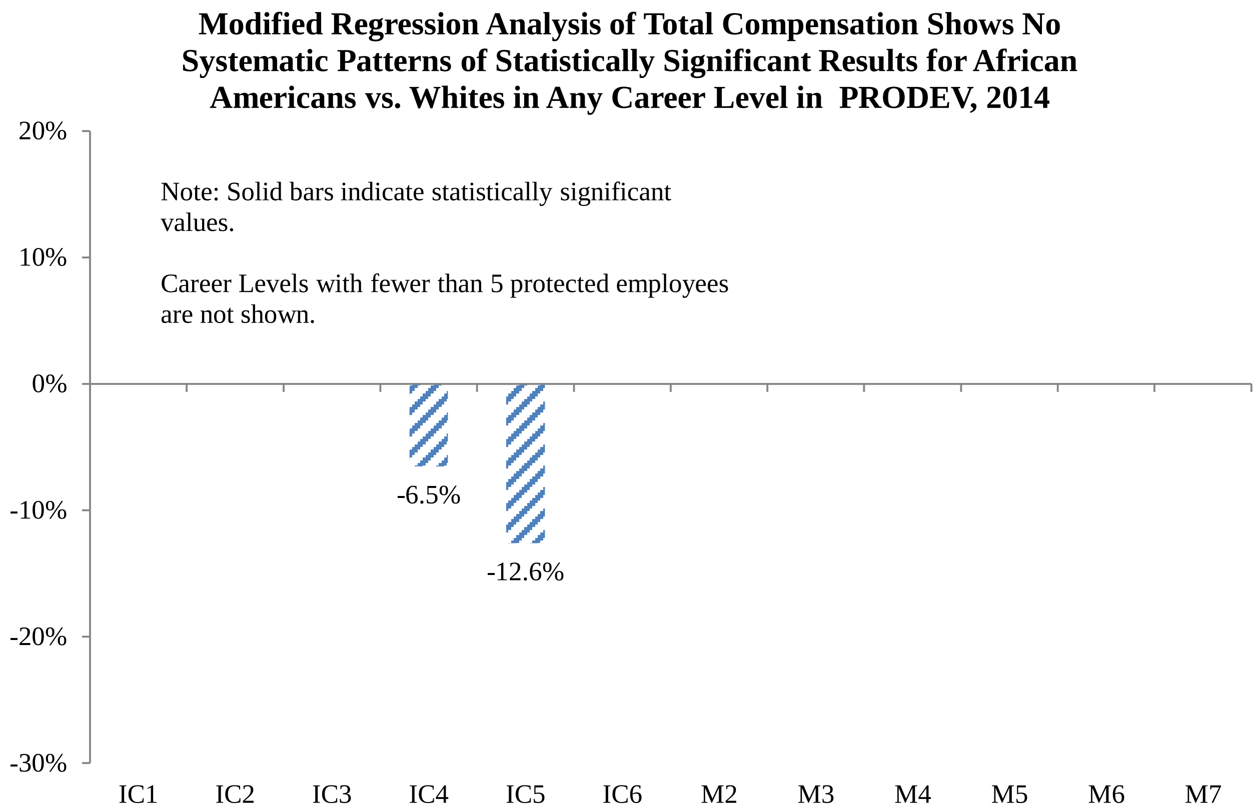


Model controls for African American, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

131. More generally, the OFCCP analysis of tenure groups compares apples and oranges. In their analysis, the pay gap for those with 1 to 3 years of tenure is smaller than the one estimated among employees with 7 to 9 years of tenure. They interpret this to mean that the pay gap opens up over time. However, the tenure groups do not follow the same individuals over time but rather are comprised of different cohorts who entered Oracle under different market conditions. For example, the 7 to 9 tenure group includes employees whose original hire date was prior to the year 2000, though most in this cohort were hired in the 2007 to 2009 recession. The career trajectories of those hired during a financial crisis are being compared to employees who were hired after 2013 under very different market conditions and demands. Economists have studied the career impact of recessions on careers, concluding that the

"match" between employers and employees tends to be lower during recessions, with long term earnings implications for those hired.[106]

132. In order to analyze patterns over time as employees' tenure rises without mixing very different cohorts of employees whose experiences could differ markedly, I limit the data to new, non-acquisition hires between 2013 and 2016 and follow the same group over time. I observe the pay difference amongst these groups of employee at the end of their first full year-end, second year-end, and so on up to four years after hire. None of the total compensation differences are statistically significant or suggest that women at Oracle fare worse with respect to total compensation relative to men the longer they are at Oracle. In fact, the results vary from year to year and I find a positive coefficient for women at the end of year four. Contrary to the conclusions of the OFCCP, these results do not support their conclusion that a male-female pay difference widens with tenure.

Modified Regression Analysis of Total Compensation Over Time Shows No Statistically Significant Results for Females vs. Males in Any Years Since Hire

- New Hires in PRODEV, SUPP, and INFTECH Between 2013 - 2016, by Years Since Hire -

Years Since Hire	# Protected Group	Pay Difference (%)	T-Value
First Year of Hire	349	-1.54%	-1.22
Second Year of Hire	290	-1.47%	-1.02
Third Year of Hire	158	-2.33%	-1.13
Fourth Year of Hire	85	1.54%	0.43

Model controls for female, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time non-US Oracle affiliates), age minus total Oracle tenure minus 22, cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire, and year.

133. The same is true in my analysis of newly hired Asians. None of the total compensation differences are statistically significant or suggest that Asians at Oracle fare worse with respect to total

[106] See for example, Oreopoulos, Philip, Till von Wachter, and Andrew Heisz (2012) "The Short- and Long-Term Career Effects of Graduating in a Recession." *American Economic Journal: Applied Economics*, 4 (1): 1-29.

compensation relative to Whites the longer they are at Oracle. Contrary to the conclusions of the OFCCP, these results do not support their conclusion that pay disparities for Asians widen with tenure.

Modified Regression Analysis of Total Compensation Over Time Shows No Statistically Significant Results for Asian vs. White in Any Years Since Hire

- New Hires in PRODEV Between 2013 - 2016, by Years Since Hire -

Years Since Hire	# Protected Group	Pay Difference (%)	T-Value
First Year of Hire	1,096	-0.14%	-0.07
Second Year of Hire	902	-4.24%	-1.92
Third Year of Hire	527	-1.84%	-0.58
Fourth Year of Hire	282	-3.67%	-0.73

Model controls for Asian, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at non-US Oracle affiliates), age minus total Oracle tenure minus 22, cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire, and year.

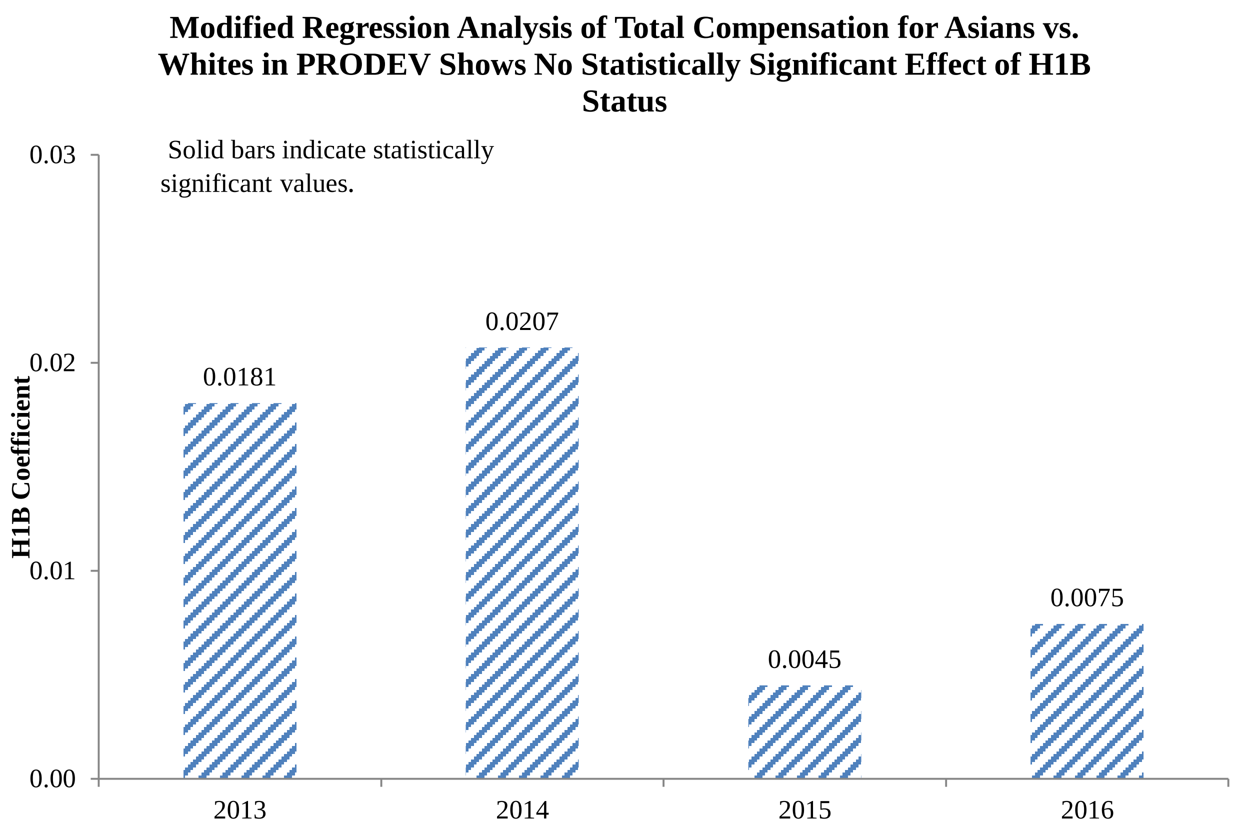
Visa holders are paid the same as other employees, contrary to the OFCCP claim

134. The OFCCP has expressed concern that Oracle prefers to hire employees on work visas as a source of less expensive labor. "This strong preference for a workforce that is dependent on Oracle for authorization to work in the United States contributes to Oracle's suppression of Asian employees' wages."[107] They did nothing to study this claim, but I examined the impact of having held an H1-B visa on pay for Asians in PRODEV.[108] On the whole, I find that the coefficient is small and positive (but

[107] SAC, paragraph 39.

[108] I limit the analysis to PRODEV because that is the job function in which the OFCCP claims there is a pay disparity for Asians. H1B status is only contained in the data for 2013-2016, and so these regression models are restricted to those years. As in the earlier modified total compensation regression models, I also control for Asian, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition,

statistically insignificant). The OFCCP claim regarding the visa-holding workforce is unsupported by the data.



Note: The coefficient is never statistically significant. Model controls for Asian, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, whether they arrived at Oracle as an experienced hire or through an acquisition, and whether on H1B visa.

THE OFCCP ANALYSIS OF STARTING PAY IS UNRELIABLE AND BIASED DUE TO KEY OMITTED VARIABLES

The OFCCP starting pay model considers everyone in a Career Level equivalent in terms of skills and responsibilities

135. The OFCCP claims that female and Asian employees (but not African Americans) were discriminated against in terms of starting pay.[109] But the models the OFCCP uses to test this claim control for Career Level and not standard job title. This means that for all intents and purposes, all jobs in a Career Level are considered equivalent in terms of skills and responsibilities. Employees sharing a Career Level are expected to have a certain level of expertise in their area, but that would certainly not translate into their being similarly situated enough that one would expect them to earn the same. Recall the enormous range in pay within Career Levels I discussed earlier. To use an analogy from an academic employment setting, an Associate Professor of English, an Associate Professor of Physics, and an Associate Professor of Business all share a career rank, but their pay scales tend to be quite different because they have different skills, different non-academic opportunities, and different abilities to attract students paying full tuition.

136. Oracle managers hire employees from varied sectors of the economy, but they are especially concerned with remaining competitive with the "premier" firms in the industry.[110] This means that jobs are mapped to salary ranges based on external surveys that track compensation.[111] Even within a career

[109] SAC, paragraph 22.

[110] For example, in 2011, these included Adobe, Apple, Applied Materials, Cadence, Cisco, Ebay, Google, HP, IBM, Intel, Microsoft, Motorola, Qualcomm, SAP, Texas Instruments, and Yahoo! (ORACLE_HQCA_0000364272_native.pptx, p. 7)

[111] "Our primary sources of data come from highly reputable 3rd party consulting firms who gather data from participants, and compile it to produce reports that keep individual company data confidential. Oracle targets to be competitive against a select list of competitor companies chosen by our board of directors. These are the companies the board feels are our biggest competitors for talent – those that we hire from, and lose employees to. It is not an exhaustive list, rather the most prominent companies only, and those that are felt to be the "premier" high tech market sector." (ORACLE_HQCA_0000364272_native.pptx, p. 7)

level, positions do not all map to the same salary scale.[112] For example, in FY2014, the base salary ranges for Project Manager 3s (Career Level IC3) was [redacted].[113] For Software Developer 3s in the same year and same Career Level, the base salary range was set from [redacted].[114]

137. All of the Career Level IC4 positions in the table below share a career level, but the high-level standard job descriptions make it clear they draw on different skills, and the average starting pay in those positions varies considerably. Average starting pay for Hardware Developer 4s was [redacted] Applications Developer 4s and [redacted] Technical Writer 4s. Yet the OFCCP model assumes they all have similar skills, and that the supply of those skills by potential employees as well as the demand for those skills by other companies are all the same.

Average Starting Pay and High-Level Descriptions of Job Titles in Career Level 4 in PRODEV		
Standard Job Title	**High-Level System Job Description**	**Average Starting Pay 2013-2018 (in $2014)**
Hardware Developer 4	Evaluates reliability of materials, properties and techniques used in production; plans, designs and develops electronic parts, components, integrated circuitry, mechanical systems, equipment and packaging, optical systems and/or DSP systems.	[redacted]
Software Developer 4	Design, develop, troubleshoot and debug software programs for databases, applications, tools, networks etc.	[redacted]
Program Manager 4	Manage the development and implementation process of a specific company product.	[redacted]
User Experience Developer 4	Responsible for creating, evaluating and modifying prototypes to support evolving hardware and software application development.	[redacted]

[112] "Salary ranges assign a minimum and maximum to the amount that we are willing to pay for a specific job. They reflect the market in the area and allow for much variation in knowledge, skills & abilities that each individual brings to the company." (ORACLE_HQCA_0000364272_native.pptx, p. 4)
[113] ORACLE_HQCA_0000581471.xlsx.
[114] ORACLE_HQCA_0000581471.xlsx.

Applications Developer 4	Analyze, design develop, troubleshoot and debug software programs for commercial or end user applications. Writes code, completes programming and performs testing and debugging of applications.	[redacted]
QA Analyst 4	Responsible for developing, applying and maintaining quality standards for company products with adherence to both internal and external standards. Develops and executes software test plans. Analyzes and writes test standards and procedures. Maintains documentation of test results. Analyzes test results and recommends corrective actions.	[redacted]
Technical Writer 4	Creates, develops, plans, writes and edits operational, instructional, maintenance, test or user manuals for paper, multimedia or web-based publications. Contributes to the timely design, production and delivery/completion of product documentation and document sets.	[redacted]

138. Not only does the OFCCP model ignore very real differences in the jobs in a Career Level, it also ignores the evidence that not all positions sharing a standard job title call on the same skills and experiences.[115] Employees working on cutting edge projects will tend to earn more, all else constant, than employees working on legacy products in well-established markets. This in turn implies that the specific skills someone has are relatively more important than just years of general work experience. In the data, one would expect to see that starting pay has less to do with generally defined experience (which the OFCCP model defines as age of hire at Oracle America, Inc. minus 18) and more to do with particular skills.[116]

[115] "[…] just as the technologies themselves differ, so do the skills, duties and responsibilities needed to develop, enhance, modify, support or service those products and services. This can be true whether or not employees share the same job title. A developer who works on Middleware or Infrastructure generally needs familiarity (to differing degrees) with how the underlying hardware functions; a developer working exclusively on Applications, by contrast, may work at a level far removed from the hardware and thus may not need that same knowledge, although she would need to be familiar with other tools and techniques to develop and shape the software that creates that interface that the end user sees and works within." Miranda declaration, paragraph 3. (ORACLE_HQCA_0000607281.pdf)

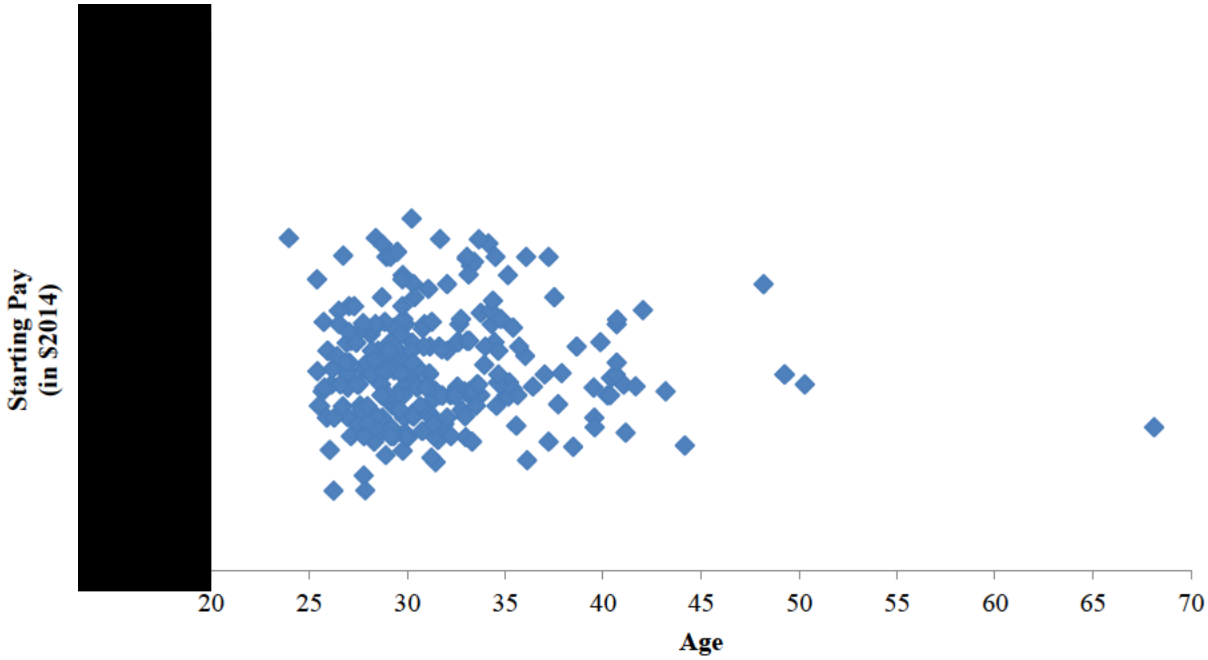
[116] "Because not all products and services have the same value to Oracle, the value of the skills, duties, and responsibilities necessary to develop, enhance, or service Oracle's wide array of products and services also differs and changes over time. […] As technology continually changes and develops, the competition and market demand for employees skilled in the latest technologies also changes, meaning

139. The charts below depict the relationship between starting pay and age for experienced hires in Software Developer 3s and 4s, large standard job titles in the data. New Software Developer 3s between the ages of 30 to 35 earn between [redacted] in starting base pay, while those between the ages of 45 and 50 earn from [redacted] The relationship between pay and age is relatively flat, such that there does not appear to be a premium for having had more years of general non-Oracle work experience. Among Software Developer 4s, those aged 30 to 35 earn from [redacted] in base pay and those between the ages of 45 and 50 earned [redacted]. Again, the scatterplot is relatively flat, rather than rising from the lower left portion of the chart to the upper right: there is no strong relationship between starting pay and years of general non-Oracle experience. This suggests that starting pay is influenced by something other than general years of experience. The other feature of interest in these two charts is that pay ranges at Oracle are far from being narrowly prescriptive, lockstep pay bands. While average Career Level 4 pay is higher than that of Career Level 3, it is possible for someone hired into [redacted]

the value to Oracle of various skills, duties and knowledge also fluctuates over time." Miranda Declaration, paragraph 7. ORACLE_HQCA_0000607281.pdf)

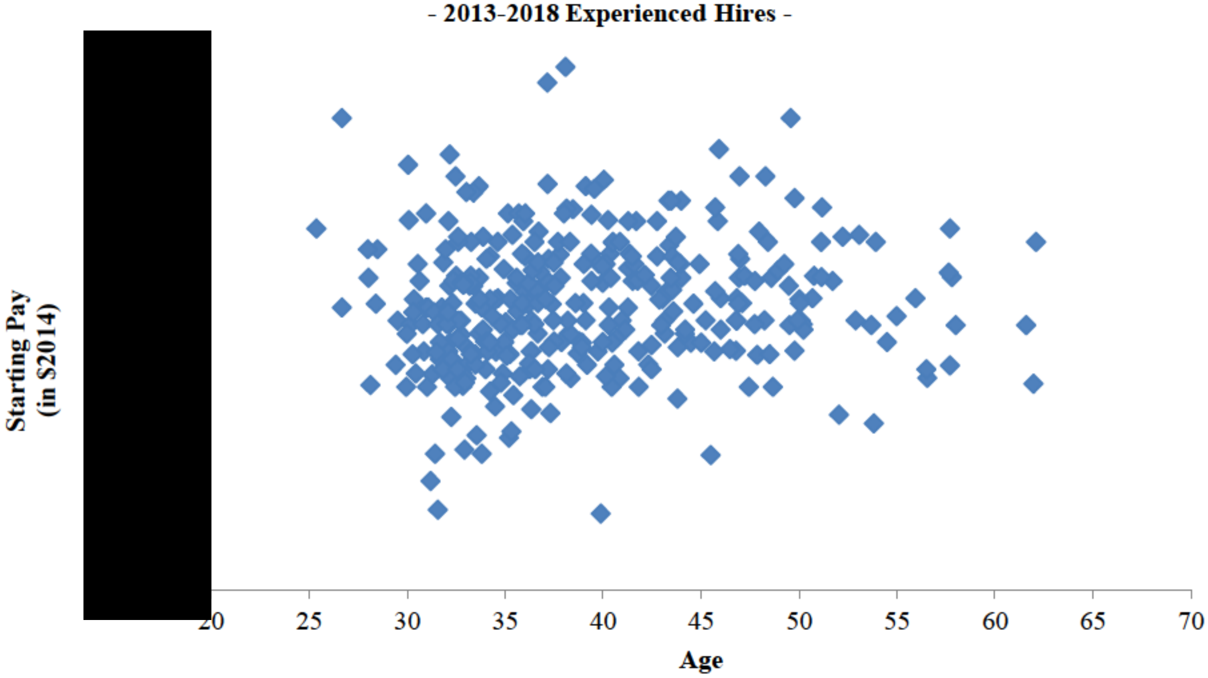
There is Virtually No Relationship Between Starting Pay and Age Among Software Developer 3s

- 2013-2018 Experienced Hires -



There is Virtually No Relationship Between Starting Pay and Age Among Software Developer 4s

- 2013-2018 Experienced Hires -



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140. The patterns in the scatterplots suggest that very specific skills and experiences, rather than general years of experience or broad categories of skill, explain initial placement and starting pay that ranges from [redacted] Standard job title alone does not distinguish between employees in the kinds of skills required, never mind the far broader Career Level used by the OFCCP in its model.

141. One factor to consider is the types of products employees work on.[117] Product data is not available, but the variable "organization" is a rough proxy for the projects and services employees work on – it is at least more informative than standard job title alone – and can be used as a way to better group employees likely to have more similar skills and prior work backgrounds. For example, in the charts below for Software Developer 3s and 4s, new hires into the "Oracle Labs" research and development organization tend to [redacted]han those in the "Corp Architecture – Development" organization supporting technologies for high speed data transfer.[118]

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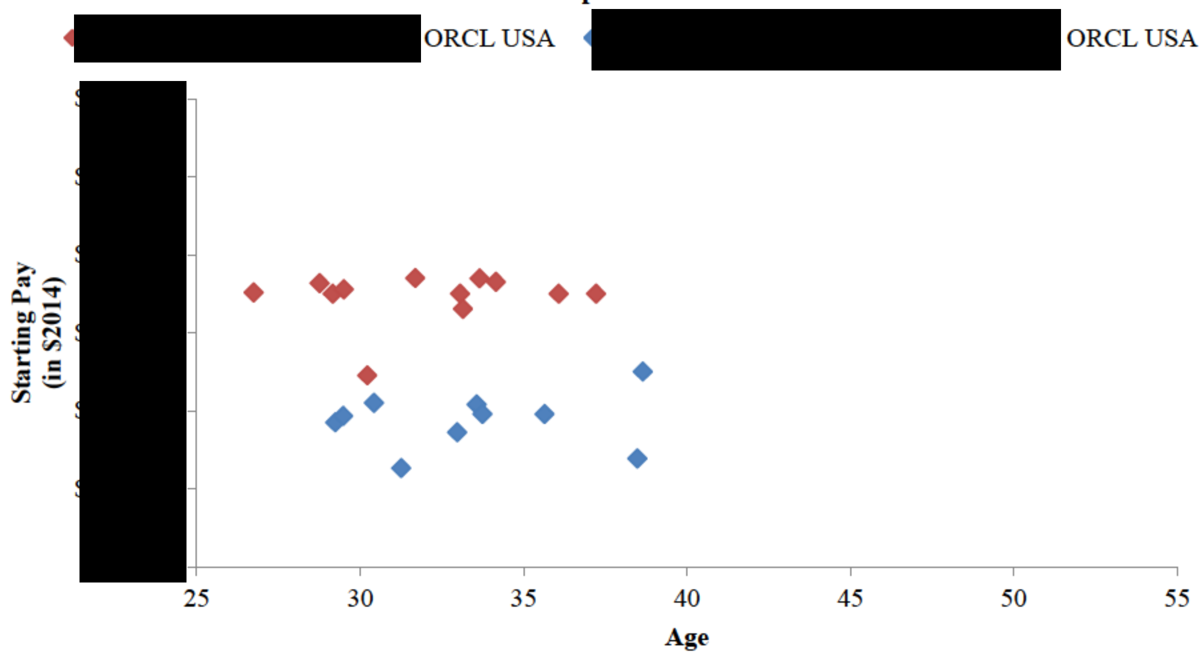
[117] When asked who are regarded as peers in making internal equity pay comparisons, Kate Waggoner replied "[…] when we talk peers, we really mean doing the same – the same role working on the same product. It's not – it doesn't come to job code or title because, as I said, those are incredibly general. We have to get down a little bit more granular to say, oh, this is our group of people with the hot skill working on AI today. Those are considered the peers, not people in the same job code but developing PeopleSoft." Waggoner May 1, 2019 deposition, 93:13-22.

[118] According to the Department Description field in the iRec recruitment database, Oracle Labs "is **researching advanced technologies** in systems, architecture, compilers, programming languages and databases " and "Oracle Labs is the sole organization at Oracle that is devoted exclusively to research." The department descriptions for Corp Architecture positions read, "The OVM infiniband group **provides support** for Mellanox OFED in Oracle Linux, Oracle VM and engineered systems." (ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx) (https://www.openfabrics.org/ofed-for-linux/)

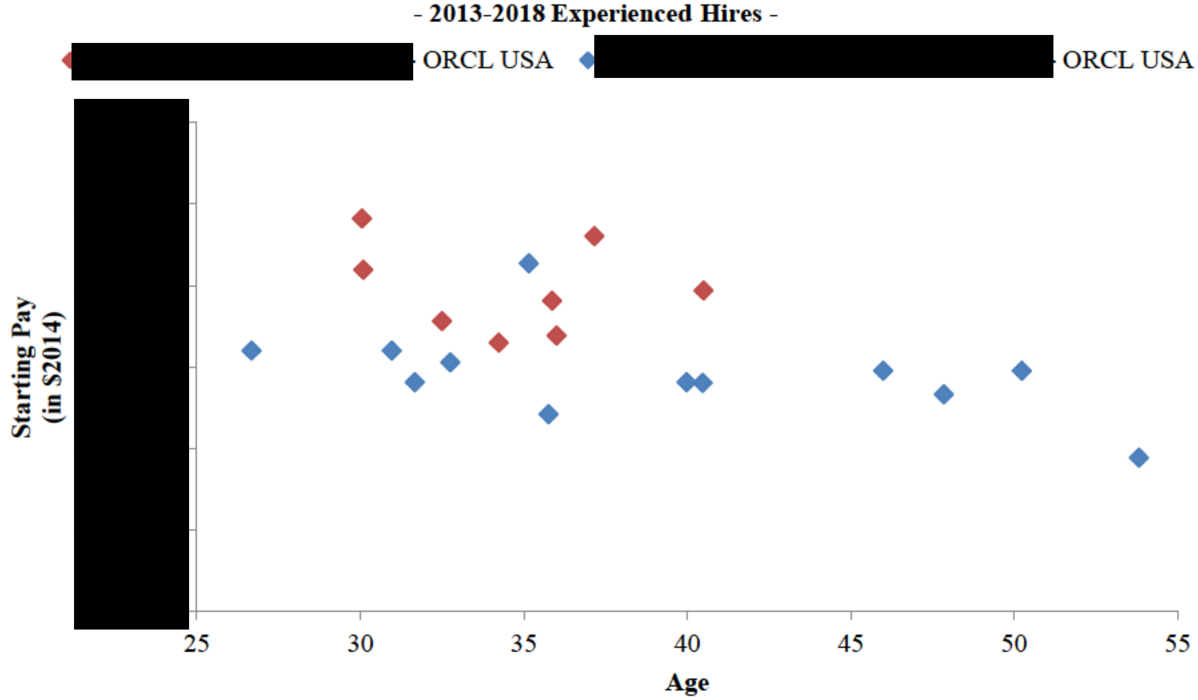
Organization Has a Stronger Relationship with Starting Pay Than Age for Software Developer 3s

- 2013-2018 Experienced Hires -



Organization Has a Stronger Relationship with Starting Pay Than Age for Software Developer 4s

- 2013-2018 Experienced Hires -



142. Given the differences even within standard job titles and organizations, there is no reason to believe that everyone sharing a Career Level should earn the same, meaning that the OFCCP's decision to control only for Career Level in their starting pay models is incorrect because it does not compare similar employees from a labor economics perspective.

<u>Prior pay is highly correlated with starting pay in all firms, not just at Oracle, because both pay sources are a function of the skills, experience and responsibilities of the employee</u>

143. The OFCCP also claims that their "preliminary analyses" show that the disparities they claim to have found in starting pay were "due, in part, to Oracle's reliance on prior salary in setting compensation […]."[119] The back-up material they produced to support their claims does not contain any analysis of prior pay, however. Such an analysis to show how prior pay <u>causes</u> disparities in starting pay is actually quite difficult. A regression coefficient is a measure of correlation, in that it indicates a relationship between two variables but does not necessarily show causality. One can regress height on shoe size, but the positive regression coefficient should not be interpreted to mean that as feet grow longer in length they cause the person to be taller. Showing that prior pay and starting pay are correlated is not enough; the claim is a *causal* one, that reliance on prior pay causes starting pay to be lower for women, Asians, and African-Americans. The OFCCP has not provided any analysis to support this claim.

144. The difficulty with studying prior pay and starting pay is that it is difficult to disentangle how much of the correlation is due to a pay practice of Oracle specifically (as the OFCCP charges) or instead how much is due to the fact that pay depends on a person's skills, experience, and how in demand those attributes are by competing companies. Starting pay and prior pay are strongly correlated throughout the economy. I reviewed National Longitudinal Survey (NLS) data on prior pay and starting pay for people who changed jobs.[120] The correlation between starting pay and prior pay is 0.75 across all individuals in

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[119] SAC, paragraph 32.

[120] The National Longitudinal Surveys (NLS) started in 1997 with 14-18 year olds and surveys them every year about a wide range of topics. My analysis examines job changes and the difference between the ending pay of the prior job and the starting pay of the new job. After limiting the data to exclude people changing occupation, changing part-time/full-time status, or who have extreme values of the reported hourly rates, I analyze data for 3,488 respondents.

the NLS, meaning that it is a factor economy-wide and not just at Oracle. According to the OFCCP's theory, if prior pay has embedded within it labor market bias against women and/or Asians, then Oracle must have simply embedded that bias in its own initial pay for its female and/or minority employees. But that conclusion does not follow, because the OFCCP's hypothesis is also consistent with Oracle setting pay based on the specific relevant skills, abilities, and job experience an applicant brings to the position. The OFCCP does not provide any empirical support for their essentially assumed explanation.

<u>The OFCCP inappropriately aggregated its starting pay analysis across very different hiring and pay-setting processes</u>

145. The OFCCP claims that Asians and women (though not African-Americans) were adversely treated from the start by lowering their starting pay. From 2013 through 2018, Oracle hired 2,819 new employees across the three job functions at HQCA.[121] 76% percent were experienced hires, who responded to requisitions for posted positions. Another 24% were hired from colleges and universities, and less than 1% (7 individuals) joined Oracle when their company was acquired at HQCA during the period studied. The OFCCP analysis combined all new employees regardless of their source.

146. This aggregation combined with the OFCCP use of Career Level as a control does not make analytical sense in terms of experienced hires, because experienced hires respond to specific posted job requisitions. Someone who specializes in database storage is unlikely to apply for a position in Oracle Labs, or in Mobile Cloud Services. Without controlling for standard job title and organization applied to, the OFCCP's model compares employees who have reached a similar career level but who have a wide variety of skills, competitive outside options, and who work on very different products.

[121] The OFCCP starting pay analysis reaches back to 2003, thereby including starting pay decisions made well outside the OFCCP audit window and based only on the subset of employees hired in that window who continued to work for Oracle ten years later.

<u>Experienced hires are not steered into career paths</u>

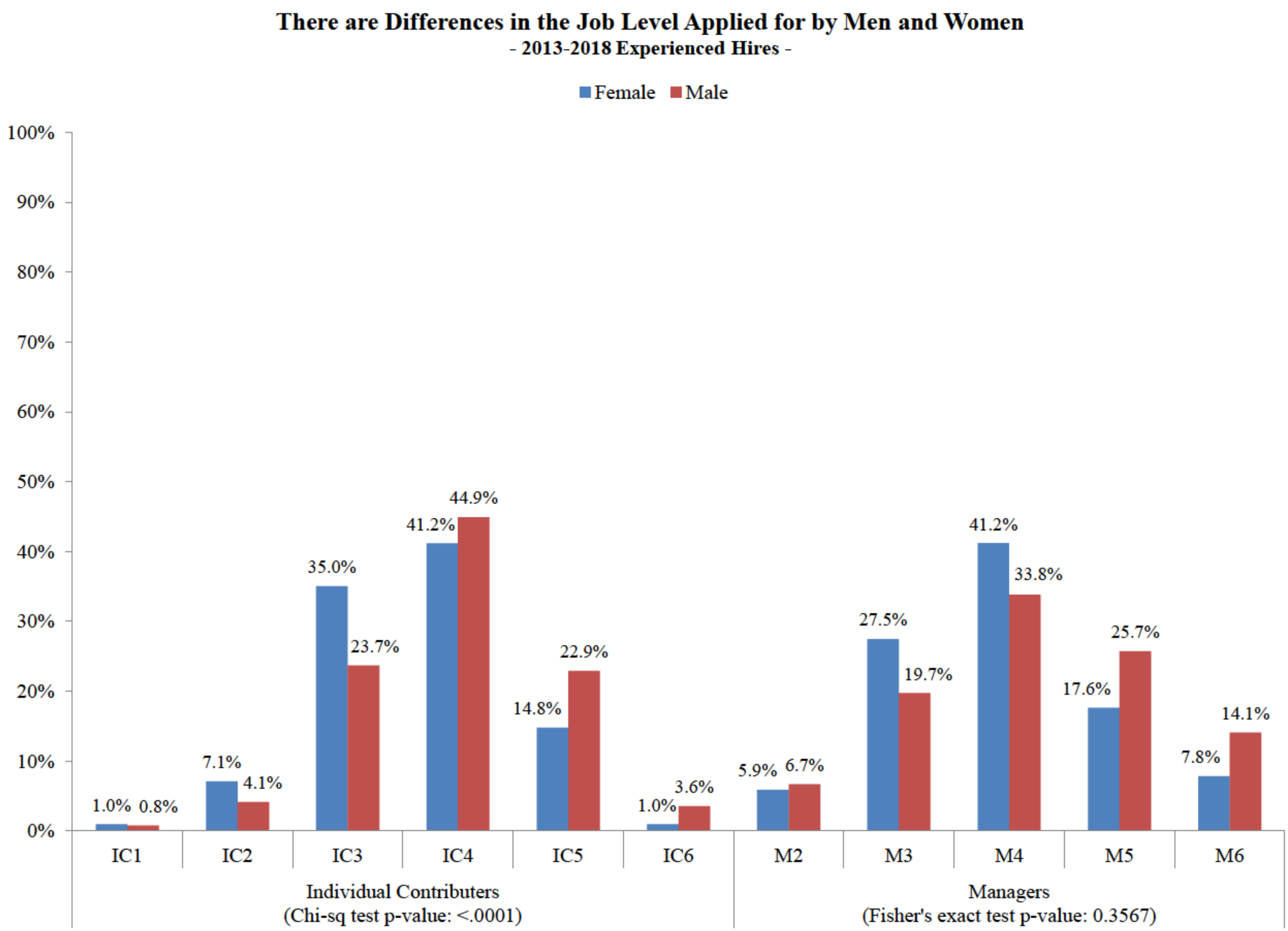
147. The OFCCP claims protected groups are “steered” into lower paying jobs, and that this is one source of their lower average earnings when compared to non-protected employees.[122] To demonstrate this, the OFCCP estimated an ordered logit model to predict initial career levels, controlling for year and years of potential prior work experience (again, age at hire minus 18).[123] They found that women were less likely to be “assigned” into higher IC career levels and less likely to be “assigned” into higher M career levels. They also reported that Asians were less likely to be “assigned” into higher M career levels; they did not report – but their backup shows – that they found that Asians were *more* likely to be “assigned” to higher IC levels. And they found that African-Americans were less likely to be “placed” in higher IC levels, and none were hired into M levels. This analysis is completely wrong on its face, for several reasons.

148. The OFCCP “initial assignment” analysis does not take into account the skills and experiences of the applicants. Most new hires by Oracle from 2013 to 2018 were experienced hires. Not only do experienced hires choose what to apply for (as opposed to being “steered” as the OFCCP suggests), but the data shows that they largely are hired into the Career Level they apply for. Hiring managers have the power to hire one career level above the posted opening if a candidate is especially qualified, or to hire one level below the posted level if a candidate warrants it.[124] My analysis of the starting career level of experienced hires relative to the position they applied for shows no statistically significant differences between men and women in terms of career level adjustments at hire.

149. The OFCCP only generates the results they do because they do not account for the fact that men and women tend to apply for different positions at different career levels at Oracle, and statistically significantly so in the IC career path. The chart below has two panels. The one on the left is the

[122] SAC, paragraph 22.
[123] An ordered logit is a type of regression model that can be used when the dependent variable is not continuous but is ordinal. Pay is a continuous variable. An ordinal variable can be ranked but there is no way to measure whether the distance between the different ranks (i.e., from rank 1 to rank 2, versus rank 2 to rank 3) is equal. An example of an ordinal scale is when surveys ask respondents whether they strongly disagree, disagree, agree, or strongly agree with a statement.
[124] Kate Waggoner May 1, 2019 deposition, 82:1-5.

distribution of applications across IC levels for men and women. The blue bars show the percent of all women who applied to IC positions who applied to each IC level. The first bar on the left, for example, shows that 1.0% of female IC applicants applied to an IC1 position. The red bars show the distribution for men who applied to IC positions. The panel shows that women are more evenly divided between IC3 and IC4 applications than men, whereas men are much more likely to apply for IC4 positions than they are IC3 positions. The difference in distributions between the genders is statistically significant. The panel on the right shows the same distribution for applicants to manager positions. Though the distributions are not statistically significantly different, women are less likely than men to apply to M5 and M6. Asians and Whites also tend to apply for different level jobs, and statistically significantly so in both the IC and M career paths.



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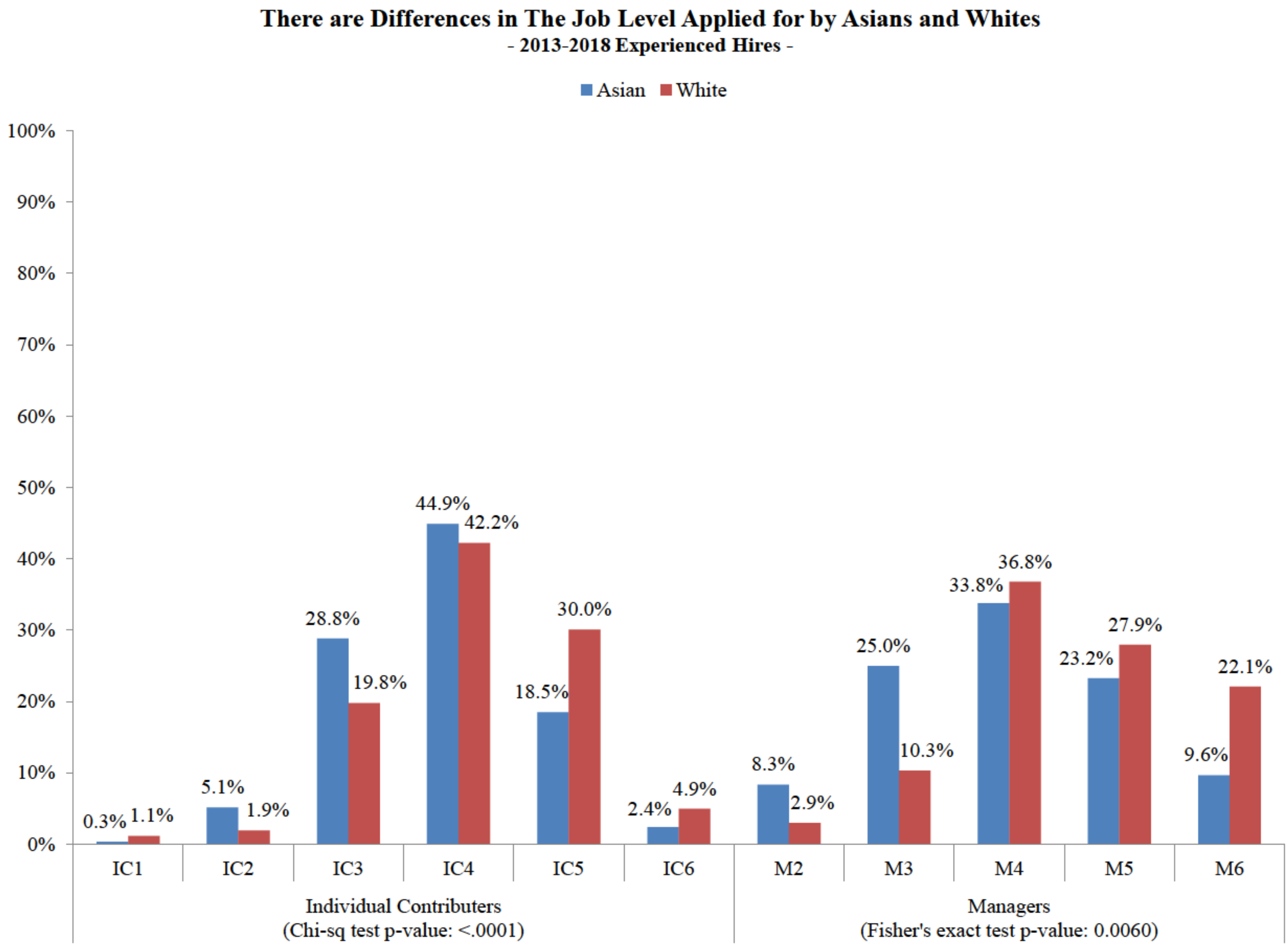

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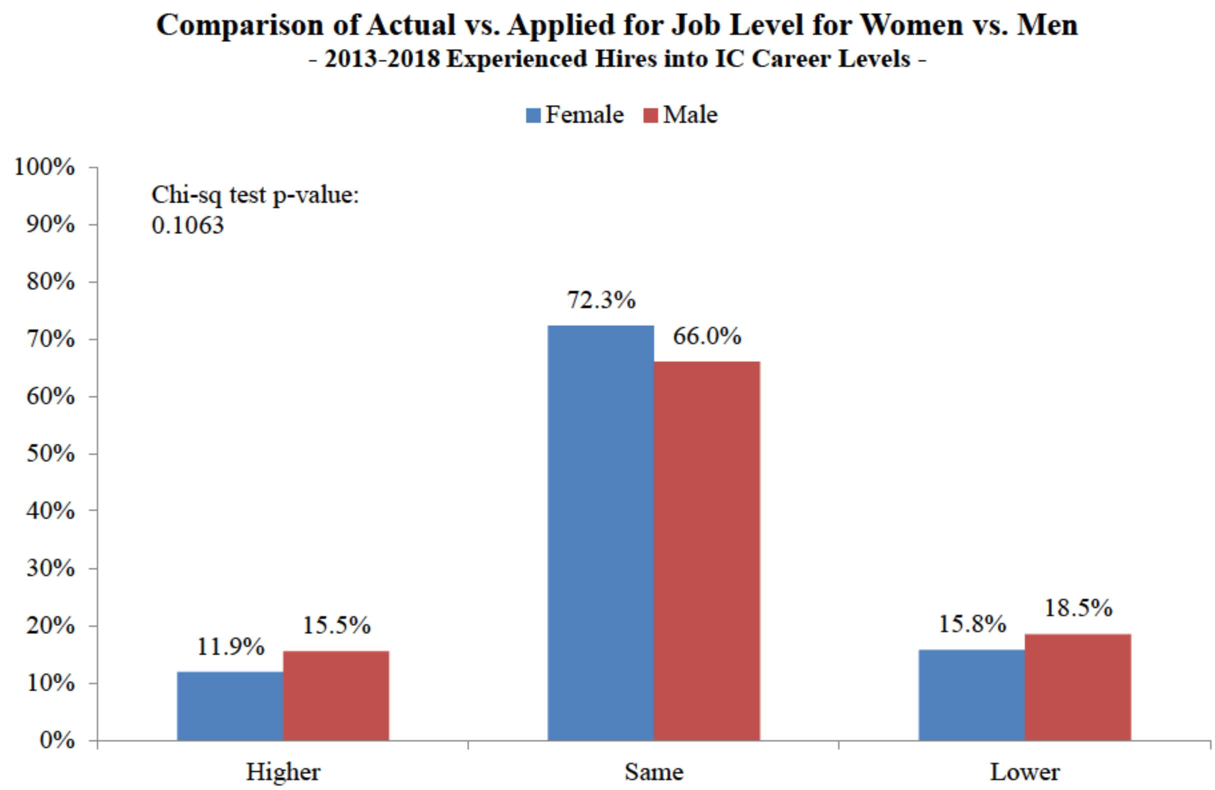
Most employees are hired into the job level they applied for

150. The OFCCP did not account for the fact that applications to IC levels differ by gender and race among experienced workers. To argue that steering is occurring, the OFCCP would have to show that Oracle systematically downgraded applicants' job level at hire relative to the position they applied for.[125] The data does not show this.

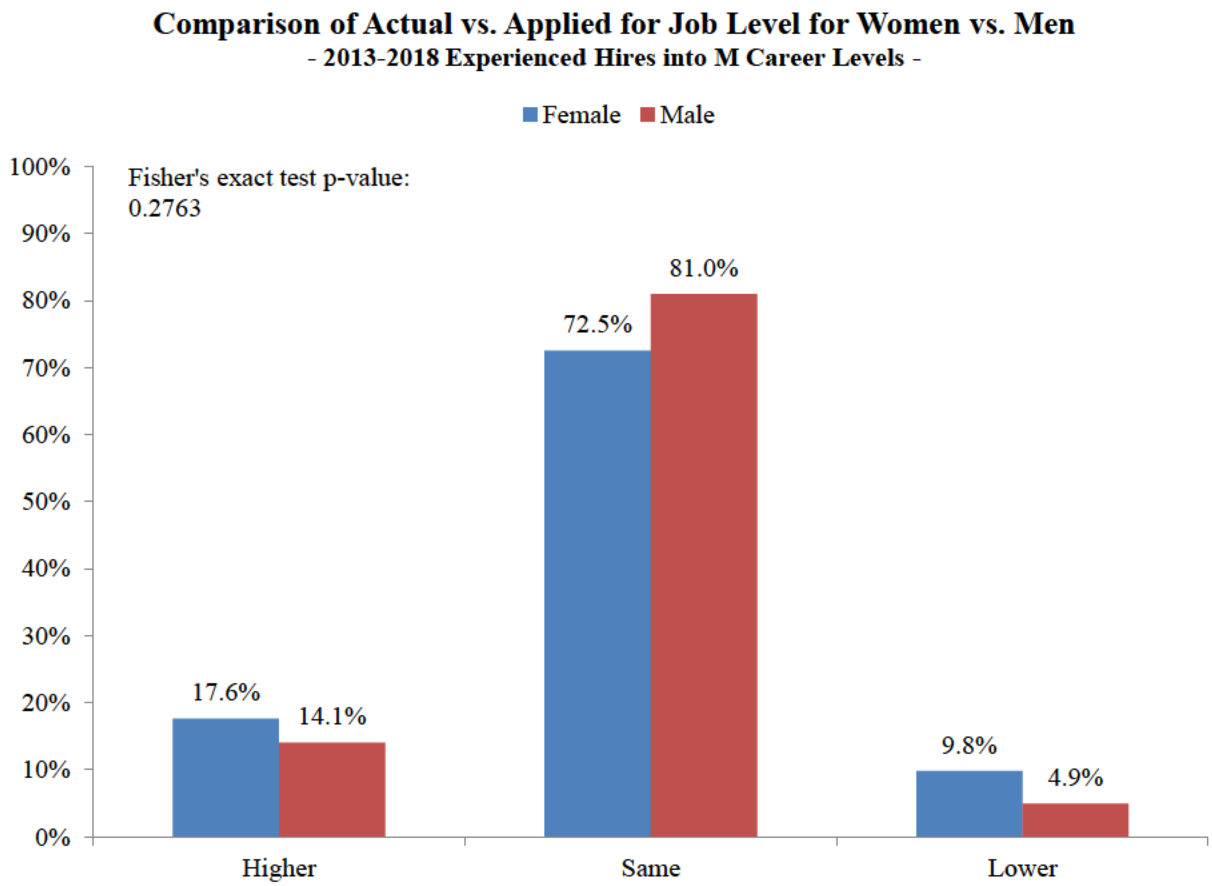
151. Instead the data show that there is no statistically significant difference between men and women in the likelihood of being placed above or below the job level applied for. Requisitions were matched to the initial standard job titles (and associated global career levels) of the new hires. For IC positions, the chart below shows that women are less likely than men to be moved up a level but also less likely to be moved down. Most women are hired into the level they applied for. The difference by gender is not statistically significant, even before taking any other factors into account such as calendar year (to take economy wide conditions into account) or age (to adopt a very rough measure of potential experience).

152. I apply the same methodology used by the OFCCP (ordered logit) to study whether individuals were hired a level up, the same level or down a level from the position to which they applied, controlling for year and age minus 22. The model confirms what the charts below show, that there is no statistically significant gender difference. Women are somewhat less likely to be moved up an IC level, but the differences are not statistically significant.

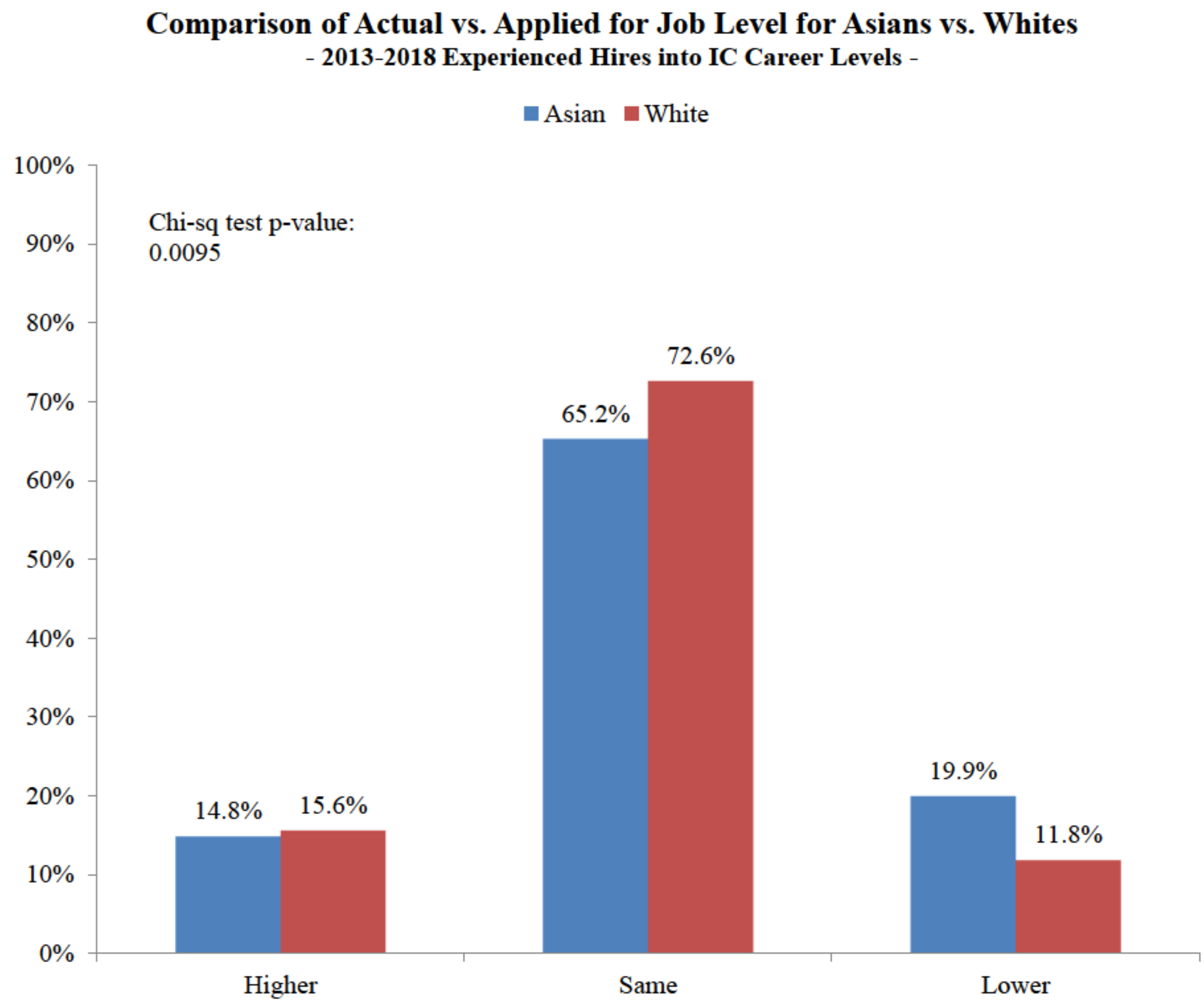
[125] Current employees seeking to transfer can apply for open requisitions, which are posted internally as well as externally. Oracle U.S. Employee Handbook, p. 45 (ORACLE_HQCA_0000000464.pdf).



153. In the management track, women are more likely to be moved up or moved down relative to men, but (as was true for IC new hires) the differences are not statistically significantly different. When I estimate the ordered logit model in order to control for year and experience, the results are the same as they were for the IC track: there are no statistically significant gender differences in the likelihood of being moved up or down a level compared to the level applied to.



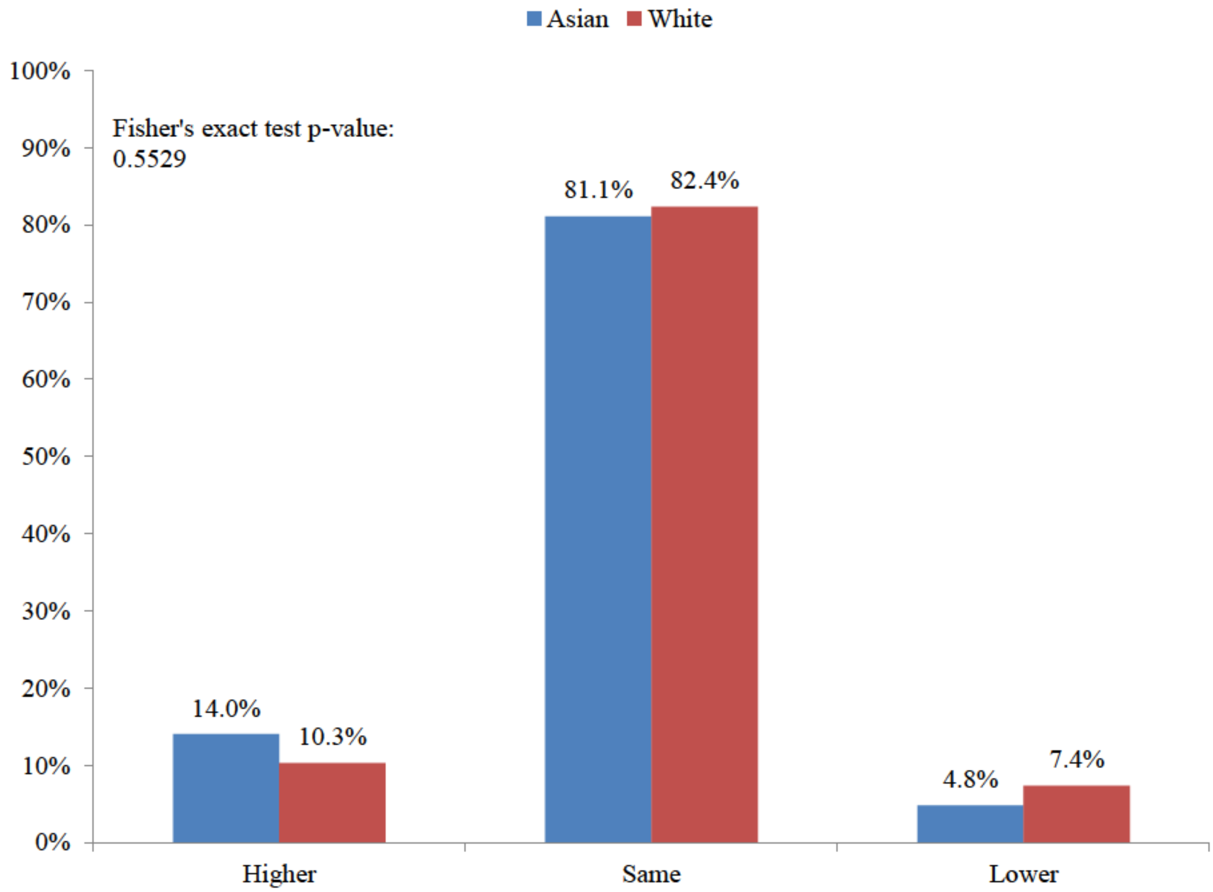
154. The results for Asians and Whites without controls in the chart below show that Asians are slightly less likely than Whites to be moved up an IC level relative to the level they applied for and more likely than Whites to be moved down an IC level, and the difference before taking any controls into account is statistically significant. In the ordered logit model that controls for year and experience, Asians are more likely to be moved up an IC level than are Whites, but the differences are not statistically significant. This corresponds to what the OFCCP back-up showed.



155. In the management track, Asians are more likely to be moved up a level relative to Whites, and less likely to be moved down, but the differences are not statistically significant. In the ordered logit model that controls for year and experience, Asians are more likely to be moved up an M level than are Whites, but again, the differences are not statistically significant.

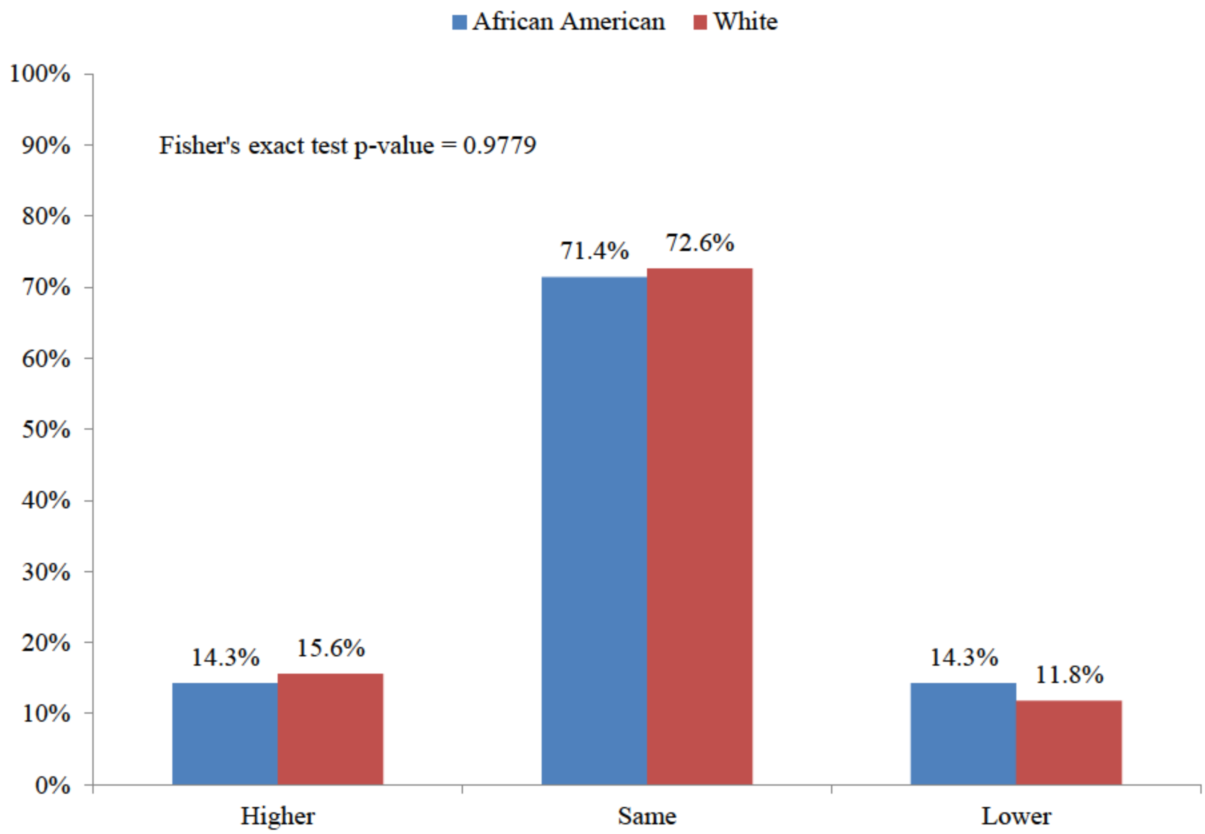
Comparison of Actual vs. Applied for Job Level for Asians vs. Whites

- 2013-2018 Experienced Hires into M Career Levels -



156. My analysis also finds that African American applicants are slightly less likely than Whites to be moved up an IC level relative to the level they applied for and more likely than Whites to be moved down an IC level, but the distributions are not statistically significantly different. The ordered logit model controls for year and experience and shows no statistically significant difference between African Americans and Whites in the likelihood of being moved up or down a level compared to the level applied to. There are no African-American applicants to the M levels for analysis.

Comparison of Actual vs. Applied for Job Level for African Americans vs. Whites
- 2013-2018 Experienced Hires into IC Career Levels -



<u>When starting pay is analyzed using refined control variables and accounting for hire source, there is no pattern indicating systemic adverse outcomes for women or Asians</u>

157. As described above, there are distinct hiring paths for new employees at Oracle. Some arrive via acquisition, and typically their pay remains the same until the next focal review cycle. During the period from 2013-2018, there are only 7 employees who were acquired into one of the three job functions at headquarters (i.e., too few to analyze). College hires are recruited most often through campus programs in a completely separate hiring stream. They also tend not to have much work experience, and tend to be paid about the same, with some premium for certain top schools or for a master's degree or Ph.D. Prior pay is not a relevant issue for this group. Experienced hires, on the other hand, have a diverse set of skills

and experiences and apply to specific job postings that often include highly detailed information about the position's scope and requirements.

158. I apply a modified version of the OFCCP's starting pay model to the experienced and college hiring streams separately, to account for differences in how different characteristics are rewarded. The model includes a rough proxy measure of general previous experience (age minus 22), whether it is full-time or part-time position, the year of hire, and standard job title and organization code in order to compare employees more similarly situated in terms of the work they do and the skills they draw upon than does OFCCPs career-level-based model.

159. Among experienced hires, the largest group of new hires, there are no statistically significant pay difference for women in any of the three job functions. Average starting pay for Asian experienced hires and White experienced hires are not statistically significantly different. The difference in starting pay for African-Americans compared to Whites in PRODEV is also not statistically significant. Taken together, I do not see evidence of a pattern of adverse results for any of the protected groups.

Regression Analysis of Starting Base Pay for Experienced Hires
Models with Gender or Race Show No Statistically Significant Differences
- 2013-2018 -

Job Function	Group	# Protected Group-Hires	Pay Difference (%)	T-Value
INFTECH	Female vs. Male	57	-2.29%	-1.06
PRODEV	Female vs. Male	383	-1.19%	-1.80
	Asian vs. White	1,292	-0.17%	-0.23
	African American vs. White	8	-9.79%	-1.59
SUPP	Female vs. Male	7	-3.13%	-0.32

Note: 12 employees in PRODEV and 1 employee in INFTECH were hired twice during the period. Model controls for gender/race, experience (age minus 22), part-time/full-time, year of hire, standard job title, and organization.

160. There are too few college hires in INFTECH and SUPPORT to analyze separately, but it is possible in PRODEV. Entry level hires from colleges are not hired into specific positions. The regression

model thus controls for experience and career level to take differences in degrees earned into account (about 5% are over age 30), and their hire year, but does not control for job title or organization. There are no statistically significant results for any of the protected groups, and in fact, the results are positive for women.

Regression Analysis of Starting Base Pay for College Hires
Model with Gender/Race Effects Shows No Statistically Significant Differences
- 2013-2018 -

Job Function	Group	# Protected Group	Pay Difference (%)	T-Value
PRODEV	Female vs. Male	212	0.77%	1.82
	Asian vs. White	592	-1.54%	-1.82
	African American vs. White	13	0.25%	0.11

Model controls for race/gender, experience (age minus 22), career level, and year of hire. They are all fulltime employees, and so no additional control was necessary.

THE OFCCP ANALYSIS OF WAGE GROWTH IS FLAWED

Women do not experience slower wage growth, contrary to the claims by the OFCCP

161. The OFCCP analyzed growth in base pay in Product Development from 2003-2016, controlling for gender or race, Career Level, whether standard job title changed from previous year, previous experience (age minus 18 minus Oracle America, Inc. tenure), time at Oracle America, Inc., whether the person worked full-time in the previous and in the current year, whether they were exempt in the previous and current year, and calendar year. They concluded that Asians and women "experienced slower wage growth […] to a statistically significant degree," though they do not show or otherwise describe the coefficients in the SAC. They also did not analyze women in the other two job functions to test whether their argument was consistent across the job functions.

162. My wage growth model adds controls for whether someone took a leave of absence during the year, whether they received a patent bonus during the year and their organization. The organization variable is important because bonuses and pay raises are set according to budgets controlled in different ways by different managers, and because employees are encouraged to explore career paths in various organizations.[126] The results show there is no pattern of statistically significant difference in wage growth by gender in any of the three job functions. For example, in INFTECH, in 2013, average pay growth was [redacted] for men and [redacted] for women (0.74 percentage points higher). The difference is small and not statistically significant. The coefficient is small and positive again in 2015 and 2016, indicating women's wage growth is slightly higher than men's, and in other years it is small and negative, but none show a statistically significant difference in wage growth. In PRODEV, the coefficient on women's wage growth is only slightly below that of men (and slightly above in 2018) and it is not statistically significant, other than in 2016. In SUPPORT, women's wage growth is slightly higher than men's in every year except 2013 and 2017, but it is never a statistically significant difference.

[126] This is described in HR documents that also discuss how different Lines of Business ("LOB") exert different amounts of control over the process. "If we have a budget, it is determined by country and function, and allocated at the very top executive level. Each LOB head uses the budget in the way that he or she believes is appropriate for the LOB. The budgets are pushed from the top down, and some LOBs may stop at a specific level of management when allocating. For example, some organizations don't push the budgets any further than the M4 level. Even if a budget is not pushed all the way down to a mgr in CWB, managers may still allocate money to their employees." (ORACLE_HQCA_0000056239_HR REFRESH_CWB_TRAINING_APR2011v3_Updated_June2013V3 (Native).PPTX , p. 5.)

"Salary increases are based on your productivity and contributions, company performance. Employees are encouraged to move around the company." Oracle U.S. Employee Handbook, p. 42. (ORACLE_HQCA_0000000464).

"Provided you have been in a position for a reasonable amount of time, we encourage you to explore opportunities for change and advancement. […] Both you and Oracle benefit when you are allowed to learn and expand your capabilities by working in different jobs in the company. […] To respond to a job posting, contact the person listed in the posting to arrange an interview with the hiring manager. You may also contact a manager of an organization where you would like to work, even if there is no listed, open position." Oracle U.S. Employee Handbook, p. 45 (ORACLE_HQCA_0000000464).

Analysis of Pay Growth for Women vs. Men Shows No Statistically Significant Difference for Women With the Exception of a Single Year Within PRODEV

Refined Model for Female vs. Male Annual Wage Growth						
Job Function	**Year**	**# Obs Used**	**# Protected Group**	**Average Pay Growth**	**Coefficient**	**T-Value**
INFTECH	2013	440	124	[redacted]	0.0074	1.20
	2014	447	124		-0.0033	-0.77
	2015	556	136		0.0023	0.55
	2016	604	143		0.0031	0.72
	2017	543	132		-0.0001	-0.03
	2018	521	127		0.0033	0.64
PRODEV	2013	3,892	1,120		-0.0017	-0.83
	2014	3,861	1,108		-0.0012	-0.70
	2015	3,804	1,076		-0.0026	-1.47
	2016	3,803	1,055		-0.0033	-2.39
	2017	3,813	1,050		-0.0013	-1.10
	2018	3,571	994		0.0013	0.60
SUPP	2013	233	42		-0.0053	-0.54
	2014	220	42		0.0036	0.32
	2015	103	31		0.0146	1.60
	2016	95	23		0.0126	1.31
	2017	85	20		-0.0070	-0.70
	2018	83	21		0.0160	1.55

Model controls for female, standard job title, part-time/full-time, part-time/full-time in previous year, exempt status in previous year, organization, total Oracle tenure (including time at acquisition and non-USA affiliate), age minus total Oracle tenure minus 22, whether employee had a patent bonus in current year, whether leave of absence was in current year, whether there was a career level change, whether there was a job title change.

Asians and African Americans do not experience slower wage growth, contrary to the claims by the OFCCP

163. My modified analyses show very similar results for Asians and African Americans: a mix of positive and negative coefficients, but no statistically significant differences between Asians and Whites or between African Americans and Whites.

Analysis of Pay Growth for Asians vs. Whites Shows No Statistically Significant Difference for Asians in Any Year

Refined Model for Asians vs. Whites Annual Wage Growth						
Job Function	**Year**	**# Obs Used**	**# Protected Group**	**Average Pay Growth**	**Coefficient**	**T-Value**
PRODEV	2013	3,774	2,743	[redacted]	0.0010	0.44
PRODEV	2014	3,745	2,761		-0.0003	-0.17
PRODEV	2015	3,677	2,743		0.0000	-0.01
PRODEV	2016	3,653	2,777		-0.0014	-0.89
PRODEV	2017	3,666	2,817		-0.0006	-0.42
PRODEV	2018	3,421	2,652		0.0025	0.98

Model controls for Asian, standard job title, part-time/full-time, part-time/full-time in previous year, exempt status in previous year, organization, total Oracle tenure (including time at acquisition and non-USA affiliate), age minus total Oracle tenure minus 22, whether employee had a patent bonus in current year, whether leave of absence was in current year, whether there was a career level change, whether there was a job title change.

Analysis of Pay Growth for African Americans vs. Whites Shows No Statistically Significant Difference for African Americans in Any Year

Refined Model for African Americans vs. Whites Annual Wage Growth						
Job Function	**Year**	**# Obs Used**	**# Protected Group**	**Average Pay Growth**	**Coefficient**	**T-Value**
PRODEV	2013	1,056	25	[redacted]	-0.0104	-0.71
PRODEV	2014	1,010	26	[redacted]	0.0008	0.08
PRODEV	2015	959	25	[redacted]	0.0014	0.11
PRODEV	2016	905	29	[redacted]	0.0007	0.08
PRODEV	2017	876	27	[redacted]	-0.0010	-0.21
PRODEV	2018	796	27	[redacted]	-0.0019	-0.17

Model controls for African American, standard job title, part-time/full-time, part-time/full-time in previous year, exempt status in previous year, organization, total Oracle tenure (including time at acquisition and non-USA affiliate), age minus total Oracle tenure minus 22, whether employee had a patent bonus in current year, whether leave of absence was in current year, whether there was a career level change, whether there was a job title change.

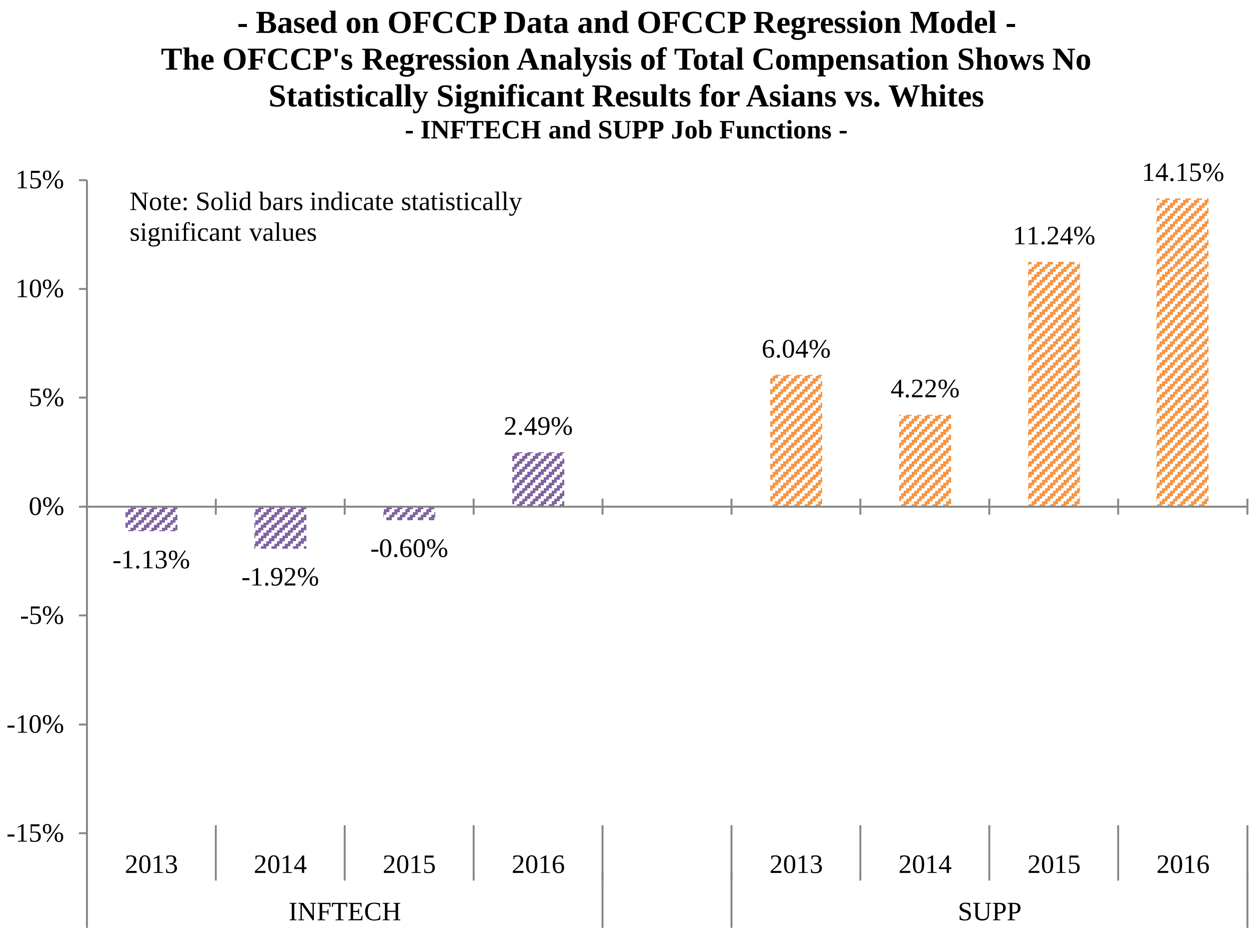
<u>THE OFCCP SELECTIVELY REPORTED RESULTS IN THE SAC</u>

<u>The OFCCP points to company-wide policies and practices to explain claimed pay disparities but to the results for Asians in SUPPORT and INFTECH are inconsistent with that theory</u>

164. The OFCCP limits its claims in the SAC to Asians in the PRODEV job function. But the OFCCP also claims the “systematic underpayment of women and Asian employees is due, in part, to suppression of those employees’ starting pay.”[127] They do not, however, explain why this theory dictates adverse pay outcomes for women in all three job functions but for Asians only in PRODEV, especially given that Asian women work in all three functions. Had the OFCCP presented the results of applying their model to Asians and Whites in the other two job functions, they would have had to discuss results that are not only statistically insignificant, but which for one year in INFTECH and all four years in SUPPORT are

[127] SAC, paragraph 22.

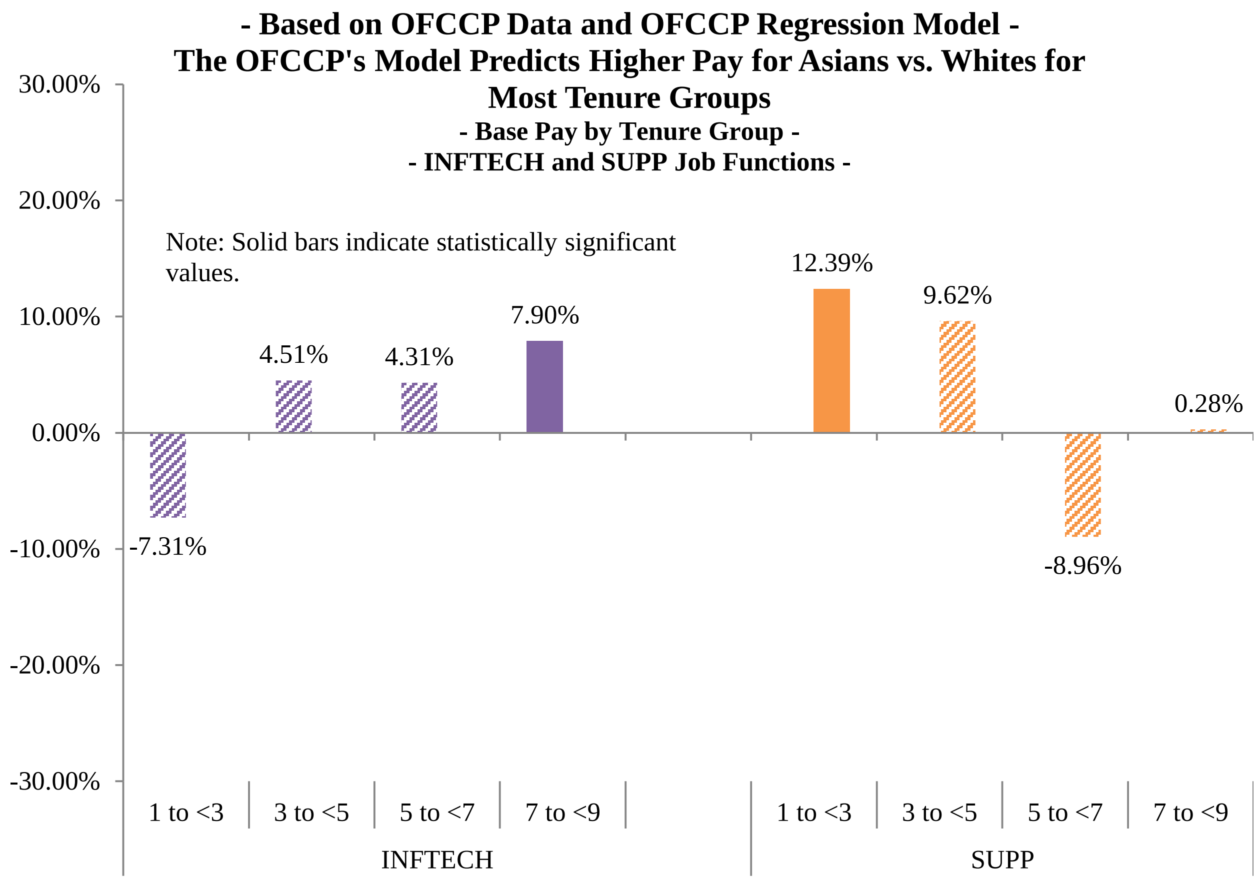
positive for Asian employees.[128] This raises questions about the consistency of their arguments and the degree to which they have cherry-picked results to fit their argument.



The OFCCP model controls for Asian, standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

165. Similarly, the OFCCP argues that the pay gap opens up with time, such that longer tenured Asian employees do worse. Yet this is not true when their exact same model is applied to the INFTECH and SUPPORT job functions.

[128] The OFCCP ran their model in the PRODEV job function but it is a straightforward change to run the same model on the same data, but on the other two job functions.



Model controls for Asian, standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

166. In fact, the OFCCP's results show that on average Asians in the highest tenure group are paid statistically significantly *more* than Whites in INFTECH. Overall, when the OFCCP model analyzing wage growth is applied to INFTECH, it shows that Asians have a slightly higher wage growth [redacted]). In SUPPORT, Asian wage growth is statistically significantly higher ([redacted]) than for whites.[129]

167. The same narrow focus combined with expansive theories about causality is at work in reporting results for starting pay. The OFCCP reports that Asians in PRODEV are paid less upon hire, yet using their own model there is no statistically significant difference in starting pay between Asians and Whites in INFTECH (Asians earn 1.94% more on average at the start using the OFCCP model) or in SUPPORT

[129] This is for years 2003-2016. For years 2013-2016, in the OFCCP's model, Asians have slightly lower but not statistically significantly different wage growth ([redacted]) in INFTECH and a statistically significantly higher wage growth ([redacted]) in SUPPORT.

(Asians earn 0.07% less on average at the start using the OFCCP model). The OFCCP does not explain why their company-wide theories about pay disparities in PRODEV do not generate the same results in their model in other job functions for Asians, but do for women.

168. Neither the data in this case nor the OFCCP's analyses of that data support the existence of company-wide discriminatory patterns and practices leading to lower starting pay and increasingly lower relative pay through time. Even the OFCCP's own model showed statistically significant adverse results for women only in PRODEV, INFTECH and SUPPORT and for Asians only in PRODEV, but somehow not for Asians in INFTECH and SUPPORT. If nothing else, Asian women also work in INFTECH and SUPPORT, which means these OFCCP explanations are supposed to apply only when they are considered as women but not when they are considered as Asian. This analytically incoherent explanation relies on the OFCCP suppressing their own results based on their own regression model on their own data in other job functions.[130]

The OFCCP selectively reported statistical results for Asians in PRODEV

169. The SAC states that Asians are only 49% as likely as Whites in PRODEV to be "assigned" into higher global career levels as managers.[131] Their back-up also contains unreported results for non-managers in the IC career levels. In the IC career levels, Asians are 17.8% *more likely* to be placed in the higher levels than are Whites according to the OFCCP's own model, though the difference is not statistically significant. I address their model's shortcomings elsewhere in this report, but I discuss them here in relation to my concern that the OFCCP is selectively picking results to support its claim.

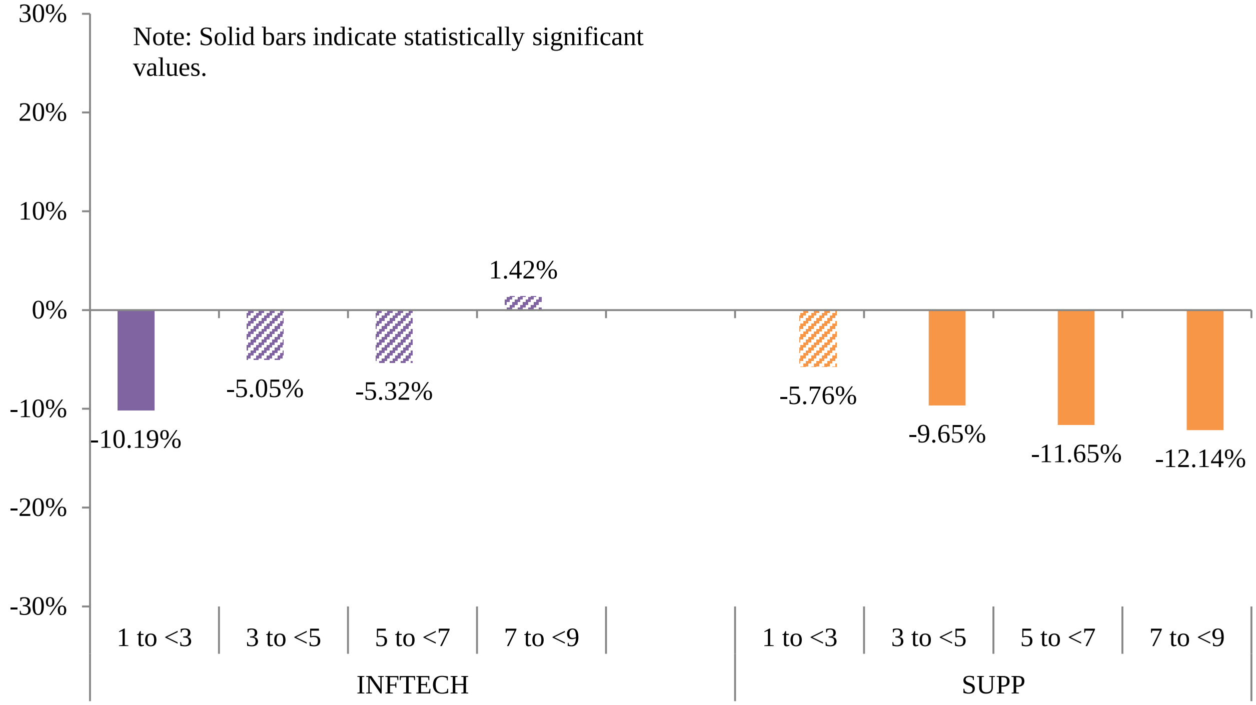
[130] Moreover, the SAC only reports their results by tenure group for base pay and not total compensation. Had they reported total compensation results for Asians in PRODEV, they would have had to acknowledge that there is no statistically significant difference in total compensation between Asian and Whites in PRODEV in the 1-3 and 3-5 year tenure groups according to their own model.
[131] SAC, paragraph 21.

The OFCCP selectively reported results for women

170. The OFCCP claims in the SAC that “the pay gap increases for female employees as they remain at Oracle for longer periods of time.”[132] However, they only show the results for women in PRODEV. When I run their SAC statistical model for women in INFTECH, I find that the pay gap (according to their model) is adverse to women and statistically significant in the 1-3 year tenure group, but that it falls in size with tenure and is positive for the highest tenure band. In SUPPORT, the trend is similar to PRODEV but the pay gap in the youngest tenure band is not statistically significant from zero, which implies according to the OFCCP interpretation of these analyses that Oracle does not suppress pay early on but suddenly decides to do so later. There are methodological issues with this analysis that I address elsewhere, but these results are based on OFCCP methods and OFCCP data which they chose not to present. The results in INFTECH contradict their claim about the pay gap growing with tenure for all women, making the claims in the SAC misleading in light of the results their own model produced.

[132] SAC, paragraph 26.

- Based on OFCCP Data and OFCCP Regression Model -
The Pay Gap Does Not Increase With Tenure in INFTECH and is Not Statistically Significant for the Youngest Tenure Group in SUPP for Females vs. Males
- Base Pay by Tenure Group -
- INFTECH and SUPP Job Functions -



Model controls for female, standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

The OFCCP selectively reported results for African-Americans

171. The OFCCP presents a table following paragraph 16 of the SAC that purports to support their claim that African-American employees in PRODEV are undercompensated relative to white employees. Had they not switched to analyzing base pay but instead reported the results for total compensation – consistent with their approach to analyzing pay of women and Asians – they would have reported that there are no statistically significant difference in pay between African-Americans and Whites, according to their own model.

172. Not only did they switch from total compensation to base pay in order to select these results, they present only the results for 2015 and 2016, which I understand to be outside the audit window. This

omission does not have to do with changing sample sizes – there are as many African American employees in 2013 and 2014 as in 2015 and 2016. They chose to present only the years in which they found statistically significant pay disparities and not the years in which the results did not demonstrate statistically significant pay disparities according to their model, and thus that there is not a longstanding pattern by year even in their own analysis.

173. As concerns their tenure group analyses, the OFCCP does not discuss why base pay by tenure group for African Americans is small and not statistically significant in the 3 to 5 year tenure group, the largest of the four tenure groups they report on in the SAC. And had they reported results for total compensation by tenure group, they would show a pay gap only in the highest tenure group, and again, a pattern across tenure groups that does not support their argument that the pay gap increases over time.

174. With regard to starting pay, in paragraph 18 of the SAC, the OFCCP notes that women and Asians earn less at hire according to their models (without noting they limited the analysis to employees in PRODEV), but they omit any discussion of the fact that there is no statistically significant starting pay gap for African Americans in any of the three job functions.

175. Finally, in paragraphs 30 and 31 of the SAC, wage growth for women and Asians is discussed, but not the fact that according to their model, wage growth for African Americans is not statistically significantly different from whites in PRODEV (or INFTECH or SUPPORT as well).

THERE IS NO EMPIRICAL SUPPORT FOR THE OFCCP CLAIM THAT DAMAGES ARE OWED

176. The OFCCP uses its regression model to compute damages. Their approach is to use the regression model coefficient on gender or race to formulaically arrive at an aggregate damages figure by multiplying the coefficient by average earnings for white men.[133] Even if such an approach were warranted, there are serious problems with the OFCCP's implementation, as I discuss next.

When the proper measure of total compensation is used, and a refined set of control variables to similarly situate employees, there is no pattern of adverse outcomes for women and therefore no damages to calculate

177. The OFCCP regression model is, as I discussed above, unreliable for a number of reasons. It incorrectly measured total compensation, mis-measured prior experience, mis-measured tenure at Oracle, failed to take leaves of absence into account, and ignored information about employee innovation as well as information about the kinds of products and services employees work on. The scatterplots showed that their regression model could not explain the widely varied outcomes for women, in which large numbers of female employees earned much more than their model predicted. The refined model I present in this report fixes those problems and shows that, once those errors are corrected, and even if one continues to aggregate the analyses into the broad job function groupings OFCCP uses, there is no pattern of adverse compensation results for women. Thus, there are no damages to estimate.

The OFCCP did not present its results for total compensation for African Americans which showed no statistically significant difference

178. The OFCCP claims that based on its (flawed) analysis, African American employees are owed "at least $1,300,000"[134] However, the analysis they presented in the SAC examined base salary instead of total compensation, unlike its other analyses. When their analysis of pay for African-Americans is re-

[133] The SAC also makes reference to the proffered damages estimates being "much higher" than even the number they present because, they claim, the "practices" at Oracle have not been corrected" since the first complaint was filed in January 2017 (SAC, paragraph 17). However, the May 24, 2019 OFCCP letter from Abigail Daquiz to Warrington Parker notes that the damages estimates also included nominal damages for 2017 and 2018 plus interest.

[134] SAC, paragraph 16.

estimated using their measure of total compensation, the OFCCP's own model shows that there is no statistically significant gap in total compensation between African Americans and Whites. Their own model shows that no damages are owed.

<u>The OFCCP calculated damages for Asian men but its own model shows there is no consistent adverse outcomes for Asian men</u>

179. The OFCCP claims that Asian employees are owed "at least $234,000,000".[135] They explained how they arrived at that number in a letter dated May 24, 2019, where they note that the estimated damages for Asians in the SAC are for men only, because Asian women were included in their overall damages estimate for women "in order to avoid double counting."[136] However, the regression model they use to justify $234 million in back pay estimated the Asian male damages compared all Asian employees to all White employees.

180. Had the OFCCP estimated their regression model only for Asian male and white male employees to generate a damages estimate for Asian men, they would have observed that only two of the four years show a statistically significant pay gap (using their data and their model and making no other corrections). In 2013 and 2016, the estimated pay difference is not statistically significantly different from zero. Yet their damages estimate includes all of these years in its calculation. There is no consistent statistically significant adverse pattern year to year, and these results do not support calculating damages for every year from 2013 on.

[135] SAC, paragraph 15.
[136] OFCCP Letter from Abigail Daquiz to Warrington Parker, dated May 24, 2019, page 2. Note that they also assigned damages to part time employees as if they worked full time.

- OFCCP Data and Model Restricted to Asian and White Men -

There is No Systematic Pattern of Statistically Significant Results for Asian Men vs. White Men

- PRODEV -

Year	# Protected Group	Pay Gap (%)	T-Value
2013	1,879	-2.60%	-1.68
2014	1,895	-7.48%	-4.58
2015	1,885	-7.26%	-4.91
2016	1,928	-2.94%	-1.84

The OFCCP model controls for Asian male, standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

<u>Due to their overly simplistic formulaic approach, the OFCCP awarded damages to part-year employees as if they worked all year</u>

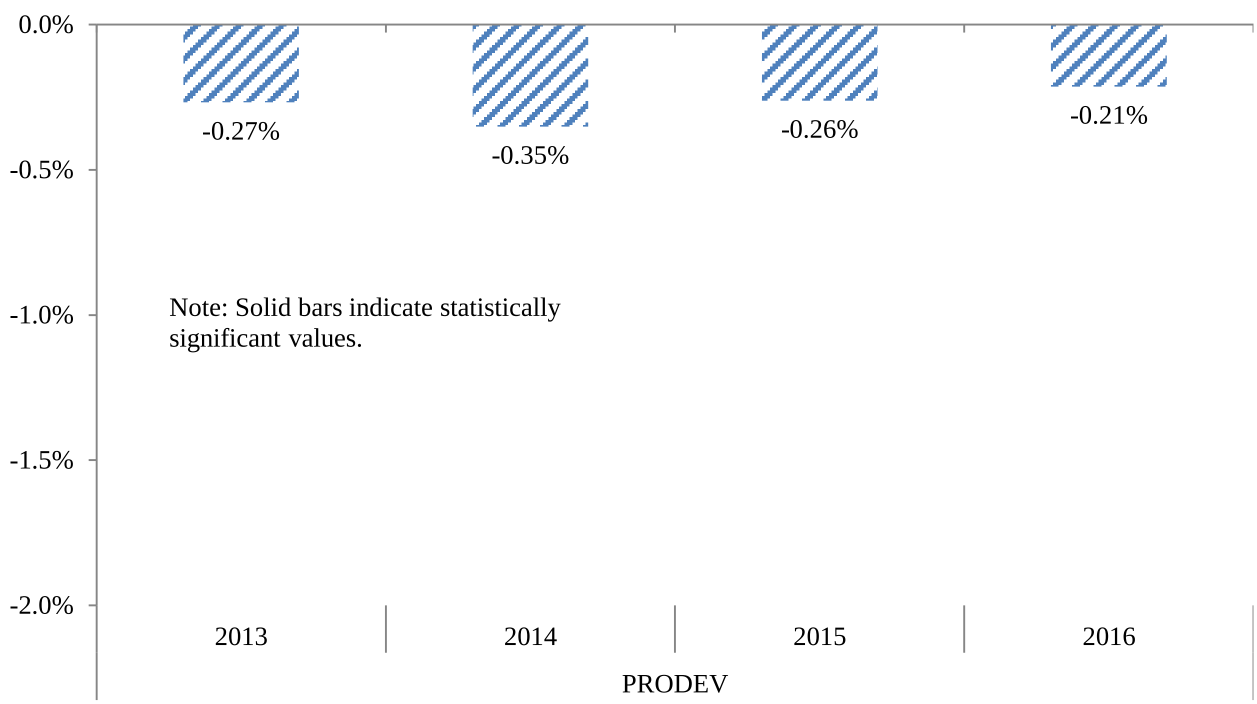
181. In addition, when the OFCCP estimated damages, it calculated damages for employees who worked part-time or part-year (including women) as if they worked full-time, full-year. To estimate damages for women, for example, the OFCCP multiplied their regression-estimated 2013 pay difference for women (-6.78% in PRODEV) by the average 2013 total compensation for white males working all year. This dollar amount was then multiplied by the total number of women each year, including those just hired or terminated part way through the year. In effect, because of a simplistic formulaic approach that does not take account of employee by employee differences, the OFCCP attributed damages to part-time or part-year employees as if they worked full-time, all year; this approach is clearly incorrect.

<u>When the proper measure of total compensation is used, and a refined set of control variables to similarly situate employees is used, there is no pay difference between Asian men and white men and therefore there are no damages to calculate</u>

182. As described above, the OFCCP controls for race/ethnicity, company tenure based on US Oracle hire date, previous experience measured as age minus company tenure minus 18, whether the employee is exempt or non-exempt, full-time or part-time, and their standard job title. This model is flawed for a number of reasons as described above.

183. The graph below shows the year by year results from my refined regression model, estimated for Asian men compared to White men. Total compensation was analyzed, controlling for race, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), age minus total Oracle tenure minus 22, cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition. The pay difference is miniscule and the t-statistics are close to zero.

Modified Regression Analysis of Total Compensation Shows No Statistically Significant Results for Asian Males vs. White Males in Any Year Within PRODEV



Model controls for Asian male, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in standard job title, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

184. When this refined model is applied, which uses the correct measure for total compensation and a more appropriate set of control variables to similarly situate employees based on skill and responsibilities,

there is no pay difference between Asian men and white men. Thus, instead of $234 million, Asian men experienced no shortfall on pay. There are no damages to award to Asian men, contrary to what the OFCCP claims, because there is no pay gap between the two groups.

CONCLUSION

185. In this final section of my report, I summarize some of the key conclusions I have reached after considering the OFCCP's SAC analyses against the data, documents, and other information available about work at Oracle. The OFCCP's analyses of compensation are flawed in a number of ways, and do not support the inference that all women in the three job functions and Asians and African Americans in the PRODEV function are paid less than men (Whites) doing similar work that demands similar levels of skills and responsibility. Even though the OFCCP was concerned only about 3 of 16 job functions at Oracle, the OFCCP aggregated all of its models to the job function level, across many managers, organizations, and types and levels of work. Yet my analysis showed there are wide variations in pay outcomes across employees even according to the OFCCP's aggregated common statistical model. This wide variation in outcomes is inconsistent with the notion that companywide explanations and a common model can be used to explain and meaningfully analyze the pay for women and Asians across Oracle.

186. The OFCCP's SAC regression model does not compare employees who are performing substantially similar work from a labor economics perspective. Standard job titles are broadly defined and the requisitions showed that employees with the same title can be doing quite different work. Those hired into the company into positions with identical standard job titles codes earn widely varying amounts. This variation has little to do with years of labor market experience or age; instead, it appears that if a successful candidate has the requisite specific skills, they can be hired and paid commensurate with the skills and responsibilities that the position requires. For Software Developer 4 jobs, the largest single job code in the data, the range of ages hired at the same pay level spans from 25 to 62, and at any given age, the range of pay is almost a [redacted] Standard job title alone is insufficient to similarly situate employees. It is very unlikely from a labor economics perspective that two individuals sharing the

identical standard job title, with one paid [redacted] what the other earns, are doing substantially similar work. Oracle standard job titles (or job codes) do not operate to "narrowly define" the nature of work from the perspective of a labor economist. That Oracle organizes its workforce with a particular hierarchical and task-type structure does not mean that this structure alone is sufficient for a labor economist asked to analyze this data in the context of a pattern and practice pay discrimination claim. These are crude measures from an analytical perspective, yet they are all that OFCCP's models use. As a result, the OFCCP regression model is not correctly specified, and does not compare employees performing substantially similar work.

187. The OFCCP tenure measures are deeply flawed. First, "previous experience" is simply the employee's age minus 18 minus years since hire at Oracle America, Inc. OFCCP's model does nothing to capture differences in relevant prior experience, which can matter significantly for pay decisions. Second, the OFCCP fails to measure and take account of number of years employees may have worked at an Oracle affiliate overseas or in an acquired firm. Many employees in the data previously worked at an Oracle affiliate outside of the USA, which plausibly constitutes relevant experience in many cases, as would experience at a firm later purchased by Oracle. OFCCP's model does not credit these employees with these types of experience. OFCCP also did not control for tenure in the current standard job title. Instead, the OFCCP model considers someone new to a position to be as skilled as someone who has worked in the position for years, as long as both were hired at Oracle America, Inc. in the same year. Finally, the OFCCP does not account for leaves of absence or other periods of unemployment, and thus does not actually compare employees who have spent equivalent amounts of time at work, improving their job-related skills and abilities.

188. The OFCCP also analyzed starting pay. But their starting pay regression models did not even control for standard job title but rather for career level, a broad measure of career advancement in which a Technical Writer and a Hardware Developer can share a level while having few skills in common. It is clear from the requisitions that experienced hires have diverse histories of skills and specialties and they do not apply at random to Oracle. Someone working in software security, for example, is unlikely to

apply for a job developing application software for use by accounting firms. The OFCCP model, however, only controls for Career Level and not for standard job title and organization to address these differences.

189. My refinements to the OFCCP's model includes a measure of general previous experience (age minus company tenure minus 22), whether the position applied to is exempt or non-exempt, whether it is full-time or part-time, the year of hire, and standard job title and organization code in order to compare employees more similarly situated in terms of the work they do and the skills they draw upon. For each demographic group, there is a mix of positive and negative coefficients, indicating no pattern across the job functions. I further find no differences in terms of pay growth thereafter, once additional readily available additional factors are introduced.

190. Finally, there are a number of other data errors and other technical issues in the OFCCP analysis. Most importantly, the OFCCP measure of total compensation is taxable pay in the year, which includes exercised stock options from years past, 401K decisions and any other adjustments that are not a reflection of actual work that year. The OFCCP total compensation results are uninterpretable, because stock awards make up sizeable percentages of compensation, especially in the [redacted] and in [redacted] in particular.

191. The OFCCP also only selectively reported its results in their SAC. In their model analyzing total compensation, there are no statistically significant differences in pay between African-Americans and Whites, but rather than report that, they switch to an analysis of base pay (unlike any of their other analyses). The SAC also reports results claiming to show that Asians are less likely as Whites in PRODEV to occupy higher global career levels on the managerial career path. Yet their back-up shows that Asians are more likely to be in higher positions in the IC path. Their analysis does not take into account the positions applied for, and when I correct for this, I show that new hires are for the most part placed where they apply – but my point here is that the OFCCP selectively reported its results to support its claims in the SAC. Similarly, the OFCCP claims that pay differences for women increase over time;

yet their own results for INFTECH contradict their claim about the pay gap growing with tenure for all women.

192. For the reasons enumerated herein, it is my opinion that the analyses presented by the OFCCP to support their claims in the SAC are mis-specified, suffer from omitted variable bias, and have a number of important methodological flaws. As a result, my opinion is that the OFCCP analyses do not support the inferences of pay discrimination that they seek to make.

Executed this 19th day of July, 2019 in Los Angeles, California.

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Ali Saad, Ph.D.

Attachment A: Saad CV and Testimony

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ALI SAAD, Ph.D., MANAGING PARTNER

Dr. Saad is the Managing Partner of Resolution Economics LLC. He has a Ph.D. in Economics from the University of Chicago. Prior to Resolution Economics, Dr. Saad was a partner at Deloitte & Touche LLP and at Altschuler, Melvoin and Glasser LLP. Before that he was in the disputes consulting group at Price Waterhouse, first in New York, and then in Los Angeles. Prior to his consulting career, Dr. Saad served as an Assistant Professor of Economics at Baruch College of the City University of New York (CUNY).

Professional Experience

Dr. Saad's experience is extensive in the area of statistical and economic analysis of liability and damages related to employment litigation matters. His experience is extensive in the application of economics and statistical methods to class action employment discrimination matters. He is also experienced in designing, implementing, and analyzing surveys and observation studies as well as conducting empirical analyses related to exempt/non-exempt status, hours worked, uncompensated time, meal and rest breaks, rounding, and other wage and hour issues. He has also performed statistical and damages analyses for a broad range of commercial litigation matters including breach of contract, insurance coverage, environmental claims, patent infringement, antitrust and real estate financing. Dr. Saad has testified a number of times at deposition and trial. Dr. Saad also regularly consults to clients regarding business issues related to employment practices.

Employment Matters

Dr. Saad provides a variety of services related to employment litigation. His experience is extensive in conducting statistical and economic analysis related to issues of liability for employment discrimination matters. He also has designed and conducted many surveys and observational studies related to wage and hour issues. Dr. Saad has also performed analyses of economic damages in both class action and single plaintiff matters.

Statistical and Economic Analysis in Discrimination Matters

Assignments representative of Dr. Saad's experience in performing analyses in connection with employment discrimination matters include the following:

- Consulting and expert witness services in national class action race discrimination matter involving issues of pay, promotion, work assignment, and a variety of other challenged employment practices. Services included creating databases from diverse and voluminous source materials, and conducting extensive statistical analyses.

- Consulting and expert witness services in national class action gender discrimination matter involving issues of job assignment and promotion. Services included creating databases from diverse and voluminous source materials, and conducting extensive statistical analyses.

- Consulting and expert witness services in a class action case alleging that contracts were misleading. Services included processing and analyzing large quantities of data, and performing statistical analysis of the criteria determining class membership.

- Consulting and expert witness services in connection with a major class action alleging gender discrimination in pay and promotion at a large high-tech employer. Services included creating analytical databases, and developing economic and statistical arguments concerning the relationship between productivity-related variables, pay/promotion, and gender.

- Consulting and expert witness services in an antitrust and discrimination matter in which a group of businesses alleged violations of antitrust and discrimination laws by another group of businesses. Services included data construction, and statistical analysis related to issues of liability.

- Consulting and expert witness services on behalf of plaintiffs' counsel in a series of cases alleging race discrimination in hiring. Services included creating analytical databases, studying the relationship between race and hiring, and examining the features of the external labor market.

- Consulting and expert witness services in connection with a class action claim of discrimination based on age in connection with a series of layoffs resulting from the combination of two large retail chains. Services included creating analytical databases, studying the relationship between layoff and age, and examining the relationship between age and workforce composition over.

- Consulting and expert witness services in connection with EEOC allegations of race discrimination in recruiting, hiring, and initial placement at a large service providing company. Services included developing databases from diverse paper and electronic sources, and providing statistical arguments concerning the relationship between race and various other factors.

- Consulting and expert witness services to defendant's counsel in connection with a major class action alleging gender discrimination in multiple employment practices at a national retail chain. Services included developing a database from voluminous paper documents, and conducting analysis related to hiring, initial placement, and initial pay.

- Consulting and expert witness services to defendant's counsel in connection with an EEOC investigation of racial discrimination in hiring by a major service providing organization. Services included developing a database, and conducting statistical analysis related to hiring.

- Consulting services to defendant's counsel in connection with a U.S. Department of Labor OFCCP investigation of pay equity at a high-tech company. Services included design and oversight of a statistical analysis of pay equity, assessment of the OFCCP methodology, and participation in conciliation discussions between the company and the OFCCP.

- Consulting and expert witness services to defendant's counsel in connection with an allegation of age discrimination in terminations resulting from a series of mass layoffs. Services provided included developing statistical arguments concerning the relationship between age and termination.

- Consulting services to defendant's counsel in connection with a Department of Justice investigation regarding allegations of racial profiling by a large city police department. Analyzed departmental data related to over 130,000 traffic stops, pedestrian stops, and other types of police contacts that occurred in four selected weeks in 1997 and four selected weeks in 1999. Cross-referenced traffic stops data with other information sources including human resources data, precinct level paper records, and the officer discipline system to test various hypotheses.

- Consulting services and expert testimony to defendant's counsel in connection with a multi-plaintiff matter alleging race and gender discrimination in promotion and placement into coveted positions by a large city police department. Performed statistical analysis of promotion and placement into coveted positions. Quantified economic damages for several plaintiffs under failure to promote and wrongful termination theories.

- Consulting services in a case against a city government alleging discrimination in recruiting and hiring of police and firefighters. Services included using Census and other large-scale data sources to assess labor market characteristics by detailed geographic location, and conducting extensive analysis of the impact of employment tests on hiring.

- Consulting and expert witness services to defendant's counsel in a matter where plaintiff alleged that defendant's hiring practices discriminated against women. Services included converting diverse paper source materials into a usable database, and developing statistical evidence concerning plaintiff's allegation.

- Consulting services in several class action recruiting and hiring matters. Services included use of detailed census and other data to estimate labor market availabilities by geographic location, and analyzing employment practices in light of these availability findings.

- Consulting services to a major bank involved in an analysis of its fair lending practices. Services included using bank data on applicants for mortgages and other loans, and adding various demographic and geographic information to assess if the bank made loans on the basis of race, or controlling for other, observable factors could explain patterns in loan making.

- Consulting services on behalf of defendant's counsel in a major class action matter involving allegations of gender discrimination in promotion. Services included building analytical database from many sources, using the database to conduct extensive statistical analysis of plaintiffs' allegations, and estimating damages resulting from non-promotion for approximately 3,000 women occupying different jobs over a ten-year period.

- Consulting and expert witness services on behalf of defendant's counsel in two related cases alleging age discrimination in termination. Prior to plaintiffs' vesting for certain long term benefits. Services included using defendant's human resource data to test plaintiffs' specific allegations, developing statistical arguments concerning the relationship between age and termination, and performing analyses of plaintiff's damages in each case.

- Consulting services on behalf of plaintiff's counsel in distribution of award in an age discrimination matter with 75 plaintiffs. Services included developing a method to efficiently compute damages for all plaintiffs, and working with counsel, an arbitrator, and plaintiffs' committee to explain the process to plaintiffs' group.

Wage and Hour Matters

Assignments representative of Dr. Saad's experience in wage and hours matters include:

- Consulting and expert witness services to defense counsel in a national class-action wage and hour matter alleging that several thousand loan originators at a large financial institution were misclassified under FLSA. Conducted statistical analyses of hours worked records, compensation data, plaintiffs' declarations, and other data to determine if select groups of plaintiffs would be representative of the class.

- Consulting and expert witness services to defense counsel in a wage and hour matter alleging that several thousand General Managers and Assistant Managers at a large office supply retailer were misclassified as exempt employees. Services included designing and conducting a survey to examine whether class members were appropriately classified, analyzing the company's labor model and human resources data, and conducting statistical analyses related to a variety of class certification issues.

- Consulting and expert witness services to defense counsel in a wage and hour matter alleging that several thousand Assistant Managers at a large general merchandise retailer were misclassified as exempt employees. Services included designing and conducting both a survey and an observational study, to examine whether or not class members were appropriately classified. Services also included conducting extensive statistical analyses of the data collected by the survey and the observational study, and preparing materials for use in class certification proceedings.

- Consulting services to defense counsel in a class action matter alleging failure to pay overtime wages to independent sales and service representatives for a large national tool franchiser. Services included designing and implementing an hours survey to determine whether the additional hours worked claimed by some plaintiffs was representative of the additional hours worked by the class as a whole. Determined that the problem was isolated to certain geographic areas rather than nationwide.

- Consulting and expert witness services to defense counsel in a wage and hour matter alleging that several hundred store managers and assistant store managers at a chain of retail discount stores were misclassified. Services included creating and implementing a survey to examine whether class members were classified appropriately and conducting statistical analyses related to commonality of class-members and other class certification issues.

- Consulting services to defense counsel in a multi-plaintiff wage and hour matter alleging that the defendant employer failed to compensate security guards for uniform changing time and other claims of off-the-clock work. Services included designing and conducting an observation study to measure time associated with various activities.

- Consulting services to defense counsel in wage and hour matter alleging that store managers at a chain of convenience store/ gas station operations were misclassified as exempt workers. Services included designing and conducting a random sampling scheme and observational study to evaluate the amount of time that class members spent on exempt and non-exempt duties.

- Consulting services to defense counsel in a class-action wage and hour matter alleging uncompensated meal periods and breaks, unpaid overtime wages, and minimum wage violations at a field maintenance company.

Services included creating a database of hours worked from paper and electronic records, and then providing damages estimates based on a variety of assumptions and legal theories.

- Consulting services to defense counsel in a class action matter alleging a variety of wage and hour violations for hourly workers at a chain of warehouse stores. Services included analyzing data to test allegations of improper time adjustments, missed meal and rest periods, uncompensated split shifts, reporting time violations, overtime and regular rate issues, and off-the-clock work.

Employment Damages

Assignments representative of Dr. Saad's experience estimating economic damages include the following:

- Consulting services to plaintiff's counsel in a case involving a breach of employment contract allegation by a high-level executive in the emerging communications industry. Services included damages analysis based on valuation of stock options and estimation of future earnings.

- Consulting services to defendant's counsel in a case involving a wrongful termination allegation by a high-level executive in the telecommunication industry. Services included damages analysis based on valuation of stock options using the Black-Scholes Option Pricing Framework and a Monte Carlo Simulation Model.

- Consulting and expert witness services on behalf of defendant's counsel in a matter brought by a former executive who alleged wrongful termination and age discrimination against a major defense contractor following a reduction in force. Critiqued work product of the opposing expert, evaluated mitigation issues, calculated loss of earnings damages and valued losses related to stock options.

- Consulting and expert witness services on behalf of defendant's counsel in a medical malpractice action where the underlying damages issue was valuing an income stream from a closely held cash business. Performed accounting of plaintiff's financial records to determine the existence and the extent of fraud. Created financial models to calculate damages under a variety of scenarios.

- Consulting and expert witness services to defendant's counsel in a wrongful termination matter brought by senior executive of a high-tech company who alleged age discrimination. Performed analysis of mitigation factors, calculated loss of earnings, and valued future stock options.

Commercial Litigation

Dr. Saad has assisted clients in a variety of commercial litigation matters, including patent infringement, insurance coverage, antitrust, breach of contract, and real estate financing. Assignments representative of Dr. Saad's experience in these areas include the following:

- Consulting and expert witness services in a series of cases involving the real property title insurance industry. Services included performing extensive statistical analyses in connection with both liability and damages issues.

- Consulting and expert witness services in a case alleging breach of loan commitment to a commercial real estate concern. Services included constructing financial models, developing economic arguments relating to fixed versus variable rate loans, and assisting counsel in deposing the opposing expert.

- Consulting and expert witness services in a case involving a breach of contract allegation in the computer hardware industry. Services consisted of performing a damages calculation, and rebutting the opposing expert's analysis.

- Consulting and expert witness services in a case alleging that one entity caused another entity's property to be misused. Services included database creation, and statistical analysis related to issues of causation. Results indicated that there was a statistically significant relationship between defendant's actions and plaintiff's economic condition.

- Consulting services on behalf of defendant's counsel in a breach of contract matter in the context of natural resource raw materials shipping. Services included developing economic arguments regarding the but-for pricing of both the shipping service as well as the material being shipped.

- Consulting and expert witness services on behalf of defendant's counsel in a major insurance coverage case, in which the underlying claims resulted from tens of thousands of asbestos claims. Services included developing strategy for dealing with large amounts of paper information, creating a database for analysis, and performing a variety of statistical analyses.

- Consulting services on behalf of plaintiff's counsel in an antitrust matter in the consumer electronics product market. The antitrust practice alleged was predatory pricing. Services included preparing a damage analysis.

- Consulting services on behalf of defendant's counsel in a patent infringement matter in the computer hardware industry. Services included researching transfer pricing issues and analyzing complex company P&L data in preparation for damages calculation.

- Consulting services on behalf of defendant's counsel in a real estate financing dispute. Dispute revolved around the financing of a major New York office property. Services included analysis of interest rates and their relationship to potential damages at various points in time, as well as the construction of a financial model of the property with the but-for financing in place.

- Consulting services on behalf of plaintiff's counsel in an antitrust matter involving allegations of non-competitive practices and predatory pricing in the home cable television market. Services included an analysis of "raising rivals costs", as well as a statistical analysis of pricing of complex products over time.

Summary of Employment Experience

Resolution Economics LLC:
Managing Partner, October 1998 to date.

University of Southern California
Adjunct Associate Professor in the Department of Economics**,** January 1999 to September 2001.

Deloitte & Touche, LLP:
Partner, Dispute Consulting Services, (Los Angeles), 1998.

Altschuler, Melvoin and Glasser LLP:
Partner, Economics and Litigation Services, (Los Angeles), 1995 to 1998.

Price Waterhouse LLP:
Senior Manager, Manager, Litigation and Corporate Recovery Services Group, (New York and Los Angeles), January 1989 – November 1989, June 1990 to 1995.

Olympia & York Companies (USA):
Assistant VP and Senior Economist, (New York), November 1989 - June 1990.

Baruch College, City University of New York (CUNY):

Instructor and Assistant Professor of Economics, Department of Economics and Finance, 1982-1988; Center for the Study of Business and Government, Research Associate, 1983-1986; U.S. Small Business and Veterans Administrations, Consultant, 1985-1986.

Education

Ph.D., Economics, The University of Chicago.

B.A., History, Economics, The University of Pennsylvania

Publications

Financial Success and Business Ownership among Vietnam and other Veterans (with S. Lustgarten) SBA - 7210 - VA - 83, 1986.

"Schooling and Occupational Choice in 19th Century Urban America", Journal of Economic History, vol. 49, no. 2, June 1989.

"Employment Discrimination Litigation", chapter in Litigation Services Handbook, ed. by Roman Weil, et al., 1995, 2001, 2006, 2012, 2017.

"Employment Discrimination", chapter in Litigation Support Report Writing, ed. by Jack P. Friedman, et al, 2003.

Paul Grossman, Paul Cane, and Ali Saad, "Lies, Damned Lies, and Statistics: How the Peter Principle Warps Statistical Analysis of Age Discrimination Claims", The Labor Lawyer, vol. 22, no. 3, Winter/Spring 2007, pp. 251-268.

Saad, Ali, "Beyond the Peter Principle – How Unobserved Heterogeneity in Employee Populations Affects Statistical Analysis in Age Discrimination Cases: Application to a Termination/RIF Case", AELC Conference Volume, 2007.

Saad, Ali, "Filling the Data Vacuum in Wage and Hour Litigation: The Example of Misclassification Cases, Emphasis on Class Certification", SIOP Annual Conference Proceedings, 2009.

Saad, Ali, "Wage and Hour Cases - Filling the Data Vacuum: Misclassification Cases and Other Observational Studies", SIOP Annual Conference Proceedings, 2012.

Presentations

Dr. Saad has delivered many presentations at professional conferences, to law firms and to industry groups.

Academic Honors

Finalist, Allan Nevins National Doctoral Dissertation Award
NIMH Doctoral Fellowship, The University of Chicago
Magna Cum Laude, The University of Pennsylvania
Honors in History, Economics, The University of Pennsylvania
Omicron Delta Epsilon, Honor Society in Economics

Professional Affiliations

American Economic Association
American Bar Association (associate membership)

Ali I. Saad, Ph.D.
Attachment to Resume

Last Four Years of Testimony:

In the matter of Scott, et al., v. Airport Management Services, et al., Case No: BC593927 (Superior Court for the State of California, County of Los Angeles) in connection with wage and hour claims. Report filed March 21, 2019. Deposition April 17, 2019.

In the matter of Cortina, et al., v. North American Title Company, Case no. 07 CE CG 01169 JH, (Superior Court of the State of California, County of Fresno), in connection with class action employment matter. Reports filed May 11, 2012, June 25, 2012, and August 13, 19, 21, and 26, 2015. Deposition September 8 and 9, 2015. Trial testimony December 3 and December 10, 2015. Hearing testimony March 14, April 12, May 18, July 12, 2018, September 18, 2018, November 26th, 2018, May 1, 2019.

In the matter of Jewett, et al., v. Oracle America, Inc., Case No: 17-CIV-02669 (Superior Court for the State of California, County of San Mateo) in connection with class action employment discrimination claims. Report filed March 6, 2019. Deposition Testimony March 18, 2019.

In the matter of Smiles, et al., v. Walgreen Company, et al., Case No: RG-17862495 (Superior Court for the State of California) in connection with wage and hour claims. Report filed February 22, 2019, deposition testimony February 25, 2019.

In the matter of Kennard v. Reeves, Case No: BD 604 788 (Superior Court for the State of California) in connection with reasonable compensation issues. Reports filed January 28, 2019 and February 4, 2019. Arbitration Testimony February 22, 2019, May 20, 2019.

In the matter of EEOC, et al., v. Jackson National Life Insurance, et al., Case No: 16-CV-2472-PAB-SKC, (United States District Court for the District of Colorado) in connection with class action discrimination claims. Reports filed August 31, 2018, October 26, 2018 and June 28, 2019. Deposition July 18, 2019.

In the matter of Leanna Delgado v. California Commerce Club, Inc., et al., Case No: BC 586727, (Superior Court for the State of California for the County of Los Angeles) in connection with allegations of age discrimination. Deposition July 25, 2018.

In the matter of Hall v. Rite Aid Corporation, Case No. 37-2009-00087938-CU-OE-CTL, (Superior Court for the State of California for the Country of San Diego) in connection with suitable seating claims. Deposition January 20, 2012, Report filed on June 11, 2018.

In the matter of Harris, et al., v. Union Pacific, Case No: 8:16-cv-381, (United States District Court For the District of Nebraska) in connection with class action discrimination claims. Report filed May 3, 2018. Deposition May 23, 2018.

In the matter of Henderson, et al., v. JP Morgan Chase, Case No. 11-CV-03428 (PLAx), (United States District Court For the Central District of California) in connection with wage and hour claims. Report filed February 26, 2018. Deposition March 21, 2018.

In the matter of Moussouris, et al., v. Microsoft, Case No. 15-CV-1483 (JLR), (United States District Court for the Western District of Washington) in connection with class action claims of gender discrimination in pay, performance and promotions. Reports filed January 5, 2018, April 6, 2018 and April 25, 2018. Deposition January 30, 2018.

In the matter of Creative Artists Agency LLC, v. Martin Lesak, et al., JAMS Ref nos. 120032335, 336 and 337 (Arbitral Tribunal of JAMS) in connection with breach of contract claims. Deposition January 16 and 21, 2018 and March 19, 2018. Arbitration testimony March 26, April 16, and September 7, 2018.

In the matter of Negrete, et al., v. Conagra Foods, Inc., Case No. 2:16-cv-631-FMO-AJW, (United States District Court For the Central District of California) in connection with class action wage and hour claims. Report filed February 28, 2018. Deposition April 18, 2018. Revised report filed on June 18, 2018 to respond to a revised report filed by plaintiff's expert.

In the matter of Woods, et al., v. JFK Memorial Hospital, Inc., Case No. INC 1205209, (Superior Court of California, County of Riverside), in connection with wage and hour claims. Report filed October 13, 2017. Deposition November 29, 2017.

In the matter of Bridewell-Sledge, et al., v. Blue Cross of California, et al., Case No. BC 477 451 c/w BC 481 586, (Superior Court of California, County of Los Angeles), in connection with employment discrimination claims. Reports filed September 7, 2017 and June 13, 2018. Deposition October 30, 2017.

In the matter of Truitt, et al., v. Atlanta Independent School System, Case No. 1:15-cv-4295-SCJ-WEJ, (United States District Court, Northern District of Georgia, Atlanta Division), in connection with allegations of employment discrimination. Report filed August 31, 2017. Deposition September 20, 2017.

In the matter of Williams, et al., v. TGI Fridays, Inc. Case No. 15-cv-0426, (United States District Court, Northern District of Illinois), in connection with allegations of wage and hour violations. Report filed August 4, 2017, deposition August 25, 2017.

In the matter of Victor Cejka, et al., v. Vectrus Systems Corporation, et al. Case No. 15-cv-02418-MEH, (United States District Court, District of Colorado), in connection with alleged employment damages. Report filed July 17, 2017, Rebuttal report filed August 14, 2017. Trial testimony June 18, 2018.

In the matter of EEOC, v. GMRI, Inc. Case No. 15-cv-20561-JAL, (United States District Court, Southern District of Florida, Miami Division), in connection with allegations of employment discrimination. Report filed April 21, 2017, deposition June 8, 2017.

In the matter of Bowerman, et al., v. FAS, Civil Action No. 13-00057-WHO, (United States District Court, Northern District of California), in connection with wage and hour allegations. Rebuttal Report filed April 6, 2017, deposition April 11, 2017.

In the matter of Romero, et al., v. Allstate Insurance Company, et al., Consolidated Cases, Civil Action No. 01-3894-MAK, (United States District Court, Eastern District of Pennsylvania), in connection with employment discrimination allegations. Rebuttal Report filed March 20, 2017, deposition March 29, 2017.

In the matter of Urbano, et al., v. SMG Holdings, et al., Case No.: 5:15-cv-00603-MMM (MRW), (United States District Court for the Central District of California), in connection with wage and hour allegations. Report filed October 14, 2016, deposition October 26, 2016.

In the matter of In re: AutoZone, Inc., Wage and Hour Employment Practices Litigation, Case No.: 3:10-cv-02159-CRB (JSC), (United States District Court for the Northern District of California), in connection with wage and hour allegations. Report filed April 29, 2016, deposition May 27, 2016.

In the matter of EEOC v. Texas Roadhouse, Inc., et al. Case No.:1:11-cv-11732 (United States District Court for the District of Massachusetts), in connection with allegations of age discrimination. Reports filed April 22, 2016 and July 20, 2016. Deposition June 17, 2016; trial testimony January 26, 2017.

In the matter of Luanna Scott, et al., v. Family Dollar Stores, Inc., Case No.:3:08-cv-540 (United States District Court for the Western District of North Carolina), in connection with allegations of gender discrimination. Reports filed January 28, 2016, May 31, 2016. Deposition February 10, 2016.

In the matter of Valerie Horvath v. Western Refining Wholesale, Inc., Case no. Case No.:CIV-ds1311846 (Superior Court for the State of California, County of San Bernardino), in connection with allegations of age discrimination. Report filed November 19, 2015. Deposition January 14, 2016.

In the matter of Curley, et al., v. Savemart, et al. Case no RG13685740, (Superior Court of California, County of Alameda), in connection with class action wage and hour matter. Report filed September 2, 2015. Deposition December 18, 2015 and January 20, 2016.

In the matter of Hurt, et al., v. Commerce Energy, Inc, et al., Case no. 1:12-CV-00758, (United States District Court for the Northern District of Ohio), regarding analysis of data in connection with federal and state class action wage and hour claims. Reports filed May 29 and June 17, 2014. Deposition June 24, 2014. Trial testimony May 22, 2018.

Attachment B: Data and Documents Considered

I. Court Documents

Amended Complaint, Filed January 25, 2017

OFCCP's Supplemental Objections and Answers to Defendant Oracle America, Inc.'s Interrogatories, Set One (As Amended), Filed October 11, 2017

OFCCP's Motion for Leave to File a Second Amended Complaint, Filed January 22, 2019

Second Amended Complaint, Filed March 8, 2019

Consent Findings and Order, Filed April 25, 2019

Order Adopting Consent Findings Regarding College Recruiting Program Allegations, Filed April 30, 2019

Order Granting in Part and Denying in Part OFCCP's Motion to Compel Historical Data of Comparator Employees, Filed May 16, 2019

II. Depositions and Declarations

a. OFCCP v. Oracle

Videotaped Deposition of Kate Waggoner, May 1, 2019

- Deposition Errata Sheet for the Deposition of Kate Waggoner, Testifying on Behalf of Oracle America, Inc. Taken on May 1, 2019
- Exhibits 1 – 16

b. Jewett, et al. v. Oracle America, Inc.

ORACLE_HQCA_0000398926_Videotaped PMK Deposition of Oracle America, Inc., By: Anje Dodson, July 17, 2018

- ORACLE_HQCA_0000398389 - ORACLE_HQCA_0000398921 (Exhibits 1 – 22)

ORACLE_HQCA_0000399391_Videotaped PMK Deposition of Oracle America, Inc., By: Chad Wayne Kidder, October 23, 2018

- ORACLE_HQCA_0000399379 - ORACLE_HQCA_0000399389 (Exhibits 74-75)

ORACLE_HQCA_0000400584_Videotaped PMK Deposition of Oracle America, Inc., By: Kate Waggoner Volume 1, July 26, 2018 and July 27, 2018

- ORACLE_HQCA_0000399631 - ORACLE_HQCA_0000400354 (Exhibits 23 – 46)

ORACLE_HQCA_0000400868_Videotaped PMK Deposition of Oracle America, Inc., By: Kate Waggoner Volume 2, July 27, 2018

- ORACLE_HQCA_0000400357 - ORACLE_HQCA_0000400577 - (Exhibits 47 – 62) ORACLE_HQCA_0000400579 (Exhibit 64)

ORACLE_HQCA_0000399314_Videotaped PMK Deposition of Oracle America, Inc., By: Kristina Karstensson Edwards, October 16, 2018

- ORACLE_HQCA_0000399311 (Exhibit 57); ORACLE_HQCA_0000399190 - ORACLE_HQCA_0000399291 (Exhibits 65 – 73)

ORACLE_HQCA_0000544833_Declaration of Anshuman Sharma in Support of Defendant Oracle America, Inc.'s Motion for Summary Judgment or, in the alternative, Summary Adjudication, executed January 11, 2019

ORACLE_HQCA_0000544765_Declaration of Ashlee Kling in Support of Defendant Oracle America, Inc.'s Opposition to Plaintiffs' Motion for Class Certification, executed February 26, 2019

ORACLE_HQCA_0000544752_Declaration of Balaji Bashyam in Support of Defendant Oracle America, Inc.'s Opposition to Plaintiffs' Motion for Class Certification, executed March 4, 2019

ORACLE_HQCA_0000544776_Declaration of Barbara Lundhild in Support of Defendant Oracle America, Inc.'s Opposition to Plaintiffs' Motion for Class Certification, executed March 1, 2019

ORACLE_HQCA_0000545106_Declaration of Campbell Webb in Support of Defendant Oracle America, Inc.'s Opposition to Plaintiffs' Motion for Class Certification, executed March 5, 2019

ORACLE_HQCA_0000544762_Declaration of Chad Kidder in Support of Defendant Oracle America, Inc.'s Motion for Summary Judgment, executed January 11, 2019

ORACLE_HQCA_0000544758_Declaration of Chad Kidder in Support of Defendant Oracle America, Inc.'s Opposition to Plaintiffs' Motion for Class Certification, executed March 1, 2019

ORACLE_HQCA_0000544820_Declaration of Chintu Patel in Support of Defendant Oracle America, Inc.'s Opposition to Plaintiffs' Motion for Class Certification, executed March 1, 2019

ORACLE_HQCA_0000544837_Declaration of Darryl Tewes in Support of Defendant Oracle America, Inc.'s Opposition to Plaintiffs' Motion for Class Certification, executed March 1, 2019

ORACLE_HQCA_0000544768_Declaration of Denise Lee in Support of Defendant Oracle America, Inc.'s Motion for Summary Judgment or, in the alternative, Summary Adjudication, executed January 15, 2019

ORACLE_HQCA_0000544746_Declaration of Joseph Albowicz in Support of Defendant Oracle America, Inc.'s Motion for Summary Judgment or, in the alternative, Summary Adjudication, executed January 10, 2019

ORACLE_HQCA_0000544846_Declaration of Kate Waggoner in Support of Defendant Oracle America, Inc.'s Motion for Summary Judgment or, in the alternative, Summary Adjudication, executed January 16, 2019

ORACLE_HQCA_0000544772_Declaration of Michael Leftwich in Support of Defendant Oracle America, Inc.'s Opposition to Plaintiffs' Motion for Class Certification, executed February 28, 2019

ORACLE_HQCA_0000544827_Declaration of Richard Sarwal in Support of Defendant Oracle America, Inc.'s Opposition to Plaintiffs' Motion for Class Certification, executed March 5, 2019

ORACLE_HQCA_0000607281_Declaration of Steven Miranda in Support of Defendant Oracle America, Inc.'s Motion for Summary Judgment or, in the alternative, Summary Adjudication, executed January 17, 2019

ORACLE_HQCA_0000544843_Declaration of Vickie Thrasher in Support of Defendant Oracle America, Inc.'s Motion for Summary Judgment or, in the alternative, Summary Adjudication, executed January 9, 2019

ORACLE_HQCA_0000545111_Declaration of Vivian Wong in Support of Defendant Oracle America, Inc.'s Opposition to Plaintiffs' Motion for Class Certification, executed March 1, 2019

III. Oracle Documents

ORACLE_HQCA_0000000407_Global Compensation Training - 2011 Managing Pay Final (Native).PPTX

ORACLE_HQCA_0000000464_USEmployeeHandbook.pdf

ORACLE_HQCA_0000014418_IRC1757825.pdf

ORACLE_HQCA_0000015152_IRC 1727737.pdf

ORACLE_HQCA_0000020125_Sourcing Handbook.pdf

ORACLE_HQCA_0000021914_Document1.pdf

ORACLE_HQCA_0000021918_Updated College Recruiting ProcessOverview.pdf

ORACLE_HQCA_0000021930_College Recruiting Internal Website - Storeyboard Template.pdf

ORACLE_HQCA_0000021971_HM Internal Site Changes.pdf

ORACLE_HQCA_0000021994_COMPLETE LIST OF SCHOOLS.pdf

ORACLE_HQCA_0000021999_Directions for Qualifying.pdf

ORACLE_HQCA_0000022000_Hardware PhDs list of schools.pdf

ORACLE_HQCA_0000022003_Oracle College Recruiting Resourcing Outline for 2011 FY.pdf

ORACLE_HQCA_0000022006_Resourcing Guidelines.pdf

ORACLE_HQCA_0000022013_Sourcing from Resume Drop Sites.pdf

ORACLE_HQCA_0000022470_BDC Pre-screen (6).pdf

ORACLE_HQCA_0000022721_EvaluationForm.pdf

ORACLE_HQCA_0000022736_ncg_undergrad_screening_rev2.pdf

ORACLE_HQCA_0000022905_HQCA Job Descriptions.xlsx

ORACLE_HQCA_0000022906 Career Level Guidelines Matrix Oracle.xls

ORACLE_HQCA_0000022922_Annual Stock Focal Process updatedJune13 updated.pdf

ORACLE_HQCA_0000022940_Equity_Award_Impact_On_Offer_140526.pdf

ORACLE_HQCA_0000022954 PD Promotion Template.pdf

ORACLE_HQCA_0000022959_FY14 Stock Grant Eligibility.pdf

ORACLE_HQCA_0000022967 IC Promotion Template.pdf

ORACLE_HQCA_0000022968 Management Promotion Template.pdf

ORACLE_HQCA_0000022973_FY14 Stock Grant Eligibility.pdf

ORACLE_HQCA_0000022980_PM Global Training Schedule FY14-15Announcement Final.pdf

ORACLE_HQCA_0000022984 Mgr Prod Dev Promotion Template Feb-09.docx

ORACLE_HQCA_0000022987_Product Development IC Promotion Template_2011.pdf

ORACLE_HQCA_0000022992_Perf Appr Comm Plan & Launch FY14 Year-End Perf Appr & FY15 GoalSetting Process EEs- 6.23.14_v2.pdf

ORACLE_HQCA_0000023006 PD Manag Promotion Template.pdf

ORACLE_HQCA_0000023012_Native_TM85_Managers_Preparing_Talent_Review_ Content_Fusion.pptx

ORACLE_HQCA_0000024196_Recruiting Support Staff (RSS) Training 09.17.2013 (Native).PPT

ORACLE_HQCA_0000024950_FY14 Recruiter Discretionary bonus plan - Admin Guidelines NA - Recruiter (Native).xlsx

ORACLE_HQCA_0000024951_1-Document.pdf

ORACLE_HQCA_0000024952_2-Document.pdf

ORACLE_HQCA_0000024953_3-Document.pdf

ORACLE_HQCA_0000040960_Self ID Form.pdf

ORACLE_HQCA_0000041852_Recruiting Operations Review (Joyce version 032414 (Native).PPTX

ORACLE_HQCA_0000041864_Oracle Performance Appraisal 20170810.pdf

ORACLE_HQCA_0000042091_MASTER US Manager Orientation 1201 (Native).PPTX

ORACLE_HQCA_0000042095_Customer Services CompTraining 3 15 final (Native).PPT

ORACLE_HQCA_0000042098_Customer Services Comp Training 3 15 - w_new arrows (Native).PPTX

ORACLE_HQCA_0000042101_MASTER US Manager Orientation 1202 lg (Native).PPTX

ORACLE_HQCA_0000053186_Global Referral Team_Knowledge Sharing_Sept 2016 (Native).PPTX

ORACLE_HQCA_0000056239_HR REFRESH_CWB_TRAINING_APR2011v3_Updated_June2013V3 (Native).PPTX

ORACLE_HQCA_0000056276_FWCBONUSMgrTrainingR4newCorpTemplate.pdf

ORACLE_HQCA_0000056566_New Recruiter OnboardingPresentation (Native).PPT

ORACLE_HQCA_0000056741_NCG & Campus Recruiting2 (Native).PPT

ORACLE_HQCA_0000056957_CWB New Manager Training (Native).PPT

ORACLE_HQCA_0000062712_HR Global Approval Matrix_HR Version_01_Nov_2014 (Native).XLSX

ORACLE_HQCA_0000364183_native.pptx

ORACLE_HQCA_0000364184.pdf

ORACLE_HQCA_0000364186.pdf

ORACLE_HQCA_0000364188.pdf

ORACLE_HQCA_0000364192.pdf

ORACLE_HQCA_0000364196.pdf

ORACLE_HQCA_0000364199.pdf

ORACLE_HQCA_0000364202.pdf

ORACLE_HQCA_0000364206.pdf

ORACLE_HQCA_0000364209.pdf

ORACLE_HQCA_0000364211.pdf

ORACLE_HQCA_0000364213.pdf

ORACLE_HQCA_0000364216.pdf

ORACLE_HQCA_0000364220.pdf

ORACLE_HQCA_0000364223.pdf

ORACLE_HQCA_0000364227.pdf

ORACLE_HQCA_0000364272_native.pptx

ORACLE_HQCA_0000364273_native.pptx

ORACLE_HQCA_0000364274_native.pptx

ORACLE_HQCA_0000364275_native.pptx

ORACLE_HQCA_0000364276_native.pptx

ORACLE_HQCA_0000364277.pdf

ORACLE_HQCA_0000364278.pdf

ORACLE_HQCA_0000364280.pdf

ORACLE_HQCA_0000364299.pdf

ORACLE_HQCA_0000364301.pdf

ORACLE_HQCA_0000414169_Oracle Patent Award Program effective 6-26-14.pdf

ORACLE_HQCA_0000414171_US Equity Choice FAQ.pdf

ORACLE_HQCA_0000414176_lisa.hanson@oracle.com_9478290_116388.pdf

ORACLE_HQCA_0000414177_lisa.hanson@oracle.com_9517664_54906.pdf

ORACLE_HQCA_0000414178_lisa.hanson@oracle.com_9517664_58670.pdf

ORACLE_HQCA_0000414179_lisa.hanson@oracle.com_9517664_60184.pdf

ORACLE_HQCA_0000414367_suzanne.castillo@oracle.com_6600384_35120.pdf

ORACLE_HQCA_0000414368_Oracle Patent FACT Sheet 2013.pdf

ORACLE_HQCA_0000414372_patent Primer 07-07-2014.pptx

ORACLE_HQCA_0000416489_Equity0Choice0FAQ[1].pdf

ORACLE_HQCA_0000416494_Equity Choice FAQ.pdf

ORACLE_HQCA_0000416500_[redacted]@oracle.com_4431785_41527.pdf

ORACLE_HQCA_0000416510_WrittenCloseOut_[redacted]pdf

Attachment B – Data and Documents Considered

ORACLE_HQCA_0000416512_RE Written Investigation Follow Up_SD.pdf

ORACLE_HQCA_0000416515_WrittenCloseOut_[redacted]df

ORACLE_HQCA_0000416517_Equal Pay Inquiry_self_[redacted]pdf

ORACLE_HQCA_0000416518_[redacted]oracle.com_28936679_25.pdf

ORACLE_HQCA_0000416519_[redacted]@oracle.com_2753331_53757.pdf

ORACLE_HQCA_0000416520_[redacted] 2017.09.19 DFEH RTS.pdf

ORACLE_HQCA_0000416526_2000 LTIP 02 01 2018.pdf

ORACLE_HQCA_0000416561_2000 LTIP 05 31 2011.pdf

ORACLE_HQCA_0000416603_2000 LTIP 06 16 2014.pdf

ORACLE_HQCA_0000416646_2000 LTIP 6 30 16.pdf

ORACLE_HQCA_0000416684_2000 LTIP Pro 020118.pdf

ORACLE_HQCA_0000416719_2000 Plan 06302016.pdf

ORACLE_HQCA_0000416757_2000 Plan 12012017.pdf

ORACLE_HQCA_0000416793_2000LTPLANPRO14.pdf

ORACLE_HQCA_0000416837_Investigation Results_[redacted]12.7.17.pdf

ORACLE_HQCA_0000416857_Amended_and Restated_2000_LTIP_2.1.18.pdf

ORACLE_HQCA_0000416892_Amended_and Restated_2000_LTIP_5.31.11.pdf

ORACLE_HQCA_0000416934_Amended_and Restated_2000_LTIP_6.14.14.pdf

ORACLE_HQCA_0000416978_Amended_and Restated_2000_LTIP_6.30.16.pdf

ORACLE_HQCA_0000417016_Amended_and Restated_2000_LTIP_12.1.17.pdf

ORACLE_HQCA_0000417061_confirm equal pay.pdf

ORACLE_HQCA_0000417062_Question on Benefits Compensation.pdf

ORACLE_HQCA_0000417063_RE quick call.pdf

ORACLE_HQCA_0000417316_shauna.holman.harries@oracle.com_9515916_112783.pdf

ORACLE_HQCA_0000417308- 417309.tif

ORACLE_HQCA_0000417318_Global Rehire Guidelines FY19 -20180913.pdf

ORACLE_HQCA_0000417382- 417642.pdfs: Job Descriptions

IV. OFCCP Produced Documents

DOL000001395-000001406.pdf

2017.10.26 [OFCCP] Attachment-DOL000039877.pdf

2017.10.26 [OFCCP] Attachment-OFCCP v Oracle - Additional Data Needed Re Statistics.docx

Backup to Second Amended Complaint:

- basepay_over_time.do
- Directive 310- Calculating Back Pay.pdf
- DOL 000040761 (SAC Tables 1-6).xlsx
- OFCCP v. Oracle; OALJ Case No. 2017-OFC-00006, SAC Tables 1-6.pdf
- ORACLE Damage Calculation.xlsx
- Oracle_Combine_Data.do
- Oracle_ordered_logits_assignment.do
- Oracle_Regressions.do
- rr-18-07.pdf
- Starting Salary.do
- wage changes.do

DOL000004722.pdf

DOL000005298-5330.pdf

DOL000026401.xlsx

DOL000026402.xlsx

DOL000026403.xlsx

DOL000030699.pdf

DOL000030705.pdf

DOL000031068.pdf

DOL000031113.pdf

DOL000031116.pdf

DOL000031119.pdf

DOL000031233.pdf

DOL000031245.pdf

DOL000031294.pdf

DOL000031345.pdf

DOL000031349.pdf

DOL000031357.pdf

DOL000031952.pdf

DOL000032196.xlsx

DOL000032197.xlsx

DOL000032198.xlsx

DOL000039442-39447.pdf

V. Data Correspondence

2017.10.11 [Oracle] Connell Ltr to [OFCCP] Bremer re prod of Database, Add'l Disc.pdf

2017.10.26 [OFCCP] [Pilotin] Email to [Oracle] Connell, et al re Info on OFCCP Analysis

2017.10.31 [Oracle] Horton email to [OFCCP] w FTP Oracle doc prod 13, 14, 15 and 16.pdf

2017.10.31 [Oracle] Horton email-attch-Hard Disk Drive Production - Bates Number Index.xlsx

2017.11.14 [OFCCP] Herold Ltr to [Oracle] Connell w Qs 10.11.2017 data prod.pdf

2017.11.28 [Oracle] Pitcher ltr to [OFCCP] re produced data.pdf

2017.12.05 [OFCCP] Pilotin Ltr to [Oracle] Connell Add'l Qs re 10.11.2017 Data Prod.pdf

2017.12.08 [Oracle] Pitcher Ltr to [OFCCP] Pilotin re Resps to Qs re 10.11.2017 Data Prod.pdf

2017.12.18 [Oracle] Pitcher Ltr to [OFCCP] Pilotin resp 12.05.2017 ltr Qs re data.pdf

2018.06.08 [OFCCP] Bremer ltr to [Oracle] Connell re data requests (DOC2....pdf

2018.06.08 [REDACTED] [OFCCP] Bremer ltr to [Oracle] Connell w Data Qs (DOC240).pdf

2018.06.29 [REDACTED] [Oracle] Connell ltr to [OFCCP] Bremer in resp 2018.06.08 dat....pdf

2018.06.29 [REDACTED] [Oracle] Pitcher ltr to [OFCCP] Bremer in resp 2018.06.08 dat....pdf

2018.07.06 [REDACTED] [OFCCP] Bremer ltr to [Oracle] Pitcher re Data Que....pdf

2018.07.13 [Oracle] [Pitcher] Ltr to [OFCCP] Bremer re Resp to 07.06.201....pdf

2019-05-24 Daquiz Letter to Mr. Parker.pdf

2019-06-13 Letter to W. Parker from Daquiz.pdf

2019.02.19 [Oracle] [Parker] Ltr to [Court] ALJ Clark re Met and Conferred on Schedule.pdf

2019.04.11 [Oracle] Parker Ltr to [OFCCP] Daquiz re Resps to Amended RFP....pdf

2019.04.12 [Oracle] Mantoan ltr to Bremer re data production.pdf

2019.04.22 [Oracle] Parker ltr to [OFCCP] Daquiz.pdf

2019.04.26 Daquiz email to Parker RE OFCCP v Oracle, Case No 2017-OFC-00....pdf

2019.05.06 [OFCCP] Daquiz Email to [Oracle] Parker re Oracle Resending N....pdf

2019.05.14 [Oracle] Fuad Ltr to [OFCCP] Daquiz re Follow Up on May 3 Ltr....pdf

2019.06.07 [Oracle] Pitcher Ltr to [OFCCP] Bremer re Supplemental Data Production.pdf

2019.07.03 Mantoan Ltr to Bremer re Additional Information re Previously Produced Data.pdf

VI. Data

ORACLE_HQCA_0000062856_Thomas Kurian HC information for Orrick v4 (USA only)_native.xlsx

ORACLE_HQCA_0000062858 (AAP_Location List.xlsx).xlsx

ORACLE_HQCA_0000062859_Candidate Offers.xlsx

ORACLE_HQCA_0000062862_Contact Info Group I Fusion.xlsx

ORACLE_HQCA_0000062863_Contact Info Group I Taleo.xlsx

ORACLE_HQCA_0000062864_Contact Info Group I.xlsx

ORACLE_HQCA_0000062865_Group I iRec docs.xlsx

ORACLE_HQCA_0000062866_Group I Taleo - File List - By Candidate.CSV

ORACLE_HQCA_0000062867_Group I Taleo - File List - By Requisition.CSV

ORACLE_HQCA_0000070721_AllEarnings.xlsx

ORACLE_HQCA_0000070722_AllEarnings2.xlsx

ORACLE_HQCA_0000070723_Application - Candidate Skills.xlsx

ORACLE_HQCA_0000070724_Application - CSW History.xlsx

ORACLE_HQCA_0000070725_Application - Education.xlsx

ORACLE_HQCA_0000070726_Application - Experience.xlsx

ORACLE_HQCA_0000070727_Application - History.xlsx

ORACLE_HQCA_0000070728_Application - Source.xlsx

ORACLE_HQCA_0000070729_Application Data.xlsx

ORACLE_HQCA_0000070730_Appraisal_Audit_All_Data.xlsx

ORACLE_HQCA_0000070731_Candidate - Demographics.xlsx

ORACLE_HQCA_0000070732_Candidate - Languages.xlsx

ORACLE_HQCA_0000070733_Candidate - Referrals.xlsx

ORACLE_HQCA_0000070734_Candidate Preferences - Job Field.xlsx

ORACLE_HQCA_0000070735_Candidate Preferences - Location.xlsx

ORACLE_HQCA_0000070736_Candidate Preferences - Organization.xlsx

ORACLE_HQCA_0000070737_CC Data Dictionary.xlsx

ORACLE_HQCA_0000070738_Emp_Personal_Experience_Qualification_Assign_Details.xlsx

ORACLE_HQCA_0000070739_File Attachments - By Candidate.xlsx

ORACLE_HQCA_0000070740_File Attachments - By Requisition.xlsx

- Attachments referenced in file; produced Volume13

ORACLE_HQCA_0000070741_gsi_comp_history.xlsx

ORACLE_HQCA_0000070742_gsi_cwb_audit.xlsx

ORACLE_HQCA_0000070743_gsi_cwb_detail.xlsx

ORACLE_HQCA_0000070744_gsi_focal_only_audit.xlsx

ORACLE_HQCA_0000070745_hcm_wfc_audit.xlsx

ORACLE_HQCA_0000070746_hcm_wfc_details.xlsx

ORACLE_HQCA_0000070747_HQCA_IREC_DATA.xlsx

- Attachments referenced in file; produced Volume13

ORACLE_HQCA_0000070748_Merged Assignment History, Medicare and Sal Admin.xlsx

ORACLE_HQCA_0000070749_Requisition - Collaborators Data.xlsx

ORACLE_HQCA_0000070750_Requisition - Description and Qualification Data.xlsx

ORACLE_HQCA_0000070751_Requisition - Other Locations.xlsx

ORACLE_HQCA_0000070752_Requisition Data.xlsx

ORACLE_HQCA_0000070753_Talent_Review_Audit.xlsx

ORACLE_HQCA_0000070754_Talent_Review_Audit_Notes.xlsx

ORACLE_HQCA_0000070755_us_audit_adhoc_comp_total.xlsx

ORACLE_HQCA_0000070756_us_audit_adhoc_comp_wf.xlsx

ORACLE_HQCA_0000070757_us_audit_adhoc_comp_wf_attach.xlsx

- Attachments referenced in file; produced Volume13

ORACLE_HQCA_0000070758_Z_PromApproverAttachmentKey.xlsx

- Attachments referenced in file; produced Volume13

ORACLE_HQCA_0000070759_Z_PromApproverMtxRpt.xlsx

ORACLE_HQCA_0000360321_H1B.xlsx

ORACLE_HQCA_0000364082-0000364182 (2013-2016 Organization Hierarchy Files)

ORACLE_HQCA_0000403939_AllEarnings_Updated_Population.xlsx

ORACLE_HQCA_0000404317_AllEarnings_Supplemental_Production.xlsx

ORACLE_HQCA_0000581268_gsi_comp_history_Updated_Population.xlsx

ORACLE_HQCA_0000581269_gsi_cwb_audit_Updated_Population.xlsx

ORACLE_HQCA_0000581270_gsi_cwb_details_Updated_Population.xlsx

- Attachments referenced in file: ORACLE_HQCA_0000581274 to ORACLE_HQCA_0000581347

ORACLE_HQCA_0000581271_us_audit_adhoc_comp_total_Updated_Population.xlsx

ORACLE_HQCA_0000581272_us_audit_adhoc_comp_wf_attach_Updated_Population.xlsx

- Attachments referenced in file: ORACLE_HQCA_0000581348 to ORACLE_HQCA_0000581392

ORACLE_HQCA_0000581273_us_audit_adhoc_comp_wf_Updated_Population.xlsx

ORACLE_HQCA_0000437695_CF_116190287_503759264.xls

ORACLE_HQCA_0000581393_AppraisalData_Supplemental Production.xlsx

ORACLE_HQCA_0000581394_AppraisalData_Updated_Population.xlsx

ORACLE_HQCA_0000581395_Emp_Personal_Experience_Qualification_Assign_Details_Supplemental_Production.xlsx

ORACLE_HQCA_0000581396_Emp_Personal_Experience_Qualification_Assign_Details_Supplemental_Updated_Population.xlsx

ORACLE_HQCA_0000581397_hcm_wfc_audit_Supplemental_Production.xlsx

ORACLE_HQCA_0000581398_hcm_wfc_audit_Updated_Population.xlsx

ORACLE_HQCA_0000581399_hcm_wfc_details_Supplemental_Production.xlsx

- Attachments referenced in file: ORACLE_HQCA_0000581415 to ORACLE_HQCA_0000581424

ORACLE_HQCA_0000581400_hcm_wfc_details_Updated_Population.xlsx

- Attachments referenced in file: ORACLE_HQCA_0000581410 to ORACLE_HQCA_0000581414

ORACLE_HQCA_0000581401_Merged_Assignment_History_Medicare_and_Sal_Admin_Supplemental_Production.xlsx

ORACLE_HQCA_0000581402_Merged_Assignment_History_Medicare_and_Sal_Admin_Updated_Population.xlsx

ORACLE_HQCA_0000581403_Stock_Data_Product_Statement_Combined.xlsx

ORACLE_HQCA_0000581404_Talent_Review_Audit_Notes_Supplemental_Production.xlsx

ORACLE_HQCA_0000581405_Talent_Review_Audit_Notes_Updated_Population.xlsx

ORACLE_HQCA_0000581406_Talent_Review_Audit_Supplemental_Production.xlsx

ORACLE_HQCA_0000581407_Talent_Review_Audit_Updated_Population.xlsx

ORACLE_HQCA_0000581408_TalentProfile_Supplemental_Production.xlsx

ORACLE_HQCA_0000581409_TalentProfile_Updated_Population.xlsx

ORACLE_HQCA_0000581425_iRec_apl_employment_history_Supplemental_Production.xls

ORACLE_HQCA_0000581426_iRec_apl_employment_history_Updated_Population.xls

ORACLE_HQCA_0000581427_iRec_apl_qualifications_Supplemental_Production.xls

ORACLE_HQCA_0000581428_iRec_apl_qualifications_Updated_Population.xls

ORACLE_HQCA_0000581429_iRec_applicant_Profiles_Supplemental_Production.xls

ORACLE_HQCA_0000581430_iRec_applicant_Profiles_Updated_Population.xls

ORACLE_HQCA_0000581431_iRec_hqca_vacancies_Supplemental_Production.xls

ORACLE_HQCA_0000581432_iRec_hqca_vacancies_Updated_Population.xls

ORACLE_HQCA_0000581433_iRec_offer_approval_comm_history_Supplemental_Production.xls

ORACLE_HQCA_0000581434_iRec_offer_approval_comm_history_Updated_Population.xls

ORACLE_HQCA_0000581435_iRec_offer_approval_history_Supplemental_Production.xls

ORACLE_HQCA_0000581436_iRec_offer_approval_history_Updated_Population.xls

ORACLE_HQCA_0000581437_iRec_offer_candidates_Supplemental_Production.xls

ORACLE_HQCA_0000581438_iRec_offer_candidates_Updated_Population.xls

ORACLE_HQCA_0000581439_iRec_offer_icds_Supplemental_Production.xls

ORACLE_HQCA_0000581440_iRec_offer_icds_Updated_Population.xls

ORACLE_HQCA_0000581441_iRec_offer_status_history_Supplemental_Production.xls

ORACLE_HQCA_0000581442_iRec_offer_status_history_Updated_Population.xls

ORACLE_HQCA_0000581443_iRec_offer_workflow_attachments_Supplemental_Production.xls

- Attachments at ORACLE_HQCA_0000590597 to ORACLE_HQCA_ 0000590815

ORACLE_HQCA_0000581444_iRec_offer_workflow_attachments_Updated_Population.xls

- Attachments at ORACLE_HQCA_0000590818 to ORACLE_HQCA_0000591452

ORACLE_HQCA_0000581445_iRec_other_attachments_Supplemental_Production.xls

- Attachments referenced in file: ORACLE_HQCA_0000591454 to ORACLE_HQCA_0000591464

ORACLE_HQCA_0000581446_iRec_other_attachments_Updated_Population.xls

- Attachments referenced in file: ORACLE_HQCA_0000591465 to ORACLE_HQCA_0000591525

ORACLE_HQCA_0000581447_iRec_Resumes_Supplemental_Production.xls

- Attachments referenced in file: ORACLE_HQCA_0000591526 to ORACLE_HQCA_0000592522

ORACLE_HQCA_0000581448_iRec_Resumes_Updated_Population.xls

- Attachments referenced in file: ORACLE_HQCA_0000592523 to ORACLE_HQCA_0000595455

ORACLE_HQCA_0000581449-0000581466: 2017-2018 Organization Hierarchy Files

ORACLE_HQCA_0000581470_CWB_international workbench _International_Transfer_Population.xlsx

ORACLE_HQCA_0000581471_Salary_Range_History.xlsx

ORACLE_HQCA_0000581472_Application_Candidate Skills_Updated Population.csv

ORACLE_HQCA_0000581473_Application_CSW History_Updated Population.csv

ORACLE_HQCA_0000581474_Application _Education_Updated Population.csv

ORACLE_HQCA_0000581475_Application _Experience_Updated Population.csv

ORACLE_HQCA_0000581476_Application_ History_Updated Population.csv

ORACLE_HQCA_0000581477_Application _Source_Updated Population.csv

ORACLE_HQCA_0000581478_Application Data_Updated Population.csv

ORACLE_HQCA_0000581479_Candidate_ Demographics_Updated Population.csv

ORACLE_HQCA_0000581480_Candidate_ GovtClearance_Updated Population.csv

ORACLE_HQCA_0000581481_Candidate_ Languages_Updated Population.csv

ORACLE_HQCA_0000581482_Candidate_Preferences_ Job Field_Updated Population.csv

ORACLE_HQCA_0000581483_Candidate_Preferences_ Location_Updated Population.csv

ORACLE_HQCA_0000581484_Candidate_ Preferences_ Organization_Updated Population.csv

ORACLE_HQCA_0000581485_Candidate _Referrals_Updated Population.csv

ORACLE_HQCA_0000581486_ Files_ by Requisition_Updated Population.csv

- Attachments referenced in file and in ORACLE_HQCA_0000581491: ORACLE_HQCA_0000581492 to ORACLE_HQCA_0000588418

ORACLE_HQCA_0000581487_Requisition_ Collaborators Data_Updated Population.csv

ORACLE_HQCA_0000581488_Requisition_Description and Qualification Data_Updated Population.csv

ORACLE_HQCA_0000581489_Requisition_ Other Locations_Updated Population.csv

ORACLE_HQCA_0000581490_Requisition Data_Updated Population.csv

ORACLE_HQCA_0000581491_ Files_ by Candidate_Updated Population.csv

ORACLE_HQCA_0000588420_Application_Candidate_Skills_Supplemental_Production.csv

ORACLE_HQCA_0000588421_Application_CSW_History_Supplemental_Production.csv

ORACLE_HQCA_0000588422_Application_Data_Supplemental_Production.csv

ORACLE_HQCA_0000588423_Application_Education_Supplemental_Production.csv

ORACLE_HQCA_0000588424_Application_Experience_Supplemental_Production.csv

ORACLE_HQCA_0000588425_Application_History_Supplemental_Production.csv

ORACLE_HQCA_0000588426_Application_Source_Supplemental_Production.csv

ORACLE_HQCA_0000588427_Candidate_Demographics_Supplemental_Production.csv

ORACLE_HQCA_0000588428_Candidate_Languages_Supplemental_Production.csv

ORACLE_HQCA_0000588429_Candidate_Preferences_Job_Fields_Supplemental_Production.csv

ORACLE_HQCA_0000588430_Candidate_Preferences_Location_Supplemental_Production.csv

ORACLE_HQCA_0000588431_Candidate_Preferences_Organization_Supplemental_Production.csv

ORACLE_HQCA_0000588432_Candidate_Referrals_Supplemental_Production.csv

ORACLE_HQCA_0000588433_Files_by_Candidate_Supplemental_Production.csv

ORACLE_HQCA_0000588434_Files_by Requisition_Supplemental_Production.csv

- Attachments referenced in file and in ORACLE_HQCA_0000588433: ORACLE_HQCA_0000588439 to ORACLE_HQCA_0000590595

ORACLE_HQCA_0000588435_Requisition_Collaborators_Data_Supplemental_Production.csv

ORACLE_HQCA_0000588436_Requsition_Data_Supplemental_Production.csv

ORACLE_HQCA_0000588437_Requisition_Description_and_Qualification_Data_Supplemental_Production.csv

ORACLE_HQCA_0000588438_Requisition_Other_Locations_Supplemental_Production.csv

ORACLE_HQCA_0000590596_RAA Job Function.xlsx

ORACLE_HQCA_0000591453_CC Data Dictionary Supplement.xlsx

ORACLE_HQCA_0000597171_AppraisalData_Historical_Population.xlsx

ORACLE_HQCA_0000597172_Emp_Personal_Experience_Qualification_Assign_Details_Historical_Population.xlsx

ORACLE_HQCA_0000597173_gsi_comp_history_Historical_Population.xlsx

ORACLE_HQCA_0000597174_gsi_cwb_details_Historical_Population.xlsx

- Available attachments at ORACLE_HQCA_0000597188 to ORACLE_HQCA_0000597680

ORACLE_HQCA_0000597175_Merged Assignment History, Medicare and Sal Admin_Historical_Population.xlsx

ORACLE_HQCA_0000597176_iRec_apl_employment_history_Historical_Population.xls

ORACLE_HQCA_0000597177_iRec_apl_qualifications_Historical_Population.xls

ORACLE_HQCA_0000597178_iRec_applicant_profiles_Historical_Population.xls

ORACLE_HQCA_0000597179_iRec_hqca_vacancies_Historical_Population.xls

ORACLE_HQCA_0000597180_iRec_offer_approval_comm_history_Historical_Population.xls

ORACLE_HQCA_0000597181_iRec_offer_approval_history_Historical_Population.xls

ORACLE_HQCA_0000597182_iRec_offer_candidates_Historical_Population.xls

ORACLE_HQCA_0000597183_iRec_offer_icds_Historical_Population.xls

ORACLE_HQCA_0000597184_iRec_offer_status_history_Historical_Population.xls

ORACLE_HQCA_0000597185_iRec_offer_workflow_attachments_Historical_Population.xls

- Available attachments at ORACLE_HQCA_0000597681 to ORACLE_HQCA_0000597701

ORACLE_HQCA_0000597186_iRec_other_attachments_Historical_Population.xls

- Available attachments at ORACLE_HQCA_0000595456 to ORACLE_HQCA_0000595512

ORACLE_HQCA_0000597187_iRec_resumes_Historical_Population.xls

- Available attachments at ORACLE_HQCA_0000595513 to ORACLE_HQCA_0000597170

ORACLE_HQCA_0000597892_AllEarnings_Historical_Population.xlsx

ORA_OFCCP018 Index.xlsb

ORA_OFCCP026.dat

ORA_OFCCP027.dat

ORA_OFCCP028.dat

ORA_OFCCP029.dat

ORA_OFCCP030.dat

ORA_OFCCP031.dat

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Attachment C: Tables

Employee Counts for HQCA
- INFTECH, PRODEV, and SUPP Job Functions -

Year	# of Unique Employees	# Protected Group
2013	5,713	3,996
2014	5,662	3,980
2015	5,687	4,020
2016	5,605	4,019
2017	5,514	3,978
2018	5,348	3,886
2013-2014	6,300	4,410
2013-2018	8,465	6,035

The Distribution of Total Compensation in 2014 by Career Level

- Full-Time, Full-Year Employees -

Career Level	N	Mean	Minimum	1st Percentile	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile	99th Percentile	Maximum
IC0	2	[redacted]									
IC1	8	[redacted]									
IC2	221	[redacted]									
IC3	664	[redacted]									
IC4	1,219	[redacted]									
IC5	844	[redacted]									
IC6	81	[redacted]									
M1	2	[redacted]									
M2	124	[redacted]									
M3	419	[redacted]									
M4	397	[redacted]									
M5	316	[redacted]									
M6	178	[redacted]									
M7	22	[redacted]									
ALL	4,497	[redacted]									

Attachment C - Tables

The Distribution of Total Compensation in 2014 by Job Title

- 15 Most Populated Job Titles Across PRODEV, INFTECH, and SUPP -

- Full Time, Full Year Employees -

Job Title	N	Mean	Minimum	1st Percentile	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile	99th Percentile	Maximum
Software Development VP	119	[redacted]									
Software Development Snr Director	188										
Software Development Director	247										
Software Developer 5	375										
Software Development Snr Manager	316										
Software Development Manager	87										
Product Manager/Strategy 5-ProdDev	138										
Applications Developer 5	154										
Software Developer 4	611										
Product Manager/Strategy 4-ProdDev	82										
Applications Developer 4	145										
Software Developer 3	295										
Software Developer 2	131										
Applications Developer 3	133										
Technical Analyst 4-Support	75										

The OFCCP's NOV Analysis Shows No Systematic Pattern of Statistically Significant Results for Women vs. Men

- OFCCP Presented the Three Statistically Significant Results and Ignored Thirteen Job Functions With Insignificant Results -

	Female vs. Male			
Job Function	**# Obs. Used**	**# Protected Group**	**Pay Diff. (%)**	**T-Value**
ADMIN	130	117	8.68%	1.42
ALLROLES	33	15	0.55%	0.04
BUSPRAC	228	139	-0.16%	-0.07
CONS	52	10	-3.08%	-0.75
FACS	54	12	-6.90%	-1.55
FINANCE	282	147	2.44%	1.61
HR	72	58	6.28%	1.17
INFTECH	484	133	-3.33%	-2.61
LEGAL	68	41	1.64%	0.84
MANUDIST	50	17	5.24%	0.92
MARKET	301	177	-2.28%	-1.26
PRESALES	229	40	-2.66%	-1.53
PRODEV	4,315	1,207	-3.91%	-8.24
SALES	827	227	-1.52%	-1.75
SUPP	248	47	-7.35%	-3.67
TRAIN	46	22	5.15%	0.90

Model controls for female, standard job title (ones with less than 5 employees are grouped together), part-time/full-time, exempt status, time in company, and estimated previous experience (age minus 18).

The OFCCP's NOV Analysis Shows No Systematic Pattern of Statistically Significant Results for Asians and African Americans

- OFCCP Presented the One Statistically Significant Results and Ignored Fifteen Job Functions With Insignificant Results -

	Asian vs. White				African American vs. White			
Job Function	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value
ADMIN	130	27	0.03%	0.01	130	4		
ALLROLES	33	18	-14.10%	-0.81	33	2		
BUSPRAC	228	67	2.06%	0.84	228	4		
CONS	52	38	4.31%	0.95	52	3		
FACS	54	10	2.06%	0.42	54	3		
FINANCE	282	131	0.25%	0.14	282	5	-6.12%	-1.09
HR	72	21	0.84%	0.17	72	2		
INFTECH	484	308	-0.91%	-0.63	484	9	-0.34%	-0.08
LEGAL	68	20	-2.93%	-1.32	68	4		
MANUDIST	50	15	5.63%	0.75	50	5	1.47%	0.14
MARKET	301	88	1.35%	0.64	301	3		
PRESALES	229	87	4.38%	2.76	229	8	3.15%	0.83
PRODEV	4,315	3,086	-3.35%	-6.37	4,315	27	-5.23%	-2.00
SALES	827	130	-1.96%	-1.80	827	30	-0.71%	-0.34
SUPP	248	192	1.65%	0.69	248	3		
TRAIN	46	20	-7.59%	-1.15	46	1		

Model controls for race, standard job title (ones with less than 5 employees are grouped together), part-time/full-time, exempt status, time in company, and estimated previous experience (age minus 18).

Organization Counts for HQCA

- INFTECH, PRODEV, and SUPP Job Functions -

Year	# of Unique Organizations
2013	681
2014	639
2015	634
2016	601
2017	528
2018	497
2013-2014	733
2013-2018	1,039

Modified Regression Analysis of Total Compensation by Gender or Race Shows No Systematic Pattern of Statistically Significant Results Across Years or Job Function

		Female vs. Male				Asian vs. White				African American vs. White			
Job Function	**Year**	**# Obs. Used**	**# Protected Group**	**Pay Diff. (%)**	**T-Value**	**# Obs. Used**	**# Protected Group**	**Pay Diff. (%)**	**T-Value**	**# Obs. Used**	**# Protected Group**	**Pay Diff. (%)**	**T-Value**
INFTECH	2013	440	124	-3.35%	-1.75								
	2014	447	124	-3.42%	-1.49								
	2015	556	136	-3.60%	-1.67								
	2016	604	143	-0.86%	-0.41								
	2017	544	132	-3.08%	-1.33								
	2018	521	127	-5.72%	-2.37								
PRODEV	2013	3,901	1,123	-1.75%	-2.12	3,783	2,746	-1.17%	-1.36	1,062	25	-0.90%	-0.17
	2014	3,872	1,110	-1.31%	-1.39	3,756	2,764	-0.94%	-0.93	1,018	26	-2.81%	-0.46
	2015	3,814	1,081	-1.41%	-1.43	3,687	2,750	-0.54%	-0.51	962	25	-6.49%	-1.05
	2016	3,809	1,055	-1.42%	-1.48	3,659	2,778	-0.40%	-0.39	910	29	-7.27%	-1.27
	2017	3,816	1,052	-0.96%	-0.93	3,669	2,820	-1.03%	-0.92	876	27	-6.53%	-1.04
	2018	3,585	999	-0.82%	-0.76	3,435	2,662	-2.52%	-2.11	800	27	-7.51%	-1.08
SUPP	2013	233	42	-5.30%	-2.16								
	2014	220	42	-6.09%	-2.57								
	2015	103	31	3.00%	0.65								
	2016	95	23	18.56%	1.66								
	2017	85	20	1.57%	0.17								
	2018	83	21	10.03%	1.00								

Model controls for gender/race, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in job, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

Attachment C - Tables

In the Individual Contributor Career Levels, Total Compensation is Comprised Largely of Base Salary
At Higher Manager Career Levels, Stock Awards Make Up the Bulk of Total Compensation

- 2013-2018, Full Time Full Year Employees, By Career Level -

Career Level	Number of Incumbent Years	Average Base Pay	Average Stock Amount	Average Bonus Amount	Average Total Compensation	% Receiving Stock	% Receiving Bonus	Base Pay as a % of Total Compensation	Stock as a % of Total Compensation	Bonus as a % of Total Compensation
IC0	11	[redacted]								
IC1	79	[redacted]								
IC2	1,166	[redacted]								
IC3	3,655	[redacted]								
IC4	7,146	[redacted]								
IC5	5,174	[redacted]								
IC6	575	[redacted]								
		[redacted]								
M1	10	[redacted]								
M2	685	[redacted]								
M3	2,275	[redacted]								
M4	2,444	[redacted]								
M5	2,033	[redacted]								
M6	1,151	[redacted]								
M7	134	[redacted]								

Modified Regression Analysis of Total Compensation by Gender or Race Shows No Systematic Pattern of Statistically Significant Results in IC Career Levels Across Years or Job Function

		Female vs. Male				Asian vs. White				African American vs. White			
Job Function	Year	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value
INFTECH	2013	313	92	-4.12%	-2.13								
	2014	316	93	-3.98%	-1.76								
	2015	384	106	-6.53%	-2.99								
	2016	422	114	-4.67%	-2.14								
	2017	368	103	-6.05%	-2.39								
	2018	342	93	-6.01%	-2.42								
PRODEV	2013	2,598	828	-0.97%	-1.15	2,512	1,847	-1.35%	-1.42	686	21	5.20%	0.98
	2014	2,587	818	-0.27%	-0.29	2,502	1,879	-2.31%	-2.16	646	23	-0.89%	-0.14
	2015	2,544	794	-0.70%	-0.71	2,456	1,868	-2.03%	-1.82	609	21	0.81%	0.12
	2016	2,548	772	-1.33%	-1.38	2,440	1,881	-0.77%	-0.68	584	25	-2.21%	-0.37
	2017	2,545	765	-1.26%	-1.21	2,439	1,894	-0.92%	-0.76	568	23	-4.18%	-0.68
	2018	2,359	727	-0.86%	-0.80	2,250	1,749	-2.25%	-1.78	524	23	-8.06%	-1.23
SUPP	2013	186	38	-4.60%	-1.84								
	2014	173	37	-3.29%	-1.47								
	2015	82	26	6.70%	1.28								
	2016	72	18	2.24%	0.22								
	2017	66	15	-17.75%	-3.20								
	2018	64	16	-6.88%	-0.84								

Model controls for gender/race, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in job, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

Modified Regression Analysis of Total Compensation by Gender or Race Shows No Systematic Pattern of Statistically Significant Results in M Career Levels Across Years or Job Function

* Results suppressed if fewer than 5 employees in the protected class.

		Female vs. Male				Asian vs. White				African American vs. White			
Job Function	Year	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value
INFTECH	2013	127	32	-4.82%	-0.93								
	2014	131	31	0.17%	0.03								
	2015	172	30	6.66%	1.08								
	2016	182	29	6.81%	1.16								
	2017	176	29	3.83%	0.65								
	2018	179	34	-1.92%	-0.32								
PRODEV	2013	1,303	295	-2.48%	-1.14	1,271	899	0.73%	0.37	376	4		
	2014	1,285	292	-1.40%	-0.54	1,254	885	1.95%	0.83	372	3		
	2015	1,270	287	-2.37%	-0.91	1,231	882	2.74%	1.13	353	4		
	2016	1,261	283	-0.38%	-0.16	1,219	897	0.17%	0.07	326	4		
	2017	1,271	287	0.73%	0.28	1,230	926	-1.59%	-0.63	308	4		
	2018	1,226	272	-0.04%	-0.01	1,185	913	-3.27%	-1.25	276	4		
SUPP	2013	47	4										
	2014	47	5	-40.62%	-9.12								
	2015	21	5	-72.60%	0.00								
	2016	23	5	38.41%	0.00								
	2017	19	5	-10.07%	0.00								
	2018	19	5	-25.40%	0.00								

Model controls for gender/race, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in job, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

Modified Regression Analysis of Total Compensation by Gender or Race Shows No Systematic Patterns of Statistically Significant Results in Any Career Level in PRODEV, 2014

- The Only Significant Result Shows Women with Higher Compensation (IC6) -

		Female vs. Male				Asian vs. White				African American vs. White			
Job Function	Global Career Level	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value
PRODEV	IC1	7	4			7	5	2237.8%	0.00	2	0		
PRODEV	IC2	203	67	2.0%	0.95	195	176	-0.5%	-0.13	20	1		
PRODEV	IC3	548	218	-0.7%	-0.53	533	451	0.7%	0.36	90	8		
PRODEV	IC4	989	336	-0.5%	-0.33	956	737	-3.4%	-1.91	226	7	-6.5%	-0.65
PRODEV	IC5	753	187	2.4%	0.91	725	480	-2.3%	-1.01	252	7	-12.6%	-0.95
PRODEV	IC6	87	6	109.4%	2.80	86	30	-1.5%	-0.10	56	0		
PRODEV	M2	105	33	3.8%	0.43	102	89	-4.5%	-0.31	13	0		
PRODEV	M3	370	104	0.5%	0.15	361	299	-1.6%	-0.40	63	1		
PRODEV	M4	347	85	-0.3%	-0.07	340	238	4.9%	1.34	104	2		
PRODEV	M5	283	44	-1.4%	-0.16	281	178	2.8%	0.43	103	0		
PRODEV	M6	161	24	-3.5%	-0.14	152	75	-21.1%	-1.05	77	0		
PRODEV	M7	19	2			18	6	-98.4%	0.00	12	0		

Model controls for gender/race, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in job, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

Modified Regression Analysis of Total Compensation for Asians vs. Whites in PRODEV Shows No Statistically Significant Effect of H1B Status

Year	Coefficient	T-Value
2013	0.0181	1.53
2014	0.0207	1.53
2015	0.0045	0.34
2016	0.0075	0.59

Note: The coefficient is never statistically significant. Model controls for Asian, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in job, organization, whether the employee ever has a patent bonus, whether they arrived at Oracle as an experienced hire or through an acquisition, and whether on H1B visa.

There are Differences in The Job Level Applied for by Men and Women

- 2013-2018 Experienced Hires -

Career level applied to		Females		Males	
		Count	Percent	Count	Percent
Individual Contributers (Chi-sq test p-value: <.0001)	IC1	3	1.0%	8	0.8%
	IC2	22	7.1%	42	4.1%
	IC3	109	35.0%	240	23.7%
	IC4	128	41.2%	455	44.9%
	IC5	46	14.8%	232	22.9%
	IC6	3	1.0%	36	3.6%
	Total	**311**	**100.0%**	**1013**	**100.0%**
Managers (Fisher's exact test p-value: 0.3567)	M2	3	6%	19	7%
	M3	14	27%	56	20%
	M4	21	41%	96	34%
	M5	9	18%	73	26%
	M6	4	8%	40	14%
	Total	**51**	**100%**	**284**	**100%**

There are Differences in The Job Level Applied for by Asians and Whites

- 2013-2018 Experienced Hires -

Career level applied to		Asians		Whites	
		Count	Percent	Count	Percent
Individual Contributers (Chi-sq test p-value: <.0001)	IC1	3	0.3%	3	1.1%
	IC2	49	5.1%	5	1.9%
	IC3	276	28.8%	52	19.8%
	IC4	430	44.9%	111	42.2%
	IC5	177	18.5%	79	30.0%
	IC6	23	2.4%	13	4.9%
	Total	**958**	**100.0%**	**263**	**100.0%**
Managers (Fisher's exact test p-value: 0.0060)	M2	19	8.3%	2	2.9%
	M3	57	25.0%	7	10.3%
	M4	77	33.8%	25	36.8%
	M5	53	23.2%	19	27.9%
	M6	22	9.6%	15	22.1%
	Total	**228**	**100.0%**	**68**	**100.0%**

Comparison of Actual vs. Applied for Job Level for Women vs. Men

- 2013-2018 Experienced Hires into IC Career Levels -

Actual Placement v. Application	# Females	% Females	# Males	% Males
Higher	37	11.9%	157	15.5%
Same	225	72.3%	669	66.0%
Lower	49	15.8%	187	18.5%
Total	**311**	**100.0%**	**1013**	**100.0%**

Chi-sq test p-value: 0.1063

Comparison of Actual vs. Applied for Job Level for Women vs. Men

- 2013-2018 Experienced Hires in M Career Levels -

Actual Placement v. Application	# Females	% Females	# Males	% Males
Higher	9	17.6%	40	14.1%
Same	37	72.5%	230	81.0%
Lower	5	9.8%	14	4.9%
Total	**51**	**100.0%**	**284**	**100.0%**

Fisher's exact test p-value: 0.2763

Comparison of Actual vs. Applied for Job Level for Asians vs. Whites

- 2013-2018 Experienced Hires into IC Career Levels -

Actual Placement v. Application	# Asian	% Asian	# White	% White
Higher	142	14.8%	41	15.6%
Same	625	65.2%	191	72.6%
Lower	191	19.9%	31	11.8%
Total	**958**	**100.0%**	**263**	**100.0%**

Chi-sq test p-value: 0.0095

Comparison of Actual vs. Applied for Job Level for Asians vs. Whites

- 2013-2018 Experienced Hires into M Career Levels -

Actual Placement v. Application	# Asian	% Asian	# White	% White
Higher	32	14.0%	7	10.3%
Same	185	81.1%	56	82.4%
Lower	11	4.8%	5	7.4%
Total	**228**	**100.0%**	**68**	**100.0%**

Fisher's exact test p-value: 0.5529

Comparison of Actual vs. Applied for Job Level for African Americans vs. Whites

- 2013-2018 Experienced Hires into IC Career Levels -

Actual Placement v. Application	# African American	% African American	# White	% White
Higher	1	14.3%	41	15.6%
Same	5	71.4%	191	72.6%
Lower	1	14.3%	31	11.8%
Total	**7**	**100.0%**	**263**	**100.0%**

Fisher's exact test p-value = 0.9779

- Based on OFCCP Data and OFCCP Regression Model -
The OFCCP's Regression Analysis of Total Compensation Shows No Statistically Significant Results for Asians vs. Whites
- INFTECH and SUPP Job Functions -

		Asian vs. White			
Job Function	**Year**	**# Obs. Used**	**# Protected Group**	**Pay Diff. (%)**	**T-Value**
INFTECH	2013	407	281	-1.13%	-0.37
	2014	411	285	-1.92%	-0.55
	2015	520	394	-0.60%	-0.20
	2016	560	427	2.49%	0.89
SUPP	2013	223	179	6.04%	1.15
	2014	212	176	4.22%	0.78
	2015	95	68	11.24%	1.54
	2016	88	63	14.15%	1.73

Model controls for Asian, standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

- Based on OFCCP Data and OFCCP Regression Model -
The OFCCP's Model Predicts Higher Pay for Asians vs. Whites for Most Tenure Groups

- Base Pay by Tenure Group -
- INFTECH and SUPP Job Functions -

Job Function	Experience	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value
INFTECH	1 to <3	257	197	-7.31%	-1.89
	3 to <5	256	195	4.51%	1.14
	5 to <7	177	134	4.31%	0.92
	7 to <9	208	157	7.90%	1.97
SUPP	1 to <3	103	92	12.39%	2.02
	3 to <5	98	78	9.62%	1.80
	5 to <7	76	60	-8.96%	-1.17
	7 to <9	95	70	0.28%	0.05

Model controls for Asian, standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

- Based on OFCCP Data and OFCCP Regression Model - The Pay Gap Does Not Increase With Tenure in INFTECH and is Not Statistically Significant for the Youngest Tenure Group in SUPP for Females vs. Males

- Base Pay by Tenure Group -
- INFTECH and SUPP Job Functions -

Job Function	Experience	# Obs. Used	# Protected Group	Pay Diff. (%)	T-Value
INFTECH	1 to <3	289	56	-10.19%	-2.99
	3 to <5	283	63	-5.05%	-1.38
	5 to <7	201	47	-5.32%	-1.25
	7 to <9	220	75	1.42%	0.44
SUPP	1 to <3	106	14	-5.76%	-1.24
	3 to <5	110	19	-9.65%	-2.15
	5 to <7	83	24	-11.65%	-2.13
	7 to <9	96	21	-12.14%	-2.50

Model controls for female, standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Modified Regression Analysis of Total Compensation Shows No Statistically Significant Results for Asian Males vs. White Males in Any Year Within PRODEV

		Asian Males vs. White Males			
Job Function	**Year**	**# Obs. Used**	**# Protected Group**	**Pay Diff. (%)**	**T-Value**
PRODEV	2013	2,688	1,884	-0.27%	-0.25
	2014	2,673	1,905	-0.35%	-0.28
	2015	2,633	1,901	-0.26%	-0.20
	2016	2,632	1,945	-0.21%	-0.17

Model controls for Asian male, standard job title, part-time/full-time, time in company (Oracle America), total Oracle tenure (including time at acquisition and non-USA affiliate), previous experience (age minus total Oracle tenure minus 22), cumulative time spent on leave of absence, whether leave of absence was in current year, time in job, organization, whether the employee ever has a patent bonus, and whether they arrived at Oracle as an experienced hire or through an acquisition.

Attachment D: Supervisor Pie Charts

Supervisors Two Levels Above Employee: Total Compensation (Medicare Wages) for Women
- Prediction Based on OFCCP Model, Without a Gender Control -
- 2014, PRODEV, INFTECH, and SUPP Job Functions -

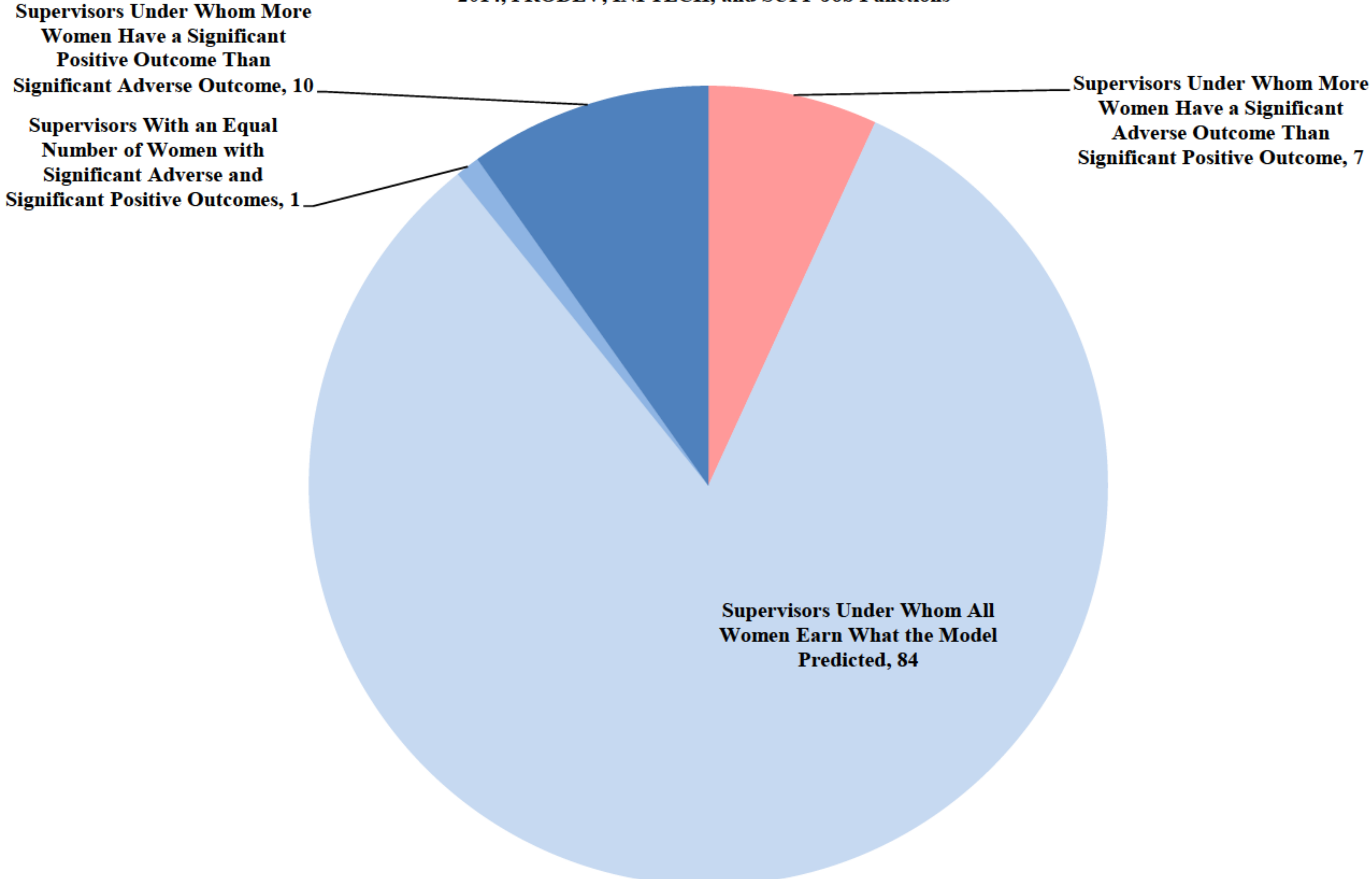

Chart is limited to supervisors with at least 10 employees and 2 women, accounting for 42.0% of women employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Employees by Supervisors Two Levels Above: Total Compensation (Medicare Wages) for Women

- Prediction Based on OFCCP Model, Without a Gender Control -

- 2014, PRODEV, INFTECH, and SUPP Job Functions-

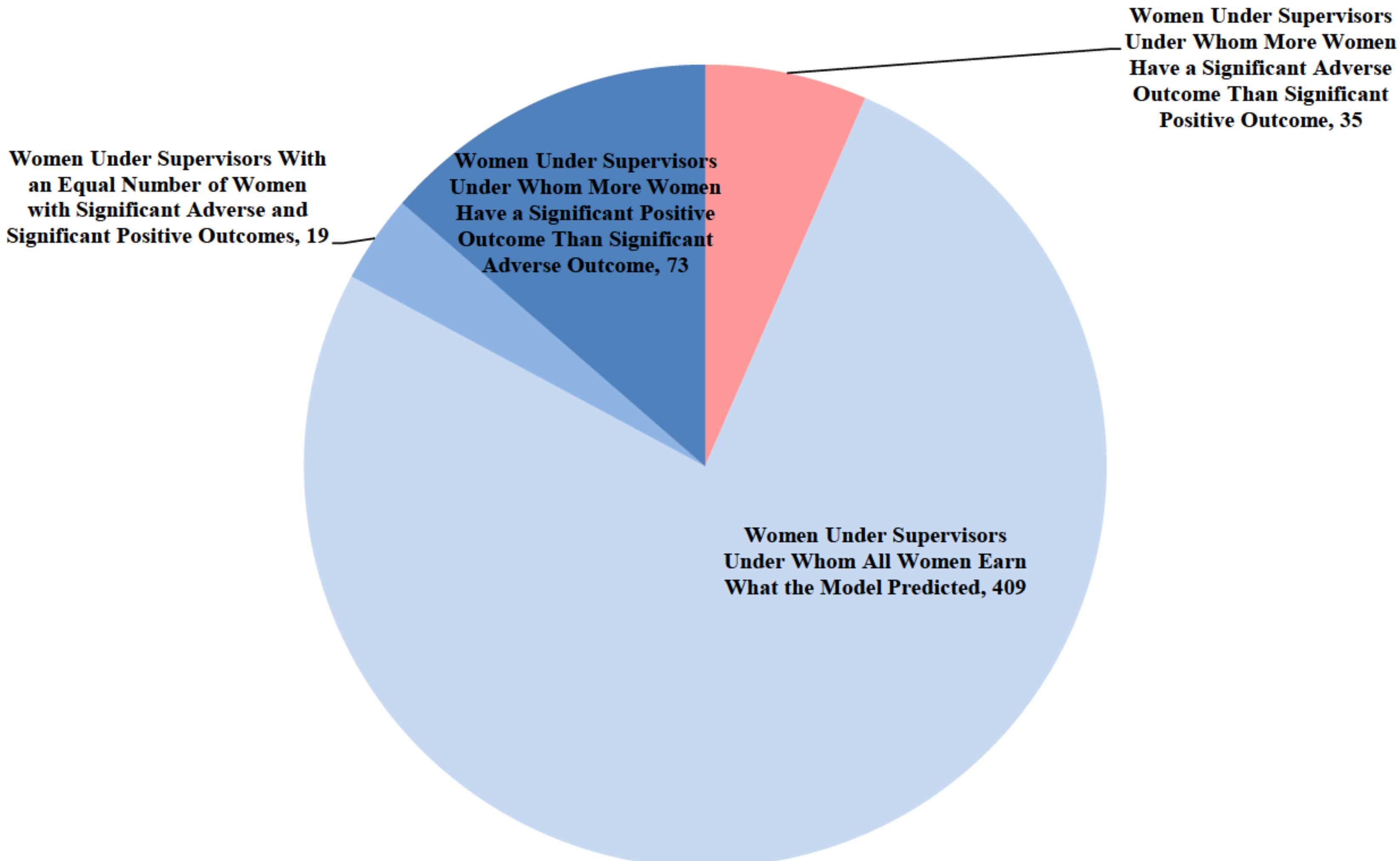

Chart is limited to supervisors with at least 10 employees and 2 women, accounting for 42.0% of women employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Supervisors Three Levels Above Employee: Total Compensation (Medicare Wages) for Women

- Prediction Based on OFCCP Model, Without a Gender Control -

- 2014, PRODEV, INFTECH, and SUPP Job Functions-

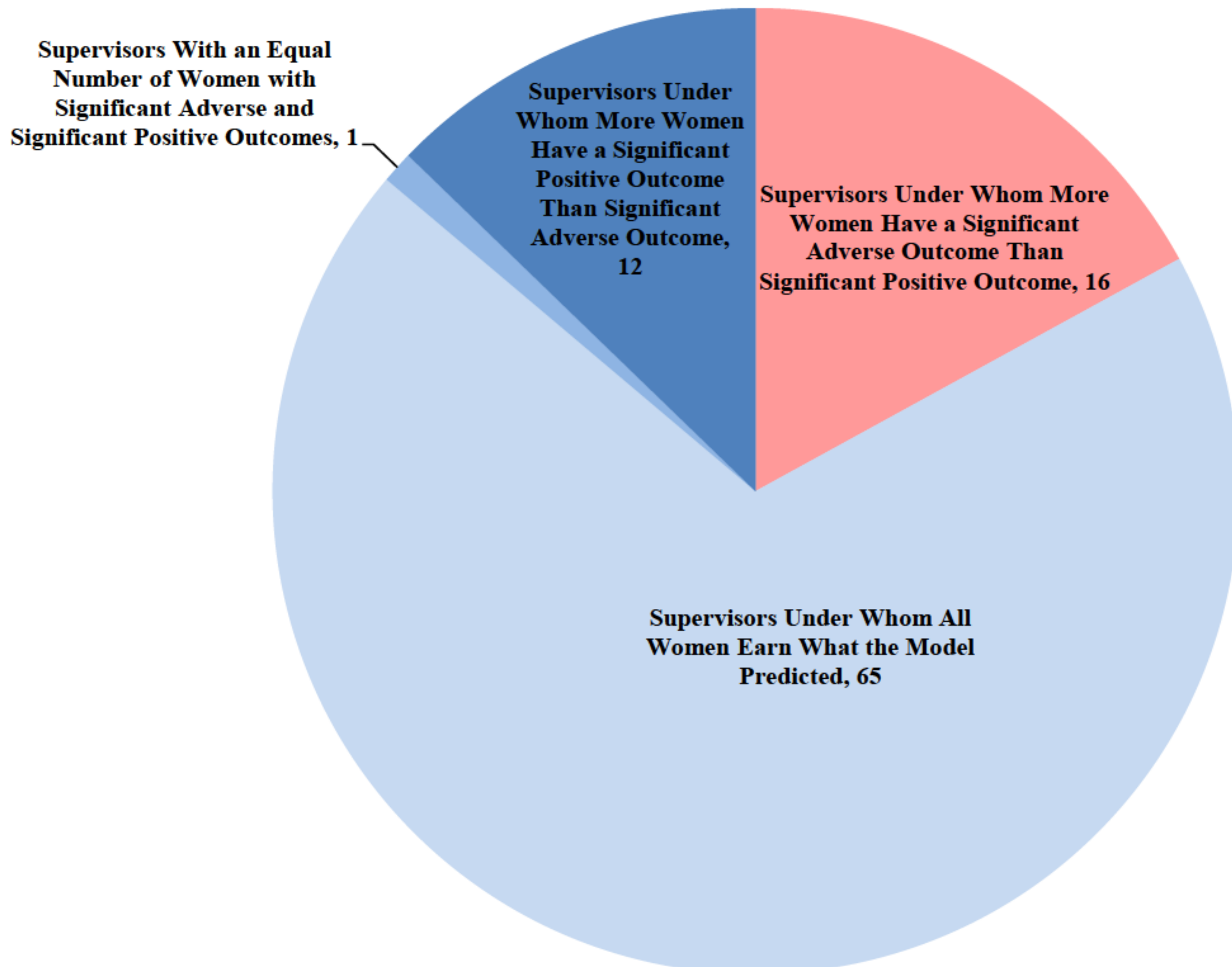

Chart is limited to supervisors with at least 10 employees and 2 women, accounting for 76.3% of women employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Employees by Supervisors Three Levels Above: Total Compensation (Medicare Wages) for Women

- Prediction Based on OFCCP Model, Without a Gender Control -

- 2014, PRODEV, INFTECH, and SUPP Job Functions-

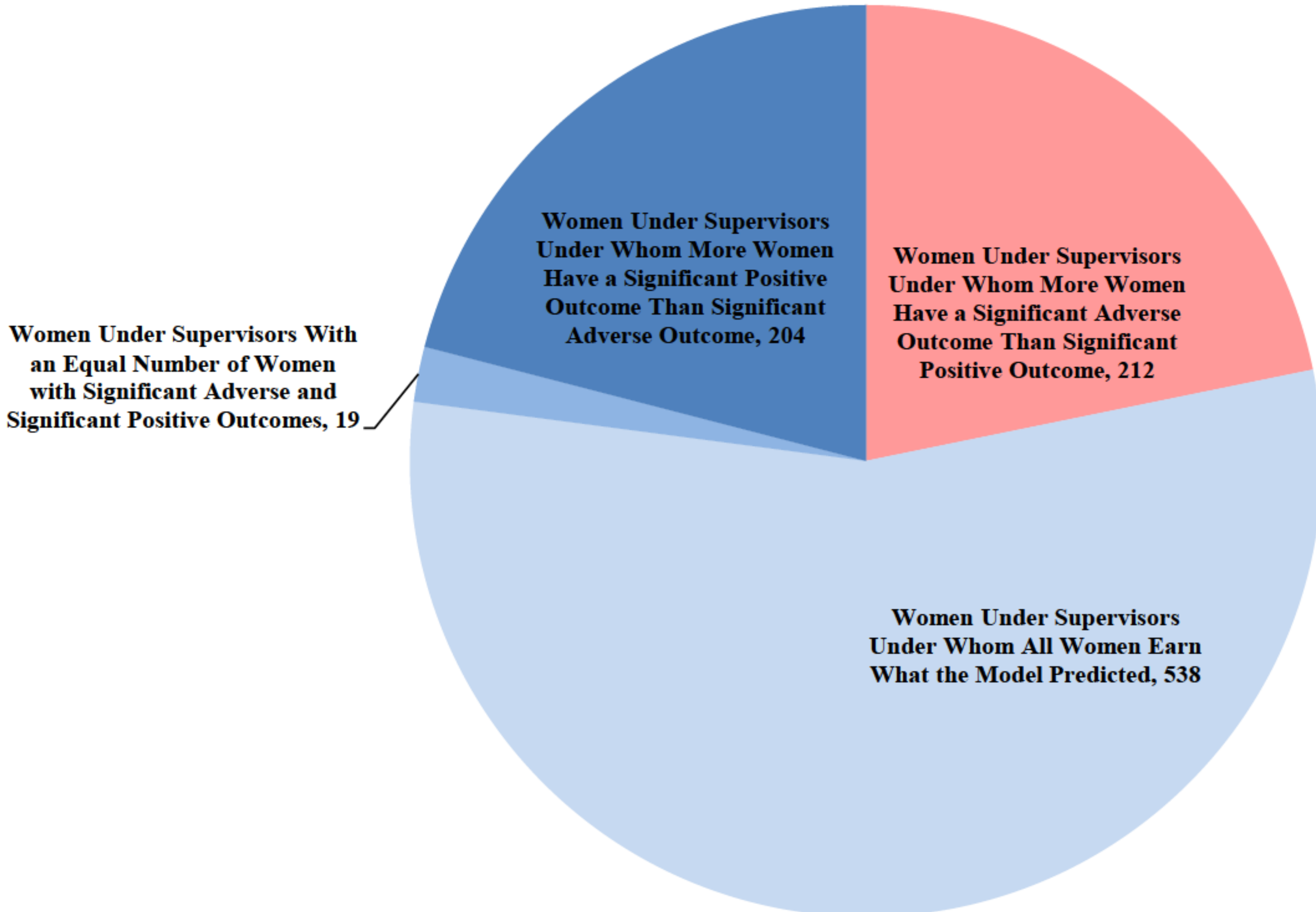

Chart is limited to supervisors with at least 10 employees and 2 women, accounting for 76.3% of women employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Attachment D - Supervisor Pie Charts

Supervisors Four Levels Above Employee: Total Compensation (Medicare Wages) for Women
- Prediction Based on OFCCP Model, Without a Gender Control -
- 2014, PRODEV, INFTECH, and SUPP Job Functions-

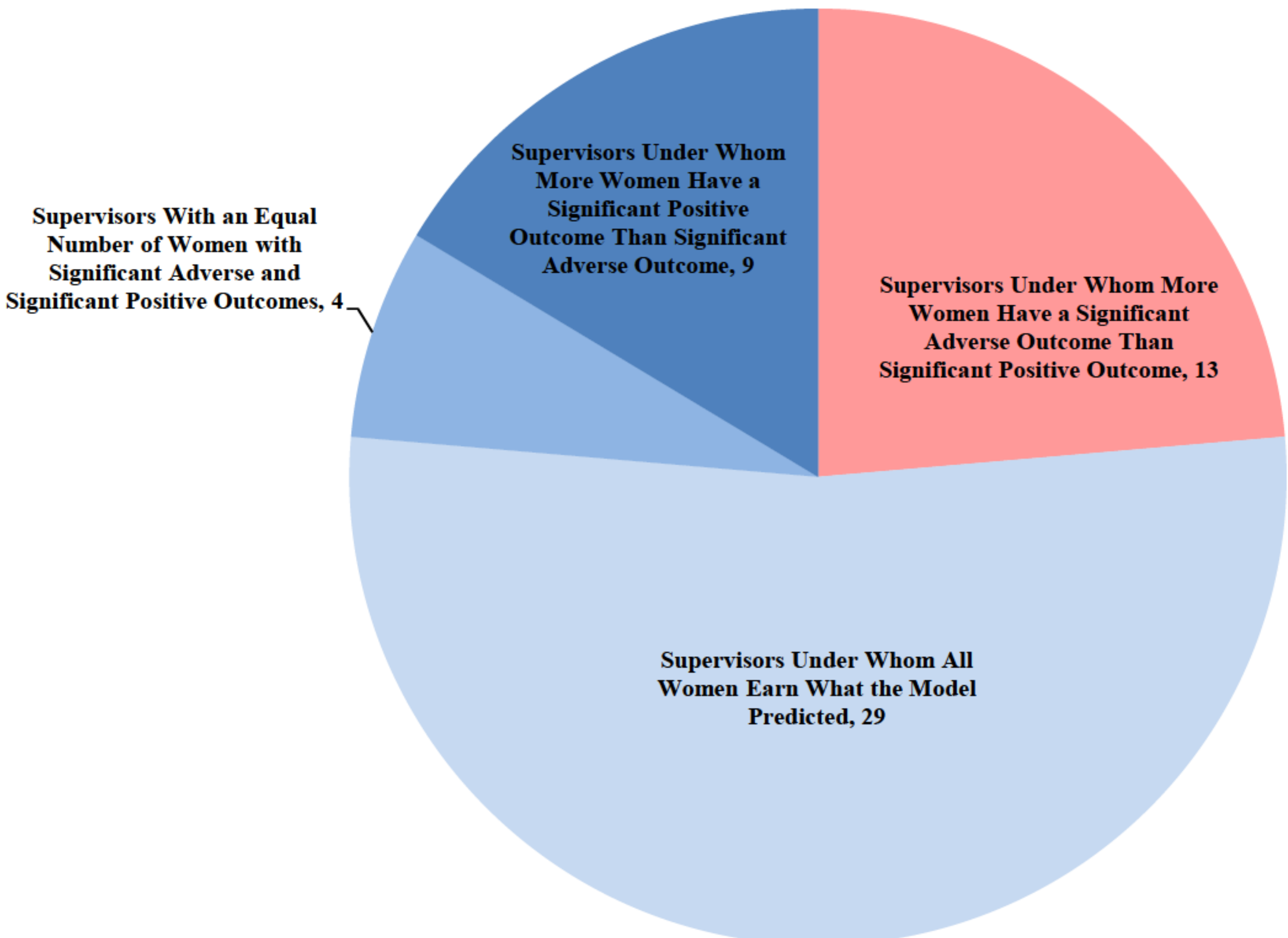

Chart is limited to supervisors with at least 10 employees and 2 women, accounting for 89.3% of women employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Attachment D - Supervisor Pie Charts

Employees by Supervisor Four Levels Above: Total Compensation (Medicare Wages) for Women
- Prediction Based on OFCCP Model, Without a Gender Control -
- 2014, PRODEV, INFTECH, and SUPP Job Functions-

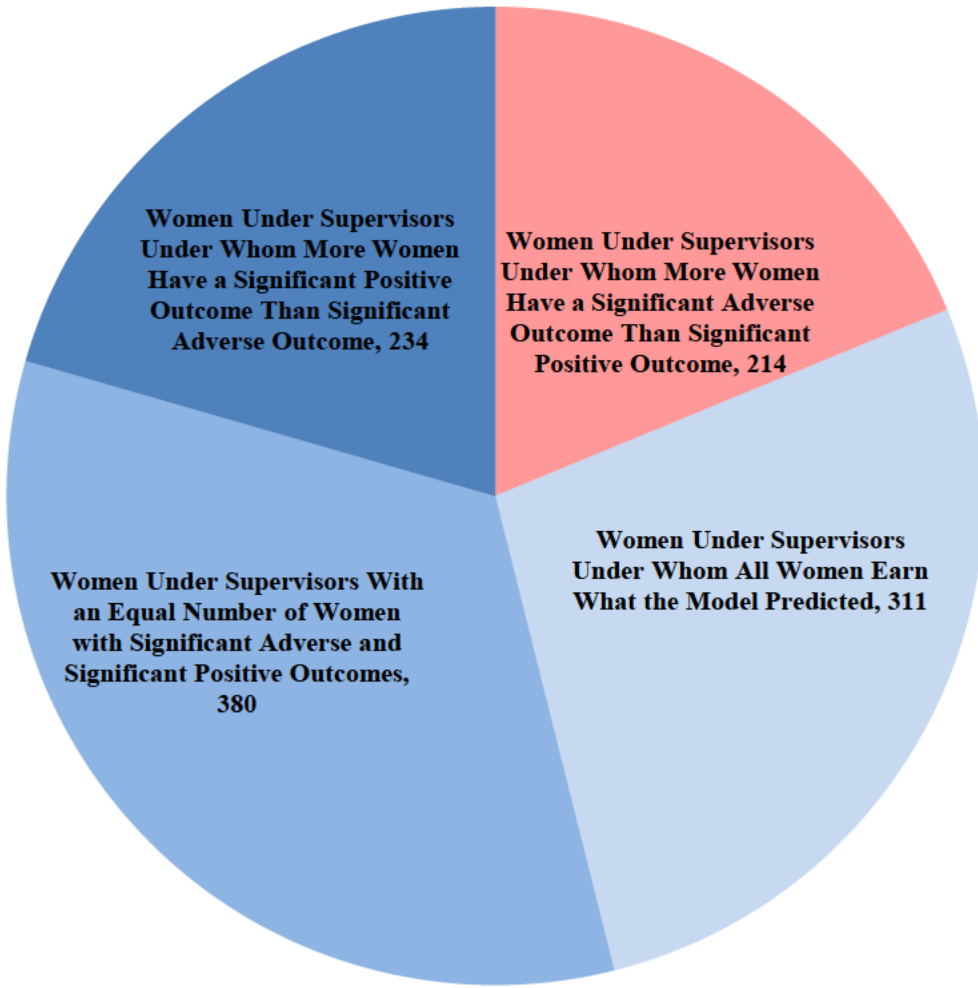

Chart is limited to supervisors with at least 10 employees and 2 women, accounting for 89.3% of women employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Supervisors Five Levels Above Employee: Total Compensation (Medicare Wages) for Women

- Prediction Based on OFCCP Model, Without a Gender Control -

- 2014, PRODEV, INFTECH, and SUPP Job Functions-

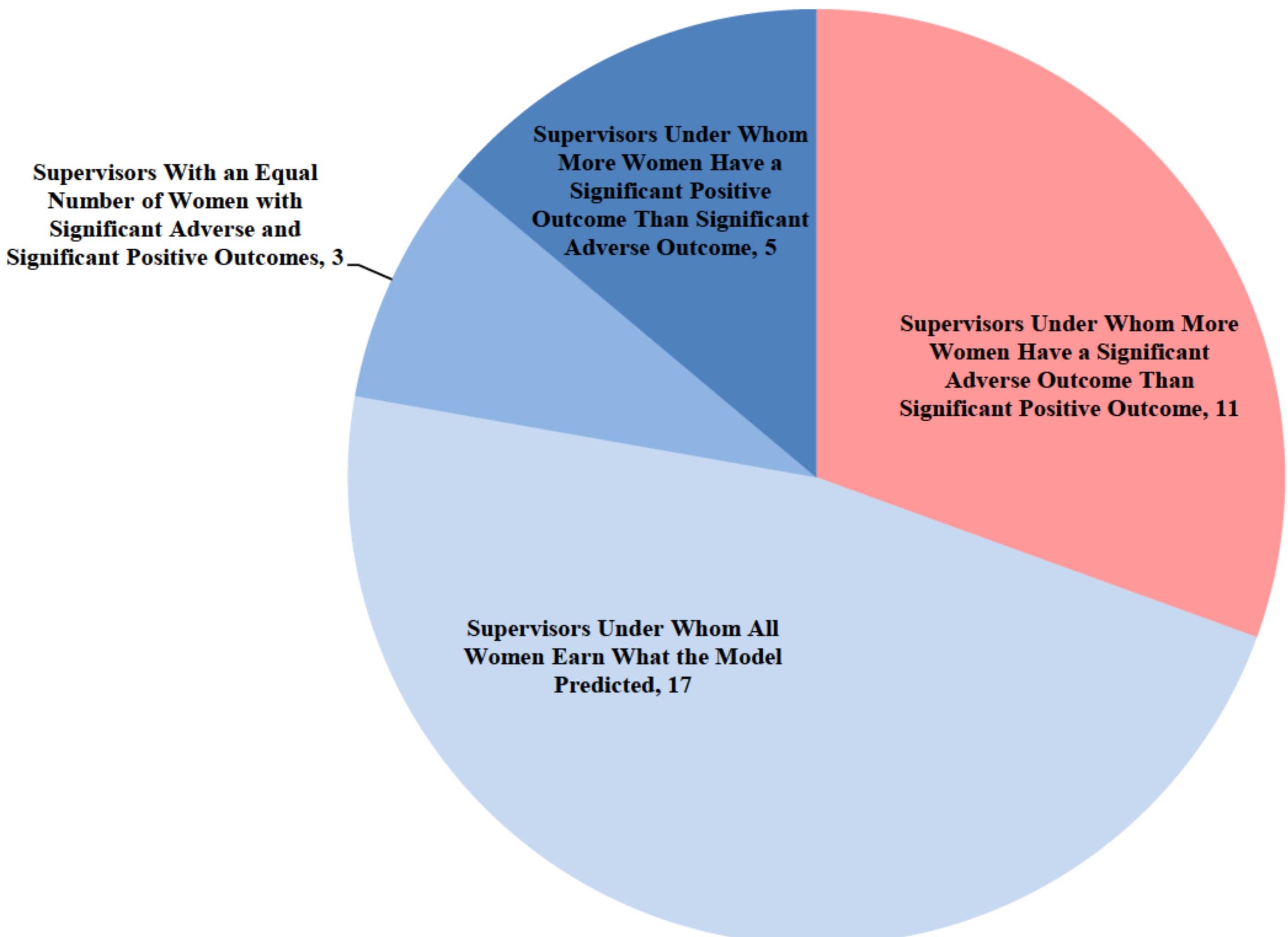

Chart is limited to supervisors with at least 10 employees and 2 women, accounting for 96.6% of women employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Employees by Supervisors Five Levels Above: Total Compensation (Medicare Wages) for Women

- Prediction Based on OFCCP Model, Without a Gender Control -
- 2014, PRODEV, INFTECH, and SUPP Job Functions-

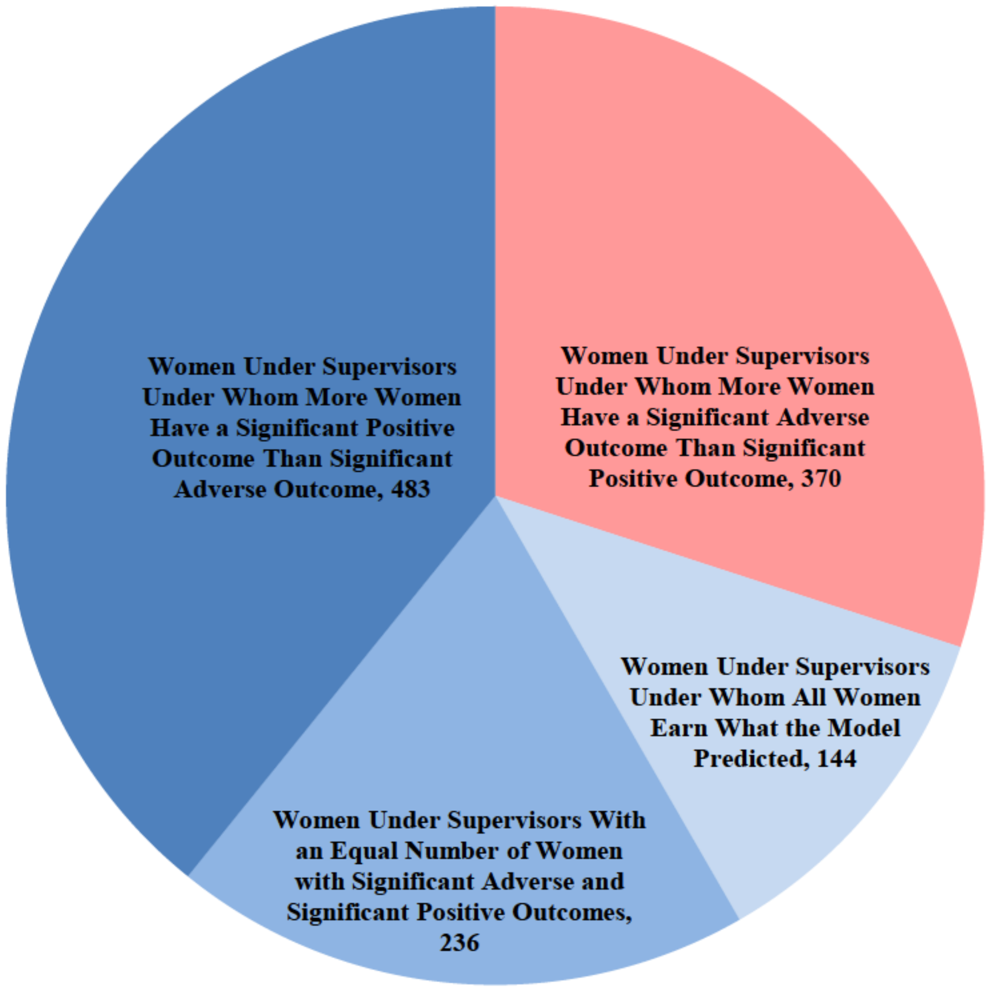

Chart is limited to supervisors with at least 10 employees and 2 women, accounting for 96.6% of women employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Attachment D - Supervisor Pie Charts

Supervisors Two Levels Above Employee: Total Compensation (Medicare Wages) for Asians
- Prediction Based on OFCCP Model, Without a Race Control -
- PRODEV Job Function, 2014 -

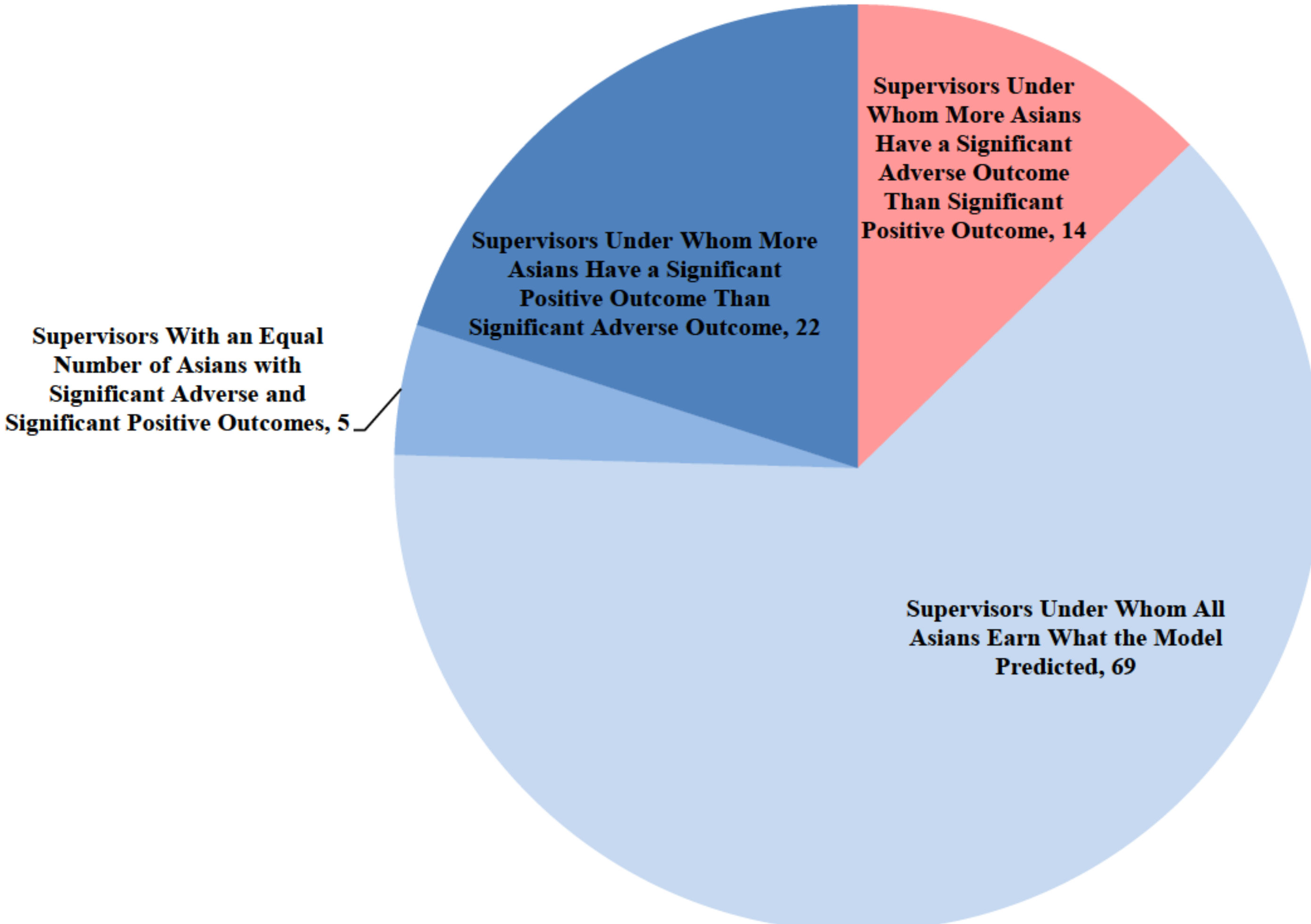

Chart is limited to supervisors with at least 10 employees and 2 Asians, accounting for 52.2% of Asian employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Employees Under Supervisors Two Levels Above: Total Compensation (Medicare Wages) for Asians

- Prediction Based on OFCCP Model, Without a Race Control -

- PRODEV Job Function, 2014 -

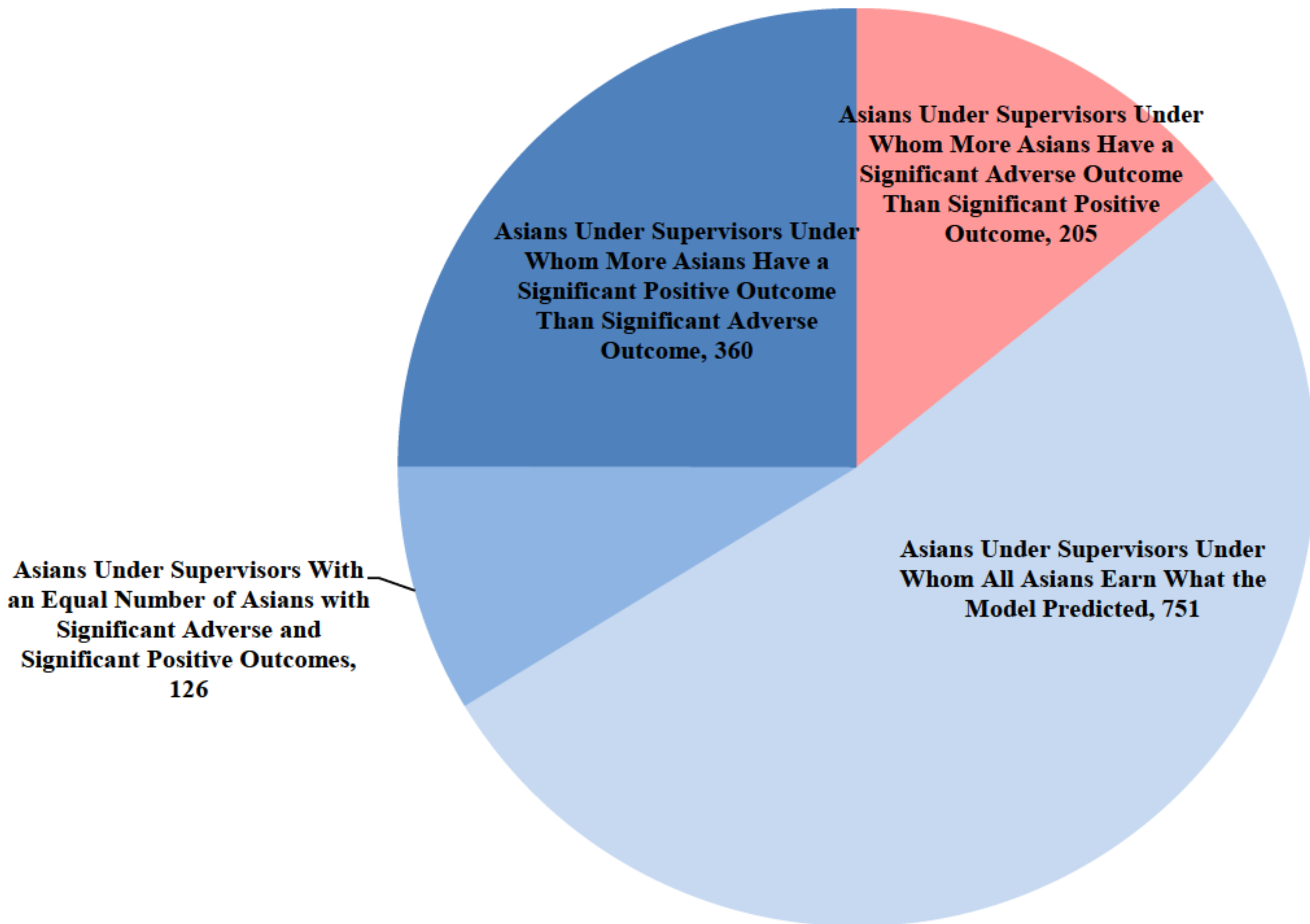

Chart is limited to supervisors with at least 10 employees and 2 Asians, accounting for 52.2% of Asian employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Supervisors Three Levels Above Employee: Total Compensation (Medicare Wages) for Asians

- Prediction Based on OFCCP Model, Without a Race Control -

- PRODEV Job Function, 2014 -

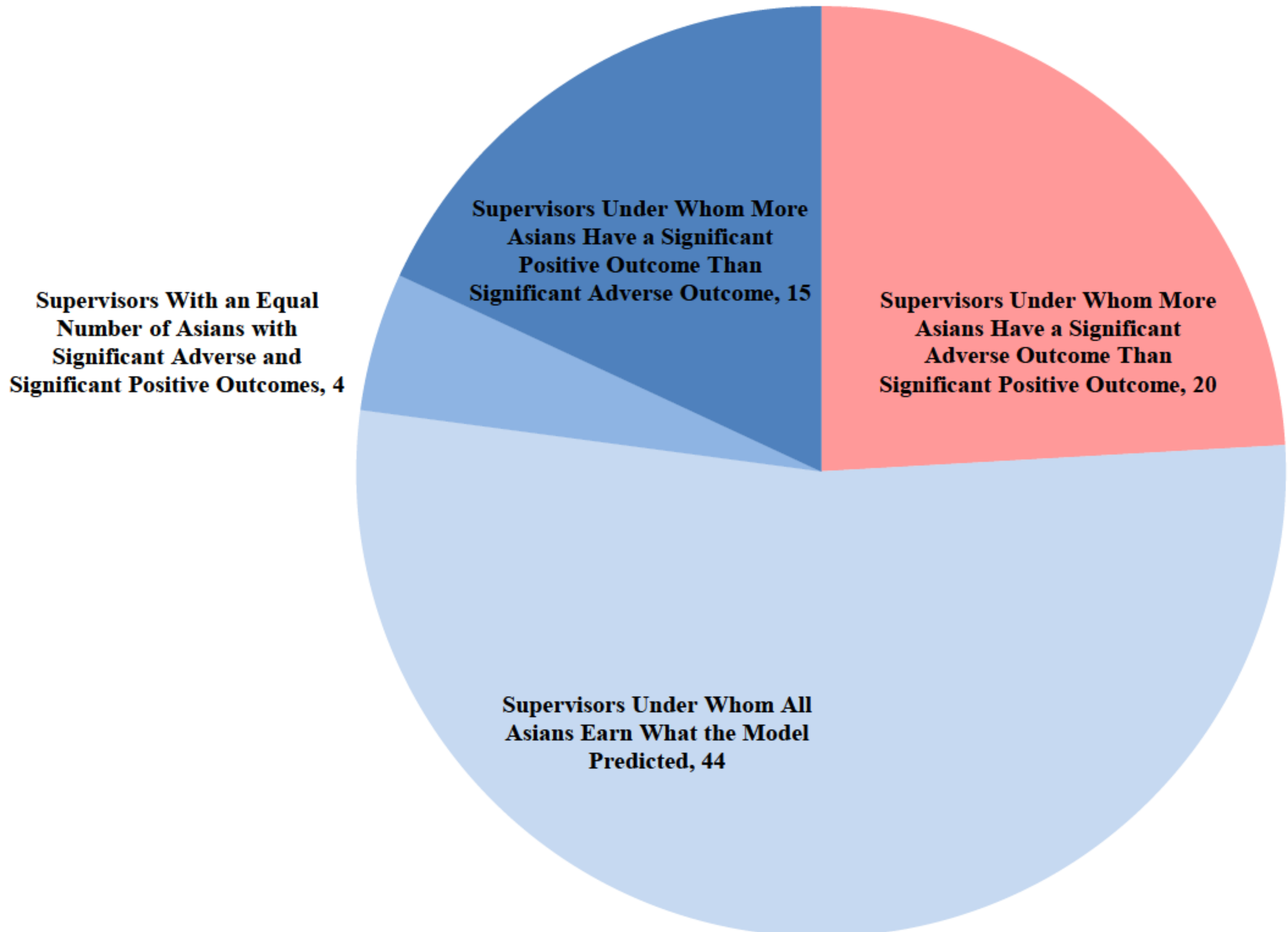

Chart is limited to supervisors with at least 10 employees and 2 Asians, accounting for 81.4% of Asian employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Employees Under Supervisors Three Levels Above: Total Compensation (Medicare Wages) for Asians

- Prediction Based on OFCCP Model, Without a Race Control -

- PRODEV Job Function, 2014 -

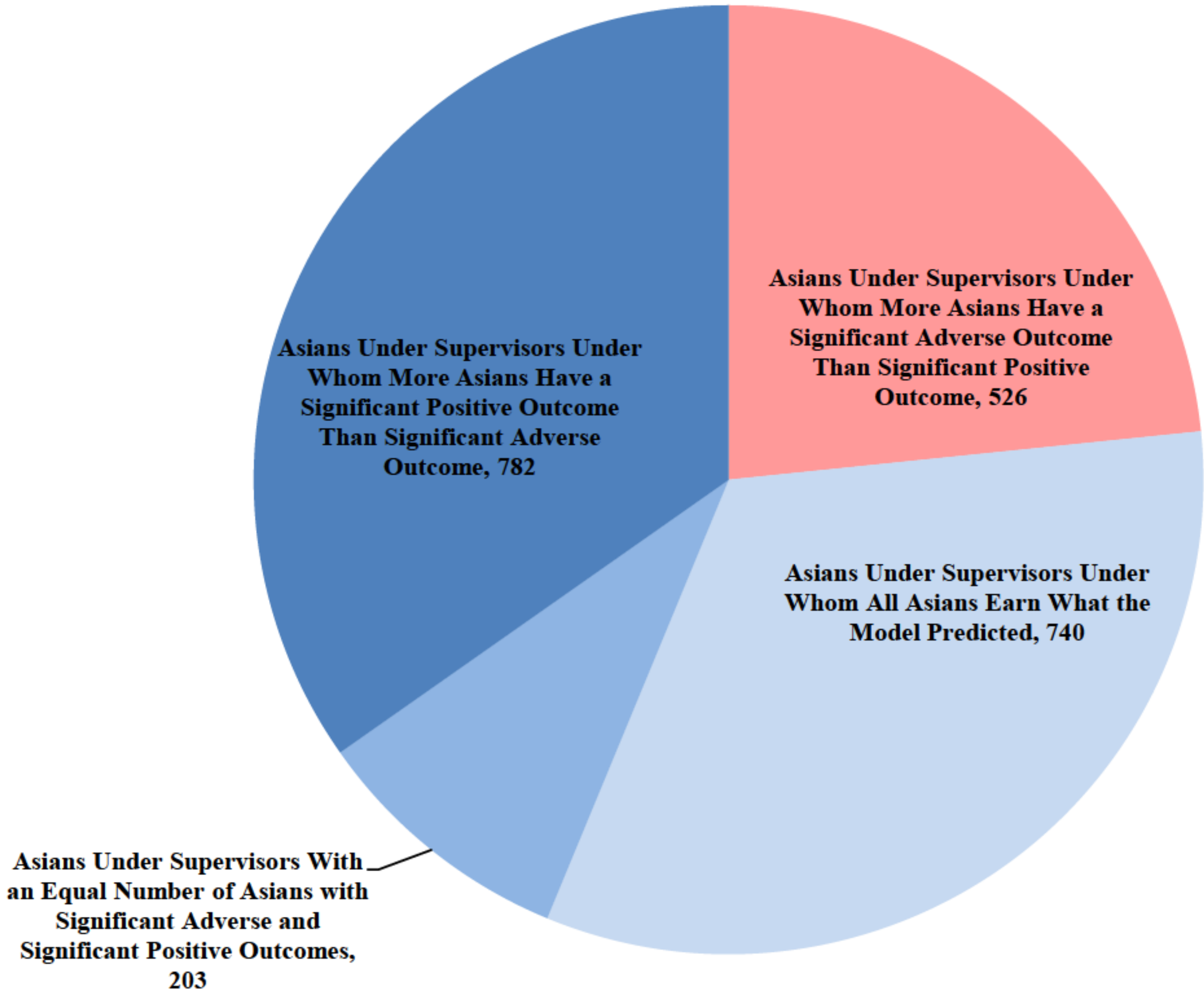

Chart is limited to supervisors with at least 10 employees and 2 Asians, accounting for 81.4% of Asian employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Supervisors Four Levels Above Employee: Total Compensation (Medicare Wages) for Asians
- Prediction Based on OFCCP Model, Without a Race Control -
- PRODEV Job Function, 2014 -

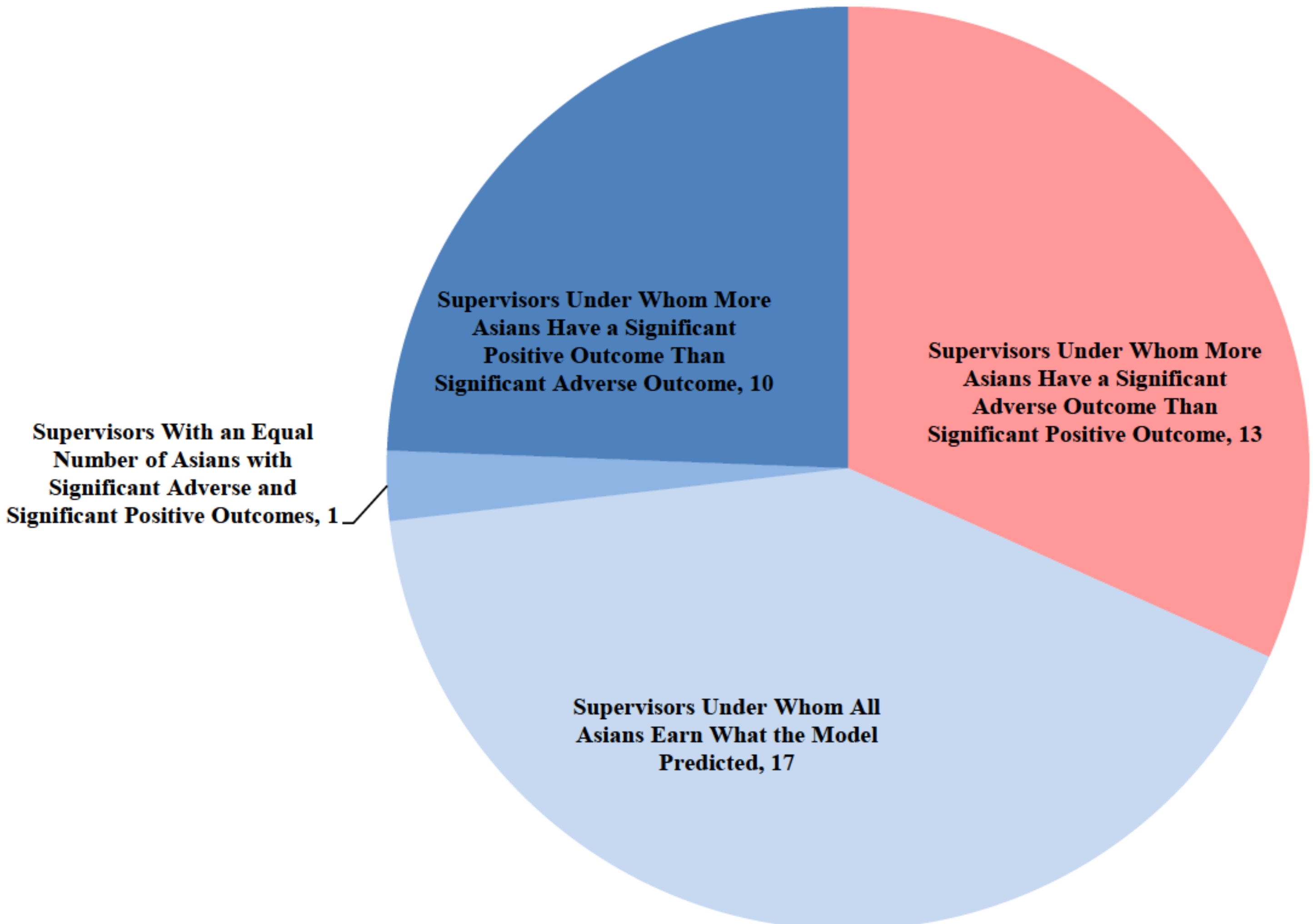

Chart is limited to supervisors with at least 10 employees and 2 Asians, accounting for 92.9% of Asian employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Employees Under Supervisors Four Levels Above: Total Compensation (Medicare Wages) for Asians

- Prediction Based on OFCCP Model, Without a Race Control -

- PRODEV Job Function, 2014 -

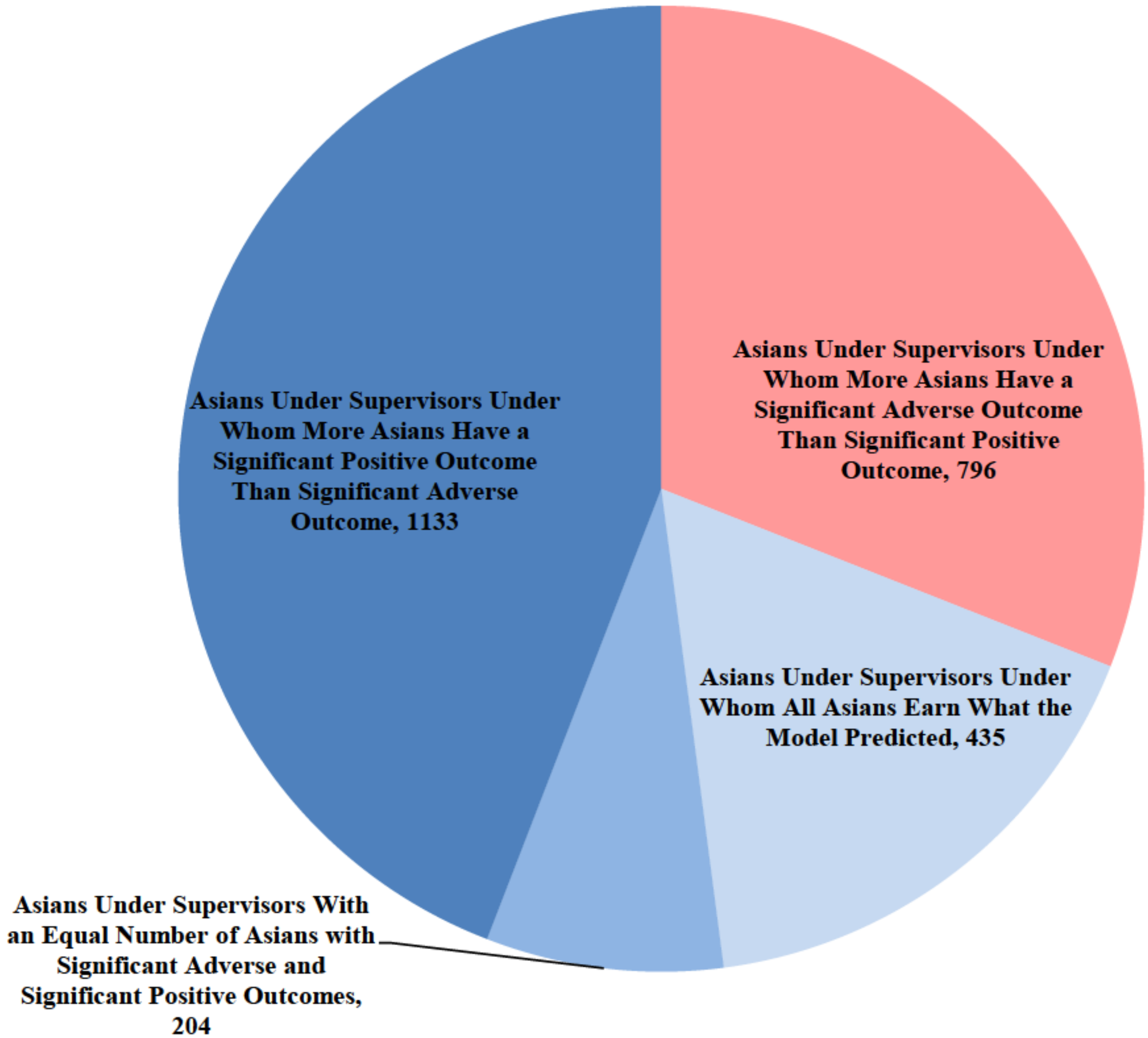

Chart is limited to supervisors with at least 10 employees and 2 Asians, accounting for 92.9% of Asian employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Employees Under Supervisors Five Levels Above: Total Compensation (Medicare Wages) for Asians

- Prediction Based on OFCCP Model, Without a Race Control -

- PRODEV Job Function, 2014 -

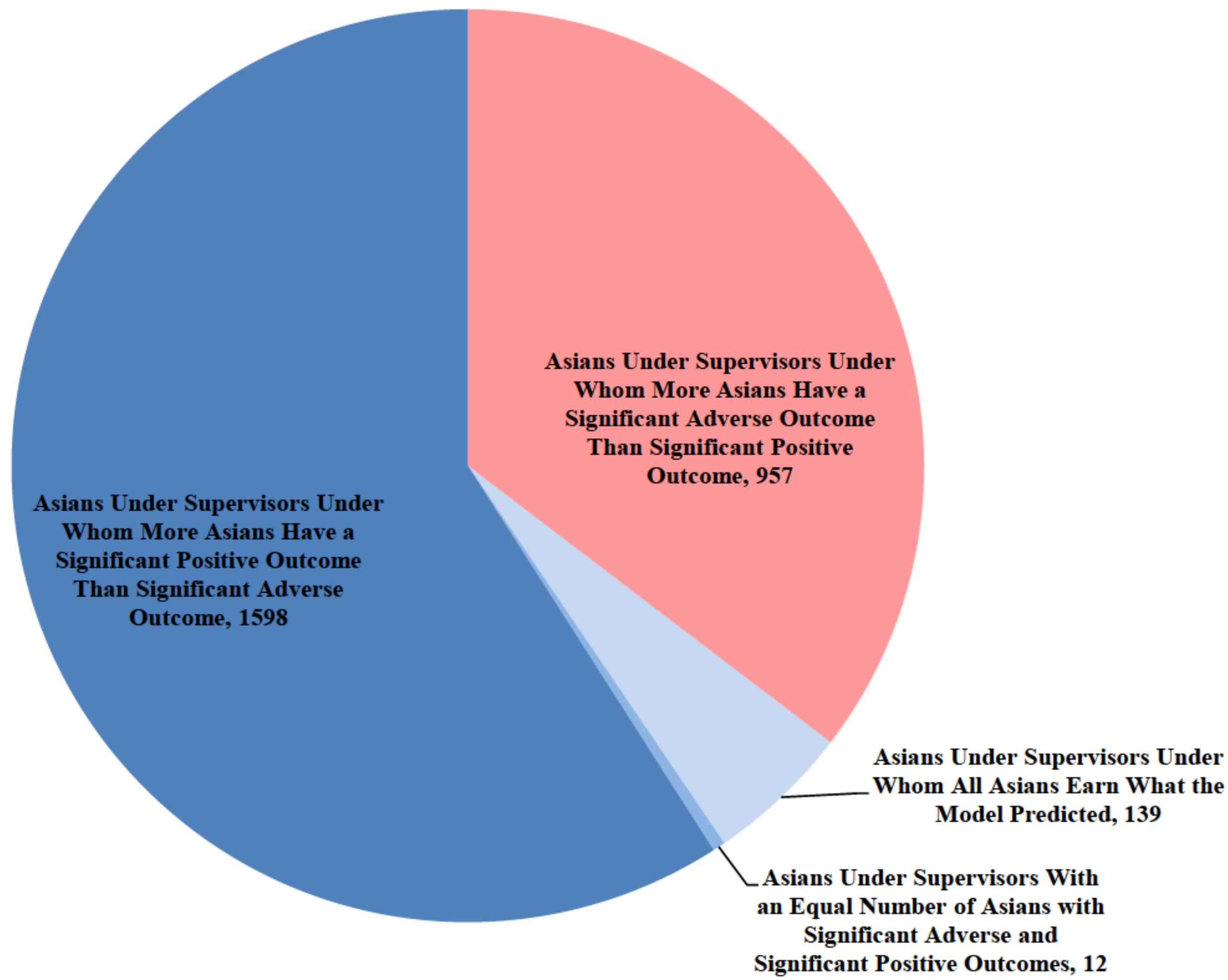

Chart is limited to supervisors with at least 10 employees and 2 Asians, accounting for 97.9% of Asian employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Attachment D - Supervisor Pie Charts

Supervisors Five Levels Above Employee: Total Compensation (Medicare Wages) for Asians

- Prediction Based on OFCCP Model, Without a Race Control -

- PRODEV Job Function, 2014 -

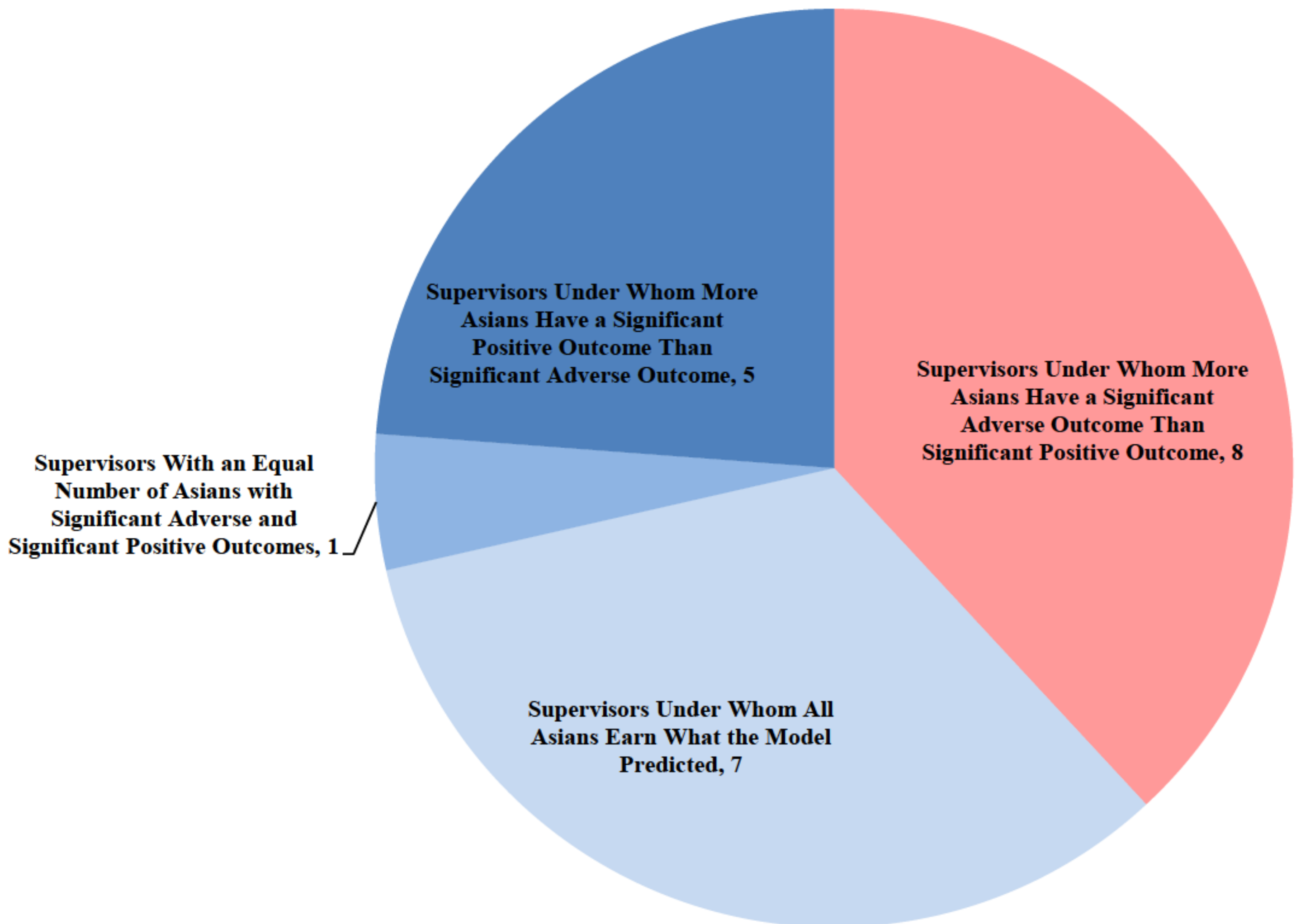

Chart is limited to supervisors with at least 10 employees and 2 Asians, accounting for 97.9% of Asian employees.
Model controls for standard job title, part-time/full-time, time in company, and previous experience (age minus time in company minus 18).

Attachment E: Clusters

Within job titles, skills and responsibilities vary widely

1. The OFCCP regression models control for "global career level, job specialty, and standard job title."[1] Although job titles can be used to segment the data to a certain extent, it appears that employees performing dissimilar work continue to be grouped together using this approach. Organization, or cost center, was used in my models to group employees by products and services they work on but it is not entirely well suited to group employees doing similar work, due to its dual business and accounting function.[2] In order to test whether job content varies within a job title, new hire requisitions were analyzed to determine whether there are other ways to think about the differences in job requirements even holding job title constant.[3]

2. Several studies have used clustering algorithms to extract skill requirements from the text of job requisitions, with a particular emphasis on identifying the specific skills required for different types of IT jobs. Much of this research stems from a need to identify high demand skills in the face of rapid change in the types of skills required by IT jobs.

3. Woweczko (2015) analyzed online job advertisements in Ireland to extract information on skills needs from job descriptions, and presents word clouds[4] showing the top bigrams[5] for

[1] Second Amended Complaint, paragraph 13, p. 6.
[2] "At the most granular level of the financial and accounting hierarchy, "cost center" (sometimes called "organizations") are used for purposes of tracking budget and other financial outcomes. A cost center can encompass a single product or service team, but not every product or service team has its own cost center." Miranda Declaration, paragraph 8.
[3] The requisition data contains information relating to job listings and included generic company information, as well as detailed text that described the specific job requirements. The generic text was not analyzed. Rather, the job specific detailed text was analyzed for this analysis.
[4] "Word cloud" is a term of art used to visually depict the importance of each word, where importance is measured using word frequency within and across documents calculated by the clustering technique. Less frequent words may appear larger if the algorithm determines they are more important.
[5] A bigram is a pair of consecutive written elements, in this case two consecutive words in a field of text.

seven different IT occupations. Woweczko concludes that the skills extracted using this method are more detailed than what would be found in standard occupational descriptions.[6]

4. Litecky, et al. (2010) examined online listings for software engineers on Monster.com, HotJobs.com and SimplyHired.com, finding that "even a brief examination of these tools shows that US job titles vary substantially and that job definitions are often misleading."[7] Their study used cluster analysis of job skill terms found in the listing text and identified 20 IT job categories and associated skill sets. They found that among the advertisements analyzed there were five clusters for software developers: "The software developers group consists of five clusters of traditional non-Web-based development, with moderate demands for programming in general, software development, and object-oriented programming skills, plus specific language skills such as C/C++, Java, or C#. For example, two clusters focus on C/C++ and generic programming skills. The two clusters are distinguished through the supplementary skills required for those jobs. C/C++ programmer jobs focus primarily on programming-language skills, whereas the system-level C/C++ programmer jobs also require skills in general programming, software development, operating systems, security, and Perl. This indicates that the latter cluster undertakes work at the operating systems level as well as supporting traditional Perl-based work."[8] In this case, the word cloud analysis revealed differences in skill requirements for different segments of the software developer job spectrum.

5. Creating economic variables from text based sources is not new. Economists have a long history of utilizing coded text data in their analyses. One familiar example is the data on

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[6] Woweczko, Izabella A. (2015) Skills and Vacancy Analysis with Data Mining Techniques, *Informatics*, 2, pp. 31-49.
[7] Litecky, Chuck, et al. (January/February 2010), Mining for Computing Jobs, *IEEE Software*.
[8] Ibid, p. 80.

workers' occupations and industries collected by the US Census Bureau.[9] The census questionnaire asks respondents "What kind of work was this person doing?" and "What were this person's most important activities and duties?" with a "fill-in-the-blank field" that allows a free-form response. There is no drop down menu option for respondents to choose from. Rather than let respondents decide what their occupational category is, the Census Bureau applies their expertise in the nature of work and what occupation it constitutes to convert free form text descriptions of what people say they do at work to a census OCC code. In the case of the Census, the written responses are then reviewed and coded into standardized occupation classifications, which can then be included as categorical or stratifying variables in quantitative analyses. Similarly, the questionnaire asks about the industry in which one works using both free-form and check-box questions which are then clerically coded by Census Bureau staff.[10] The resulting coded occupations and industries can then be utilized by economists and other researchers in their analyses.

6. I have in my previous work performed conversion of detailed textual descriptive material into job categories. For example, in a hiring case I and my team processed 30,000 handwritten employment applications and created a set of job categories. These categories were then used in statistical analysis of hiring. In another case, I and my team processed tens of thousands of promotion job postings, and converted qualitative material into data that would be subjected to statistical analysis. In short, processing of text and other qualitative material into quantitative or categorical formats is nothing new.

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[9] United States Census Bureau: Industry and Occupation (https://www.census.gov/topics/employment/industry-occupation/about/occupation.html).
[10] Ibid.

7. Economists and other professionals have increasingly incorporated in their research analysis of text-based data sets to extract and classify textual information.[11] Some of these studies have focused on using textual analysis to examine media sentiment,[12] policy uncertainty,[13] and the health and stability of financial systems.[14] Economists have utilized text data derived from analysis of Google searches,[15] Yelp reviews,[16] and Twitter messages[17] in empirical analyses.

8. Here, I use these techniques to analyze the 521 detailed text job requisitions for the largest job title in the data, Software Developer 4. Following methodology that is typical in the application of text processing, the job posting text was prepared for analysis by removing what are referred to as stop words, as well as punctuation and irregular characters that are not useful

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[11] See, for example: Einav, Liran and Jonathan D. Levin (2014) The Data Revolution and Economic Analysis. *Innovation Policy and the Economy*, 14, pp. 1-24; and Gentzkow, Matthew, Bryan T. Kelly and Matt Taddy. (Forthcoming) Text as Data. *Journal of Economic Literature*.
[12] See, for example: Gentzkow, Matthew, Jesse M. Shapiro and Michael Sinkinson (2014). Competition and Ideological Diversity: Historical Evidence from US Newspapers. *American Economic Review*, 104(10), pp. 3073-3114; Gentzkow, Matthew and Jesse M. Shapiro (2010), What Drives Media Slant? Evidence from U.S. Daily Newspapers. *Econometrica*, 78(1), 35-71; and Groseclose, Tim and Jeffrey Milyo, A Measure of Media Bias. *The Quarterly Journal of Economics*, 120(4), pp. 1191-1237.
[13] See Baker, Scott R., Nicholas Bloom and Steven J. Davis (2016), Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, 131(4), pp. 1593-1636.
[14] See, for example: Romer, Christina D. and David H. Romer (2017) New Evidence on the Aftermath of Financial Crises in Advanced Countries. *American Economic Review*, 107(10), pp. 3072-3118; and Born, Benjamin, Michael Ehrmann and Marcel Fratzscher. (2013) Central Bank Communication on Financial Stability. *The Economic Journal*, 124, pp. 701–734.
[15] See, for example: Chae DH, Clouston S, Hatzenbuehler ML, Kramer MR, Cooper HLF, Wilson SM, et al. (2015) Association between an Internet-Based Measure of Area Racism and Black Mortality. *PLoS ONE* 10(4):e0122963; and Saiz, Albert and Uri Simonsohn (2013) Proxying for Unobserved Variables with Internet Document-Frequency. *Journal of the European Economic Association*, 11(1), pp. 137-165.
[16] Taddy, Matt. (2015) Distributed Multinomial Regression. *The Annals of Applied Statistics*, 9(3), pp. 1394-1414.
[17] Taddy, Matt. (2013) Measuring Political Sentiment on Twitter: Factor Optimal Design for Multinomial Inverse Regression. *Technometrics*, 55(4), Special Issue (November 2013), pp. 415-425.

for analysis.[18] Hierarchical clustering, a type of machine learning algorithm, was applied to the text in the qualifications section of the requisitions data to identify similarities and differences between words used to describe the job requirements of each requisition. The algorithm calculates these similarities and differences found in the text by determining the uniqueness of words using a mathematical equation. No analyst judgement is applied at the requisition level.

9. The measure used here to evaluate the importance of a specific term or word is called "Term Frequency, Inverse Document Frequency" (TF-IDF). The TD-IDF is equal to the term frequency weighted by the fraction of documents the word appears in. Technically, the TF-IDF score of a word equals the frequency of word multiplied by the log of the ratio of the number of documents to the number of documents with that word. The algorithm places a higher value on words that from their frequency appear to delineate required skills within subsets of requisitions – such as "cloud" or "fusion."

10. For example, the word "Oracle" appears in almost all requisitions and thus does not provide any information for distinguishing among requisitions. A word's "importance" is scored by combining the frequency of a word in a document, adjusted by the frequency with which it appears in the other documents. Suppose we have a sample of 100 requisitions. Suppose the requisition we are looking at includes the word "computer" 10 times and the word "manage" twice; assume 97 of the other requisitions for this job code also include the word "computer" and just 9 include the word "manage." We calculate the TF-IDF score of the word "computer" by computing "10 * ln(100/97)" which is equal to 0.274. The TF-IDF score of the word "manage" is calculated as "2 * ln(100/9)" which is equal to 4.816. If a particular term appears in every document then it is not useful for distinguishing between subsets of documents; the TF-IDF score for that word equals zero and it is not given any weight.

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[18] Stop words are commonly used words such as "a," "the," "is," etc.

11. Ultimately the algorithm clusters similar requisitions into groups that are most similar based on the importance and frequency of the specific terms contained in the descriptions. The analysis applied to the Software Developer 4 requisitions resulted in the creation of 24 unique clusters. The first indication of differences between the clusters can be seen by examining the average starting salary across clusters in the graph below. If one were to place all fulltime Software Developer 4 requisitions into one group, the overall average starting salary would be roughly $[redacted] However, after clustering the requisitions by the descriptions, it is evident that there are distinct differences in starting pay within the Software Developer 4 requisitions at Oracle Headquarters. As the chart shows, there is a range of average starting salaries between employees in each of the clusters ranging from an average starting salary of $[redacted] in Cluster 13 to an average starting salary of [redacted] in Cluster 2.

Cluster ID	Average Starting Salary By Requisition Cluster
1	[redacted]
2	
3	
4	
5	
6	
7	
8	
9	
10	
11	
12	
13	
14	
15	
16	
17	
18	
19	
20	
21	
22	
23	
24	

13. The differences between the clusters can be seen when the text in the qualifications portion of the requisitions is depicted by importance of words in a cluster in a visual "word cloud."[19] The word clouds for all 24 clusters of requisitions for Software Developer 4s are below but I will discuss two clusters here as examples. Each word cloud below presents the 50 most important words per cluster, with the most important terms being presented in large blue or

[19] For the purpose of presenting terms or words in a word cloud, important terms are identified as those with the highest proportion in a cluster minus their proportion across all clusters.

purple font, and the less important terms being presented in small red font. When visually comparing the word clouds, it is evident that there are distinct differences in the importance of terms that appear in each of the clusters.

Cluster 13

Exhibit 25

14. The word cloud above is based on the 10 requisitions in Cluster 13, which has an average starting salary of $122,151. The terms with the greatest weight that appears in Cluster 13 are "test" and "testing," which suggests that this cluster of requisitions relates to testing applications that are developed by others. Closer manual inspection of the text in the qualifications section of the requisitions supports this finding. As just one example, a portion of the responsibilities section of requisition IRC2797620 in Cluster 13 states,

"As fusion apps system testing team, we are responsible for fusion apps SAAS setups OVM, high availability, enterprise manager, enterprise deployment, and lifecycle testing, which includes

• design, implement, and execute test cases based on design specifications

• develop automation framework in java for web 2.0 applications

• develop programs in java to automate test cases

• execute, debug, and fix automated test suites

• report bugs and track for a resolution

• work with global development teams to build testing solutions and troubleshoot issues in order to deliver product in high quality"

<u>Cluster 2</u>

Exhibit 26

15. The average starting salary of Cluster 2 is higher, at $160,077. The chart above shows that the incidence of terms for Cluster 2 is different than those that appear in Cluster 13. The

highest weighted term in Cluster 2 is "exadata," with "database" and "storage" also being common terms. The prominent terms that appear in Cluster 2 indicate that this group of requisitions is associated with developing Oracle's Exadata database machine. For example, an excerpt of requisition IRC2189577 in Cluster 2 states,

"As a member of the sustaining engineering database team, specializing in the future technology of engineered system, you will articulate, manage, integrate and test critical security and database fixes for Exadata engineered systems. You will work at the forefront of defining the future direction of releases, by being responsible for articulating all necessary security and other critical fixes from across the Exadata stack which includes Linux, storage, networking and database components, and finally, integrating, testing and filtering out the critical and important content by working in close collaboration with various technical teams across the organization and Linux community."

16. The cluster analysis is consistent with the idea that controlling only for job title and not more detailed aspects of work does not group employees doing substantially similar work. This will bias the OFCCP estimates of gender and race pay disparities if employees are not distributed similarly by demographic group across clusters. For example, if women are distributed across these clusters differently than men are – and women were 20.0% of new hires in Cluster 13 and 7.7% of new hires in Cluster 2 – then not accounting for within-job title differences in skills and responsibilities will lead to omitted variable bias in regression models. Because the OFCCP does not accurately or fully control for the nature of the work employees are doing, their analysis suffers from measurement error.

<u>Word Clouds for All 24 Clusters:</u>

Cluster 1

Cluster 2


sustaining
distributed
utilities
hardware
appliance
tuning
fixes
features
future
scripting
environment
engineered
smart
shell
asset
fast
work
paced
systems
linux
high
solaris
platform
exadata
database
virtualization
upgrades
storage
perl
networking
deployment
job
software
critical
years
oracle
machine
aspects
technology
flash
history
scripts
life
industry
workloads
end
multiple
cycle
maintenance
offerings

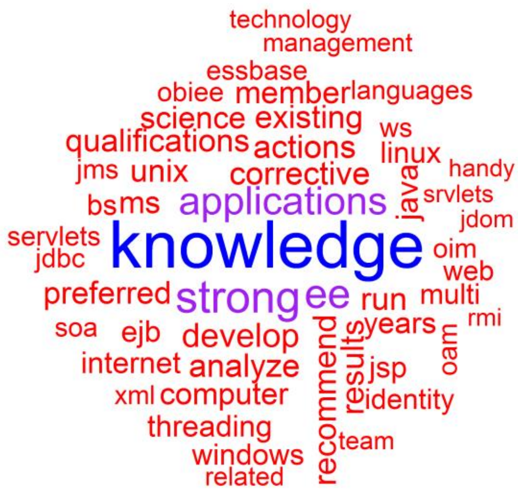
Cluster 3


willingness
configuration
vm
engineer
development
system
networking
working
backup
virtualization
disaster
systems
level
os
knowledge
nfs
firmware
test
recovery
linux
solaris
hands
excellent
soc
labs
storage
san
infiniband
sun
driver
protocols
software
hardware
oracle
tests
nas
kernel
device
background
drivers
hw
understanding
experience
programming
languages
candidate
debug
python
appliance
virtual

Cluster 4


benchmarks
manageability
databases
hardware
problems
market
algorithms
cluster
programming
important
computer
availability
scalability
server
storage
operating
exadata
data
oracle
vos
ms_
clusterware
high
systems
asm
sql
rdbms
highly
file
processor
database
query
performance
rac
columnar
research
phd
group
memory
division
transaction
system
optimization
processing
network
scheduling
technologies
language
designing
future

Cluster 5


technology
management
essbase
obiee
member
languages
science
existing
ws
qualifications
actions
linux
jms
unix
corrective
handy
java
srvlets
bs
ms
applications
jdom
servlets
jdbc
knowledge
oim
web
preferred
strong
ee
run
multi
rmi
soa
ejb
develop
years
oam
internet
analyze
recommend
results
jsp
xml
computer
identity
threading
team
windows
related

Cluster 6


jmeter
analyzer
response
network
achieve
products
improving
recorder
highest
reliability
hardware
make
web
profiling
programming
flight
server
java
technology
load
python
ee
status
drive
fusion
apps
bottlenecks
performance
jprofiler
areas
latest
psr
demonstrated
cpu
memory
tools
scalability
aspects
engineering
standard
elite
middleware
end
high
se
expertise
application
businesses
software
problem

Cluster 7


candidate
service
technical
drive
ready
innovation
senior
professional
rigorous
proven
ensuring
fields
bug
high
search
discovery
reviews
solution
secure
java
cloud
strong
scalable
code
big
principal
detail
passion
end
quality
fixing
ee
talented
highly
staff
unit
enterprise
experience
build
include
design
responsibilities
seeking
servlets
writing
framework
easy
member
related
oriented

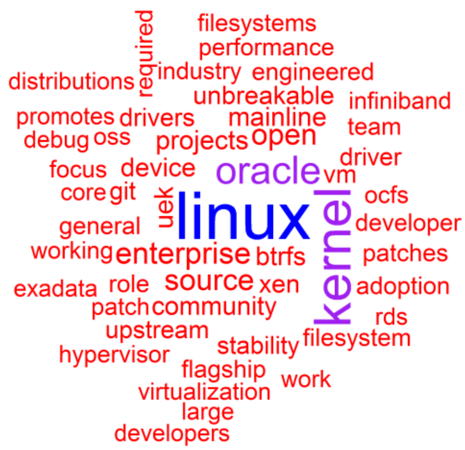
Cluster 8


industry
opportunity
seeking
openstack
technology
devops
employment
continuous
build
processing
ruby
distributed
analytics
marketing
large
big
services
monitoring
develop
hadoop
data
service
spark
saas
cloud
public
drive
join
real
leverage
platform
scale
private
paas
solutions
business
engineers
engineer
building
techniques
part
agile
production
iaas
infrastructure
verification
blockchain
work
paced
bluekai

Cluster 9


geographically
background
operating
percolate
replication
complex
databases
consensus
motivated
projects
good
concepts
guard
group
innovative
strong
distributed
limited
top
problems
valued
deal
bottom
system
ideas
database
availability
fashion
skills
software
active
data
deliver
timely
proficient
sql
highly
talented
customer
individuals
driven
programming
relational
build
supervision
proficiency
concurrent
solve
engineers
debugging

Cluster 10


filesystems
required
performance
distributions
industry
engineered
unbreakable
infiniband
promotes
drivers
mainline
team
debug
oss
projects
open
focus
device
oracle
driver
vm
core
git
ocfs
uek
linux
kernel
general
developer
working
enterprise
btrfs
patches
exadata
role
source
xen
adoption
patch
community
rds
upstream
filesystem
stability
hypervisor
flagship
work
virtualization
large
developers

Cluster 11


implementation
independently
complex
members
ensure
practices
resolve
situations
role
engineering
internal
customers
area
expertise
effectively
solutions
workshops
engagements
teamwork
manner
product
solid
products
technical
pre
demonstrates
understanding
pocs
rapidly
works
sales
customer
issues
team
creativity
teams
field
support
limited
oracle
leadership
resources
successful
consultants
external
architecture
frequently
escalations
complete
manages

Cluster 12


communication
improve
parallelizing
client
patching
environment
frameworks
enabling
deployments
parsing
developing
operations
occurring
member
lifecycle
xml
services
complex
experience
premise
latest
skills
fusion
jmx
upgrade
existing
critical
excellent
applications
web
frequent
loading
product
english
software
apis
projects
cross
time
sdks
performance
providing
solve
equivalent
small
dynamic
orchestrating
reducing
application
spoken

<u>Cluster 13</u>

Cluster 14


unauthorized
customers
external
internal
hosting
concepts
compliance
wide
sensitive
vulnerabilities
defense
threats
information
authentication
audit
provide
consolidating
attacks
secure
oracle
detect
data
protect
group
security
member
gbu
systems
desirable
database
key
groups
access
vault
oci
assist
firewall
application
product
cloud
cryptography
management
service
sql
controls
products
building
encryption
privacy
enterprise

Cluster 15


execution
pooling
cleanup
consideration
sophisticated
specific
advanced
classes
architectures
tool
designing
documenting
planning
locking
debugging
hierarchical
testability
routing
apis
multi
os
runtime
transport
ee
java
concurrency
management
threaded
sh
analysis
design
threading
opc
features
environment
abstraction
domain
tuning
paas
load
free
patterns
resource
performance
orm
api
reflection
balancing
synchronization
offerings

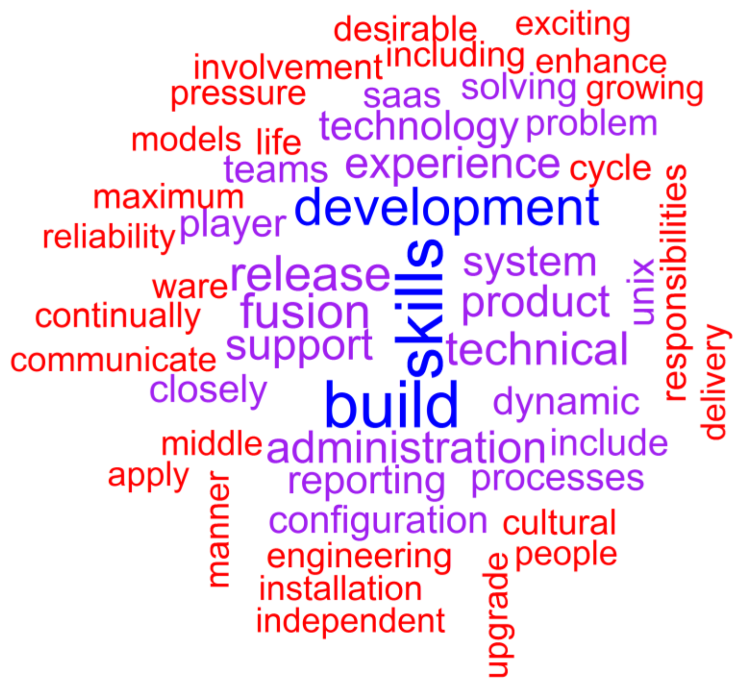
Cluster 16


identity
cloud
management
development
products
features
implement
ibm
standard
server
party
ldap
product
focus
part
design
involved
variety
ui
access
service
requirements
tasked
soa
market
directory
provisioning
offering
infrastructure
architect
services
oracle
key
fusion
security
idcs
manager
solutions
administration
public
generation
backend
managing
architecture
ee
paas
team
emerging
committees
conferences

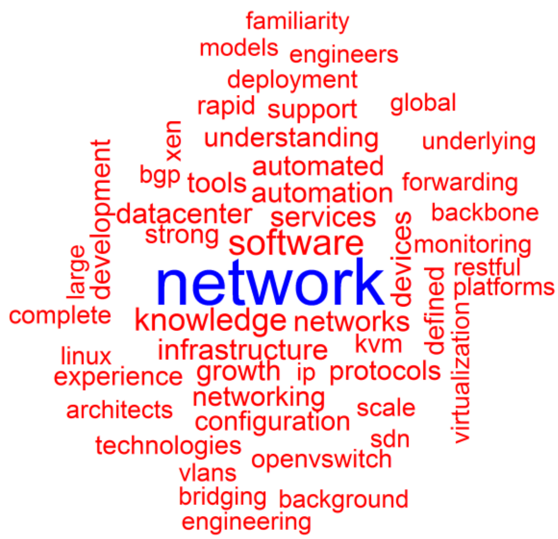
Cluster 17


participate
infrastructure
infrastructures
leadership
independently
years
automated
specifications
agile
service
cloud
preferred
abbot
manual
integration
continuous
frameworks
teams
release
automation
jsf
understanding
coverage
testing
test
technical
selenium
plans
qa
jsp
processes
work
tools
quality
junit
identity
tests
experience
development
involved
engineer
lead
adf
home
required
oats
grown
candidate
jdeveloper
product

Cluster 18

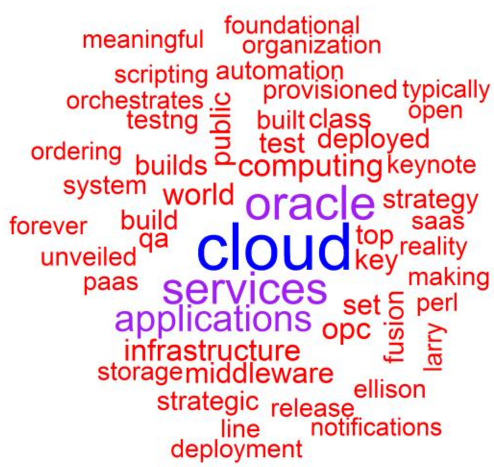

desirable
exciting
involvement
including
enhance
pressure
saas
solving
growing
models
life
technology
problem
teams
experience
cycle
maximum
development
reliability
player
responsibilities
system
ware
release
unix
continually
fusion
skills
product
communicate
support
technical
delivery
closely
build
dynamic
middle
administration
include
apply
reporting
processes
manner
configuration
cultural
engineering
people
installation
upgrade
independent

Cluster 19


familiarity
models
engineers
deployment
rapid
support
global
xen
understanding
underlying
development
bgp
tools
automated
automation
forwarding
datacenter
services
backbone
strong
software
devices
monitoring
large
network
defined
restful
platforms
complete
knowledge
networks
virtualization
infrastructure
kvm
linux
experience
growth
ip
protocols
architects
networking
scale
configuration
technologies
sdn
openvswitch
vlans
bridging
background
engineering

<u>Cluster 20</u>

Cluster 21


meaningful
foundational
organization
scripting
automation
orchestrates
public
provisioned
typically
testng
built
class
open
ordering
test
deployed
builds
computing
keynote
system
world
oracle
strategy
forever
build
saas
qa
cloud
top
unveiled
key
reality
paas
services
making
applications
set
fusion
perl
opc
larry
infrastructure
storage
middleware
ellison
strategic
release
line
notifications
deployment

Cluster 22


enterprises
principle
professionalism
academic
continuing
component
effort
implementation
ownership
social
design
act
middleware
management
lifecycle
degree
participating
ultimately
technologies
patch
core
complete
enable
global
primary
consists
team
fusion
objectives
support
addition
facing
development
block
building
integrity
responsible
sql
oracles
distributed
years
intelligent
integrated
ddl
highly
interacting
outstanding
leverages
engine
taking

<u>Cluster 23</u>

Cluster 24


individually
complex
advanced
degree
standard
networks
code
develop
direction
definition
based
databases
developing
management
relevant
member
equivalent
customer
skills
tasks
programs
applications
ability
background
evolution
software
troubleshoot
active
bs
engineering
focus
idm
sustaining
members
strong
area
teams
identity
ms
debugging
operating
procedures
team
projects
debug
division
functional
related
practices
designing

Exhibit N

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

Janice Fanning Madden, PhD
Econsult Corporation

July 19, 2019

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 precise[1] and

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

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

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

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

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

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

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

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

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

Statistical Methods

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

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

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

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

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

There are several ways to measure compensation, including Medicare-taxed compensation (“Medicare compensation”) as reported to the Internal Revenue Service (IRS), base pay, bonuses, and stock awards. I use all of these measures in my analyses. Medicare compensation is the most comprehensive measure in the database as it includes bonuses, realized stock award payments, and pension contributions (but not medical insurance and other fringe benefits). Because Medicare compensation varies with weeks worked by an employee, the analyses must control for this characteristic. Base pay is the annual rate of pay assigned to each employee. Because this is the rate of pay, there is no need to adjust it for leaves of absence or work hours. Base pay does not include total compensation, however, because it does not include fringe benefits, bonuses, or stock awards. Between 2013 and 2018, Oracle awarded bonuses in 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.

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

Results

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

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

Gender Compensation Differentials

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

Basic analysis

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

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

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

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

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

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

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

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

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

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

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

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

Adding endogenous characteristics

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

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

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

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

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

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

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

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

Robustness of results

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

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

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

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

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

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

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

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

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

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

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

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

Base pay rate analyses

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

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

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

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[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.

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

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

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

Adding endogenous characteristics

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

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

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

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

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

Robustness of results

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

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

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

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

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

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

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

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

Base pay rate analyses

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

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

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

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

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

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

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

Stock Awards

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

Table 2(g) analyzes all employees in the class, as did Tables 2(a) and 2(d). The first column indicates that Asian employees averaged 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]

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

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

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

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

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

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

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

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

Adding endogenous characteristics

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

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

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

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

Robustness of results

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

Base pay rate analyses

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

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

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

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

Stock Awards

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

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

Summary

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

ASSUMPTIONS

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

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

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

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

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

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

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

SALARY AND JOB ASSIGNMENT AT HIRE

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

Base Salary at Hire

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

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

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

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

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

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

Job Assignments at Hire

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

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

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

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

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

LOST EARNINGS: DAMAGES

Damages Experienced by Women

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

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

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

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

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

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

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

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

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

Damages Experienced by Asian Employees

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

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

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

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

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

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

Damages Experienced by African American Employees

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

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

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

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

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

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

CONCLUSIONS

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

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

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

TABLES

Table 1(a)																		
2013 through 2018 Gender Differences in Medicare Earnings at Oracle Headquarters by Year, with Various Characteristics Controlled																		
Controls for ...																		
			Gender Only (1)		Adds Race/Ethnicity (2)		Adds Age (3)		Adds Education (4)		Adds Time at Oracle (5)		Adds Exempt/Non Exempt and Job Descriptor (6)		Adds Management Control (7)		Adds Global Career Level (8)	
Year	Number of Workers	% Women	Gender Coefficient	ST DEV*	Gender Coefficient	ST DEV	Gender Coefficient	ST DEV	Gender Coefficient	ST DEV	Gender Coefficient	ST DEV	Gender Coefficient	ST DEV	Gender Coefficient	ST DEV	Gender Coefficient	ST DEV
2013	4327	26.3%	-0.213	-11.96	-0.199	-11.33	-0.200	-12.07	-0.201	-12.17	-0.199	-12.40	-0.157	10.50	-0.128	-9.21	-0.055	-4.96
2014	4279	26.4%	-0.232	-11.69	-0.217	-11.09	-0.221	-11.85	-0.223	-12.05	-0.221	-12.29	-0.166	-10.07	-0.134	-8.70	-0.063	-5.21
2015	4225	26.1%	-0.188	-10.60	-0.173	-9.94	-0.174	-10.61	-0.176	10.80	-0.177	-11 06	-0.132	-8.95	-0.105	-7.57	-0.046	-4.27
2016	4273	25.5%	-0.199	-10.63	-0.189	-10.23	-0.198	-11.35	-0.203	-11.70	-0.199	-11.72	-0.150	-9.68	-0.119	-8.23	-0.052	-4.74
2017	4241	25.8%	-0.237	-11.05	-0.228	-10.72	-0.231	-11.46	-0.238	-11.91	-0.239	-12.15	-0.178	-9.92	-0.146	-8.80	-0.058	-4.71
2018	4019	26.2%	-0.242	-11.23	-0.235	-11.02	-0.231	-11.38	-0.238	-11.78	-0.239	-12.04	-0.187	-10.19	-0.151	-8.91	-0.058	-4.71
* ST DEV stands for Standard Deviation																		

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

Table 1(c)																				
2013 through 2018 Gender Differences in Medicare Earnings at Oracle Headquarters by Year, 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 thorugh 2018 Asian Differences in Medicare Earnings at Oracle Headquarters by Year, Employees with Recorded Educational Characteristics, with Various Characteristics Controlled																		
Controls for ...																		
			Asian Only (1)		Adds Gender (2)		Adds Age (3)		Adds Education (4)		Adds Time at Oracle (5)		Adds Exempt/Non Exempt and Job Descriptor (6)		Adds Management Control (7)		Adds Global Career Level (8)	
Year	Number of Workers	% Asian	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV
2013	1173	76.1%	-0 220	-7.72	-0 209	-7.40	-0.123	-4.41	-0.130	-4.59	-0.128	-4.57	-0.124	-4.45	-0.126	-4.93	-0 037	-1.71
2014	1222	77.2%	-0 253	-8.84	-0 247	-8.75	-0.168	-5.96	-0.188	-6.56	-0.185	-6.49	-0.183	-6.51	-0.170	-6.64	-0 064	-3.11
2015	1300	77.0%	-0 219	-8.90	-0 214	-8.79	-0.149	-6.12	-0.161	-6.48	-0.156	-6.33	-0.162	-6.66	-0.154	-6.90	-0 062	-3.55
2016	1417	80.2%	-0 208	-7.70	-0 205	-7.71	-0.133	-5.12	-0.148	-5.60	-0.144	-5.48	-0.137	-5.31	-0.138	-5.82	-0 055	-3.06
2017	1587	81.0%	-0 229	-7.17	-0 228	-7.27	-0.129	-4.34	-0.135	-4.44	-0.133	-4.41	-0.126	-4.17	-0.156	-5.59	-0 077	-3.47
2018	1396	82.3%	-0.175	-5.17	-0.178	-5.35	-0.100	-3.04	-0.110	-3.31	-0.112	-3.37	-0.098	-2.97	-0.135	-4.40	-0 063	-2.73

Table 2(c)

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

Controls for ...

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

Table 2(d)																		
2013 through 2018 Asian Differences in Base Pay Rate at Oracle Headquarters by Year, with Various Characteristics Controlled																		
Controls for ...																		
			Asian Only (1)		Adds Gender (2)		Adds Age (3)		Adds Education (4)		Adds Time at Oracle (5)		Adds Exempt/Non Exempt and Job Descriptor (6)		Adds Management Control (7)		Adds Global Career Level (8)	
Year	Number of Workers	% Asian	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV
2013	4297	73.3%	-0.147	-15.75	-0.136	-14.84	-0.075	-8.09	-0.078	-8.36	-0 069	-7 57	-0.071	-8.31	-0.072	-9.49	-0.027	-5.16
2014	4256	74.1%	-0.141	-14.52	-0.128	-13.50	-0.076	-7.89	-0.080	-8.27	-0 071	-7.48	-0.073	-8.27	-0.072	-9.19	-0.025	-4.67
2015	4233	75.5%	-0.142	-14.48	-0.129	-13.46	-0.078	-8.03	-0.082	-8.36	-0 074	-7.68	-0.072	-8.10	-0.074	-9.32	-0.028	-5 24
2016	4171	76.7%	-0.130	-12.85	-0.119	-12.04	-0.069	-6.89	-0.074	-7.26	-0 066	-6.61	-0.062	-6.77	-0.072	-8.73	-0.024	-4.40
2017	4069	77.4%	-0.129	-12.51	-0.119	-11.84	-0.068	-6.78	-0.070	-6.92	-0 062	-6 25	-0.055	-6.04	-0.067	-8.14	-0.028	-5.16
2018	3854	77.5%	-0.111	-9.87	-0.099	-9.11	-0.064	-5.85	-0.064	-5.85	-0 056	-5.17	-0.047	-4.60	-0.063	-6.90	-0.024	-3 92

Table 2(e)																		
2013 through 2018 Asian Differences in Base Pay Rate at Oracle Headquarters by Year, Employees with Recorded Education Characteristics, with Various Characteristics Controlled																		
Controls for ...																		
			Asian Only (1)		Adds Gender (2)		Adds Age (3)		Adds Education (4)		Adds Time at Oracle (5)		Adds Exempt/Non Exempt and Job Descriptor (6)		Adds Management Control (7)		Adds Global Career Level (8)	
Year	Number of Workers	% Asian	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV
2013	1555	75 9%	-0.161	-10.81	-0.151	-10.43	-0.087	-6.21	-0.097	-6.81	-0.090	-6.36	-0.086	-6 38	-0.080	-6.72	-0.029	-3.48
2014	1652	76 0%	-0.140	-9.35	-0.131	-8.99	-0.083	-5.87	-0.094	-6.52	-0.085	-5.94	-0.085	-6 21	-0.077	-6 36	-0.023	-2 57
2015	1749	78 3%	-0.134	-9.37	-0.124	-8.96	-0.081	-5.94	-0.090	-6.50	-0.084	-6.19	-0.082	-6 24	-0.079	-6 81	-0.032	-4 02
2016	1947	80.7%	-0.131	-9.30	-0.126	-9.21	-0.068	-5.13	-0.078	-5.81	-0.074	-5.62	-0.068	-5 33	-0.077	-6 85	-0.032	-4 28
2017	1819	81 8%	-0.121	-8.25	-0.119	-8.35	-0.062	-4.56	-0.068	-4.92	-0.066	-4.80	-0.057	-4 25	-0.072	-6 05	-0.032	-3 91
2018	1548	81 9%	-0.094	-5.67	-0.094	-5.86	-0.053	-3.36	-0.057	-3.60	-0.055	-3.47	-0.045	-2 93	-0.065	-4.67	-0.031	-3 27

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

Table 2(g)

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

			Controls for ...															
			Asian Only (1)		Adds Gender (2)		Adds Age (3)		Adds Education (4)		Adds Time at Oracle (5)		Adds Exempt/Non Exempt and Job Descriptor (6)		Adds Performance Rating (7)		Adds Global Career Level* (8)	
Year	Number of Workers	% Asian	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV
2013	3584	72.5%	-5767.3	-4.51	-5116.9	-4.01	-4863.9	-3.58	-5217.0	-3.83	-4889.5	-3.62	-3021.0	-2.72	-2874.3	-2.61	-60.4	-0.06
2014	3534	73.7%	-6841.5	-5.19	-6209.8	-4.73	-6422.9	-4.58	-6740.0	-4.78	-6261.9	-4.50	-4133.1	-3.85	-4192.3	-3.98	-605.0	-0.64
2015	3425	74.4%	-5141.3	-3.71	-4584.3	-3.31	-5298.5	-3.56	-5710.3	-3.82	-5345.1	-3.58	-3484.1	-2.94	-3794.9	-3.21	-387.8	-0.35
2016	3418	76.0%	-3264.0	-3.19	-2859.9	-2.81	-3201.3	-2.93	-3257.3	-2.98	-2996.5	-2.76	-1772.9	-2.14	-1807.3	-2.24	555.3	0 80
2017	3494	76.5%	-2459.1	-2.15	-2140.0	-1.88	-2713.7	-2.23	-2845.2	-2.34	-2550.3	-2.11	-1073.5	-1.20	-902.4	-1.02	734.5	0 96
2018	3300	77.4%	-7240.1	-1.53	-6806.6	-1.44	-11890.4	-2.34	-11925 2	-2.35	-10672.5	-2.10	-7036.0	-1.47	-5904.7	-1.17	-3219.5	-0.64

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

Table 3(a)																		
2013 through 2018 African American Differences in Medicare Earnings at Oracle Headquarters by Year, with Various Characteristics Considered																		
Controls for ...																		
			African American Only (1)		Adds Gender (2)		Adds Age (3)		Adds Education (4)		Adds Time at Oracle (5)		Adds Exempt/Non Exempt and Job Descriptor (6)		Adds Management Control (7)		Adds Global Career Level (8)	
Year	Number of Workers	% African American	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV
2013	1008	2.3%	-0.229	-1.84	-0.219	-1.78	-0.148	-1.25	-0.159	-1.34	-0.139	-1.21	-0.096	-0.95	-0 007	-0.08	0.027	0.04
2014	954	2.4%	-0.490	-3.43	-0.459	-3.24	-0.391	-2.83	-0.416	-3.03	-0.383	-2.91	-0.314	-2.77	-0.194	-1.86	-0.089	-1.12
2015	916	2.8%	-0.431	-3.73	-0.412	-3.58	-0.335	-2.99	-0.362	-3.24	-0.336	-3.09	-0.298	-3.09	-0 221	-2.49	-0.082	-1.20
2016	867	3.5%	-0.501	-4.46	-0.479	-4.27	-0.343	-3.15	-0.352	-3.24	-0.336	-3.17	-0.273	-3.00	-0 203	-2.42	-0.075	-1.19
2017	848	3.3%	-0.538	-4.19	-0.508	-3.97	-0.446	-3.53	-0.440	-3.50	-0.413	-3.36	-0.320	-2.97	-0 255	-2.58	0.123	-1.74
2018	772	3.5%	-0.514	-3.88	-0.495	-3.75	-0.410	-3.15	-0.394	-3.06	-0.367	-2.92	-0.222	-2.03	-0 202	-2.02	-0.074	-1.07

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

Table 3(c)

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

Controls for ...			African American Only (1)		Adds Gender (2)		Adds Age (3)		Adds Education (4)		Adds Time at Oracle (5)		Adds Exempt/Non Exempt and Job Descriptor (6)		Adds Performance Rating (7)		Adds Global Career Level* (8)	
Year	Number of Workers	% African American	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV	Race Coefficient	ST DEV
2013	1008	2.3%	-25823.1	-2.00	-25888 9	-2.07	-25197 2	-2.00	-26647.8	-2.12	-24550.4	-2.01	-18642.7	-1.91	-14649.3	-1.46	-7986.2	-0.82
2014	954	2.4%	-33392.2	-2.60	-32412.9	-2.52	-29576 3	-2.32	-30831.4	-2.42	-28742.4	-2.32	-21501.6	-2.22	-20443.2	-2.12	-8705.5	-0.99
2015	903	2.9%	-30649.7	-2.25	-29688.1	-2.18	-25177 0	-1.86	-26223.4	-1.94	-24743.0	-1.84	-18777.1	-1.80	-16908.6	-1.56	-3055.4	-0.29
2016	848	3.4%	-14932.2	-2.32	-14145.9	-2.19	-12114.6	-1.86	-12379.4	-1.91	-11904.8	-1.86	-7266.6	-1.80	-6169.4	-1.54	-1107.6	-0.33
2017	848	3.3%	-15117.7	-2.16	-14823.8	-2.11	-14193 3	-2.01	-13507.8	-1.93	-12245.9	-1.78	-6561.2	-1.53	-5759.9	-1.35	-752.0	-0.21
2018	772	3.5%	-12760.4	-0.29	-13435.0	-0.31	-14885 2	-0.34	-11671.9	-0.27	-15291.0	-0.35	-3819.6	-0.10	-11609.2	-0.27	-15897.3	-0.36

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

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

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

** Base pay regression controls for time in company

Table 5(a)						
2013 through 2018 Gender Differences in Medicare Earnings at Oracle, by Year 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

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

Table 9

Lost Compensation Damages for Asian Employees at Oracle, 2013-2018

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

Table 10

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

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

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

APPENDICES

Appendix A: Job Descriptors

Appendix A

Table linking Oracle Job Titles to Job Descriptors Used in Analyses

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Appendix B: Table

Regression Analyses of Movement from IC3 and IC4 by Gender

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

Appendix C: Glossary

Appendix C
Glossary

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

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

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

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

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

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

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

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

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

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

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

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

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

ATTACHMENTS

Attachment A: Janice Madden Curriculum Vitae

ATTACHMENT A
CURRICULUM VITAE OF DR. JANICE F. MADDEN

June 2019

JANICE FANNING MADDEN

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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.

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

HONORS AND AWARDS:

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

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

PUBLICATIONS:

Books:

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

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

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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.

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"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.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Comments and Reviews:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Working Papers:

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

Academic Conference and Invited Presentations (last five years):

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

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

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

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

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

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

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

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

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

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

Reports:

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

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

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

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

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

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

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

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

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

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

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

FELLOWSHIPS AND GRANTS:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

OTHER PROFESSIONAL ACTIVITIES:

North American Regional Science Council:

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

Association for Public Policy Analysis and Management (APPAM):

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

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

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

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

Association of Graduate Schools (AGS):

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

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

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

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

Editorial Boards:

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

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

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

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

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

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

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

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

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

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

Friends Select School:

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

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

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

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

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

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

Board of Commissioners, Fellowship Commission, 1981-82.

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

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

COURSES TAUGHT:

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

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

FACULTY COMMITTEES AT PENN:

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

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

Attachment B: Janice Madden Testifying History

ATTACHMENT B

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

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

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

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

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

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

Attachment C: Janice Madden Fees

ATTACHMENT C

STATEMENT REGARDING COMPENSATION OF JANICE FANNING MADDEN

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

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

Attachment D: Material Considered for the Report

ATTACHMENT D
MATERIAL CONSIDERED FOR REPORT

ORACLE_HQCA_0000089013
ORACLE_HQCA_0000089024
ORACLE_HQCA_0000062858
ORACLE_HQCA_0000089010
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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
DOL000039918
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
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ATTACHMENT D
MATERIAL CONSIDERED FOR REPORT

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ORACLE_HQCA_0000382402
ORACLE_HQCA_0000382403-404
ORACLE_HQCA_0000400489-518
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ORACLE_HQCA_0000400868-1021
ORACLE_HQCA_0000416118
ORACLE_HQCA_0000416489-499
ORACLE_HQCA_0000547858-867
PT1_HQCA_IREC_MAIN.xlsx
Requisition - Collaborators Data.xlsx
Requisition - Description and Qualification Data.xlsx
Requisition - Other Locations.xlsx
Requisition Data.xlsx
Saad Expert Rebuttal regarding Neumark
Waggoner Declaration - Evidence Compendium in Support of Motion for Summary Judgement