How to Compute Liability WHEN STATISTICAL EVIDENCE OF PAY DISPARITIES EXIST *Part II*

Daniel Kuang, Ph.D. | *Biddle Consulting Group, Inc.*
Dan A. Biddle, Ph.D. | *Biddle Consulting Group, Inc.*

In Part I, we detailed the process for computing liability within a multiple linear regression framework. This article covered the statistical mechanics of computing liability, as well as important concepts and steps that analysts should understand and consider prior to making any pay adjustments. The prior article detailed only one of two steps in a comprehensive pay adjustment study—how to compute the total amount *(i.e., the amount still outstanding after accounting for differences that may exist in job qualification factors) necessary to diminish the pay gap between focal and reference members in a pay study. In this article (Part II), we describe the methods of* distributing *the computed liability to the individuals in the affected class.*

After the total pay liability has been determined (using the procedures outlined in the first article), the next step is to *distribute* the liability among impacted group members. This component of the process, while absolutely critical, is not well understood and often ignored. This is understandable because the typical analysis of compensation focuses on group mean (average) differences. Since differences among individuals within a group do not alter the group mean, liability distribution is often largely ignored.

In practice, however, liability distribution is an *essential* component of correcting systemic compensation imbalances. This is because the legitimate variables (*e.g.*, tenure, education, experience) that contributed (legitimately, free of discrimination) to making up the pay differences that exist between individuals in the study need to be taken into account. And, because the individuals in the study will possess these factors in varying levels, they need to be taken into account when determining how the remedial pay is distributed among focal group members based on how far each person is below their predicted pay. Compensation adjustments based on individual employee salaries and individual differences in job-related factors will:

1. ensure optimal and stable pay equity for all individuals;
2. create a more coherent and strong statistical compensation model;
3. increase perceptions of organizational fairness; and
4. reduce (potential) legal exposure associated with making compensation adjustments.

If these steps are not done correctly, the employer can be left open to various types of liability (examples of this are provided below).

OPTIMAL AND STABLE COMPENSATION ADJUSTMENTS

Compensation is often analyzed within a static framework (*e.g.* a 12/31 snapshot dataset, amount of pay increases), because this is a required constraint when testing for group differences or computing pay disparities. However, this places the analyst in a very tenuous situation. Compensation disparities are constantly changing and vary as a function of time, workforce changes, and individual attributes (*e.g.*, gender, race, age and job-related criteria). Proper liability distribution strategies will take into account these influences to ensure that the adjustments are as fair and optimally stable as possible.

Compensation varies as a function of dynamic influences across time. Two major events occur as time passes: First, compensation naturally (and typically) increases as a function of tenure. Second, workforce composition changes due to such events as promotions, terminations, transfers, and hires. Consequently, compensation adjustments that may eliminate group differences at one point in time may unravel after one cycle of pay raises and personnel changes if the liability adjustments are not optimally distributed to employees based upon their individual level of "underpayment" or impact. Compensation follows a growth curve; if compensation adjustments are distributed blindly without regard to individual levels of "underpayment," pay disparities that are eliminated at one point in time at the group level may easily resurface because the underlying disparities still exist.

FAIRNESS OF COMPENSATION ADJUSTMENTS

There are volumes of literature on the importance of the perception of organizational justice.[1] Fairness (and *perceived* fairness) has been tied to positive organizational citizenship behavior and a decrease in counter-productive behaviors. Moreover, a perception of unfairness is a primary trigger for individuals to seek litigation against their employers. In brief, it is to the benefit of the employer to ensure that the distribution of compensation adjustments is fair. Proper liability distribution strategies take into account individual differences and are therefore, arguably, most fair.

LIABILITY DISTRIBUTION MODELS

Important Note: *There are several liability distribution models, each with specific strengths and weaknesses. Competent practitioners may differ in their opinions of which are the most appropriate even under similar circumstances. For these reasons, we believe it is critical to consider the context, cohort review results, data (e.g., sample size), and regression model before deciding which liability distribution model to apply. In most circumstances, however, we believe the Proportionate Distribution Model should be used for reasons explained below.*

Liability distribution models can be divided into

TABLE 1: Distributing Compensation Adjustments Equally to All Impacted Group Employees

ID	Compensation ($)	Liability Distribution ($)
1	$12.00	$0.80
2	$11.00	$0.80
3	$9.00	$0.80
4	$16.00	$0.80
5	$7.00	$0.80

two categories: dual regression models (where a regression model is developed for each group) and single regression models (where a single regression model is used for the entire group and the gender/race status is dummy-coded). Because the single regression model methods are more common, these are discussed first and in more detail.

Three of the most common liability distribution models that are based on a single regression model include:

1. Even Distribution for All;
2. Even Distribution for Individuals Below the Mean; and
3. Proportionate Distribution (Based Upon Model Prediction)

Liability Distribution—Even Distribution for All

This is the simplest of the three distribution models. As the name of this model implies, the total liability is evenly distributed to all individuals within the impacted group. Consider the following example of five negatively-impacted women where the computed liability for the group is $4.00 (see Table 1). Liability is evenly-distributed by dividing total liability ($4.00) by the number of individuals in the group (5): $4.00 / 5 = $0.80.

The authors do not recommend this method because it does not take into account *individual* employee differences and may require liability payments to employees already paid more than their predicted salary.

Liability Distribution—Even Distribution for Individuals Below the Mean

One of the major limitations of the *Even Distribution for All* model is that it ignores individual differences. Extending the example above (see Table 2), the average[2] salary is computed ($11.00) and each individual's salary is compared against this mean. Among the five records, three are at or above the mean (1, 2, and 4). Notably, the 4th person is overpaid by $5.00 when compared to the mean. Only two individuals' salaries fall below the mean (ID #3 and #5). Given this, it is inappropriate to evenly distribute the liability across all individuals. As an improvement to the Even Distribution for All model, the liability is evenly distributed for those individuals who fall below the mean. This is a four-step process:

1. Compute the overall group mean (including *both* Focal and Reference).
2. Compute the difference from the mean for all individuals in the negatively-impacted group.
3. Identify and count the number of impacted group members below the mean ($n_{Below\ Mean}$).
4. Compute the even distribution for impacted group members below the mean: Total Liability / n (below mean)

TABLE 2: Distributing Compensation Adjustments Equally to All Impacted Group Employees with Below Mean Compensation

ID	Compensation ($)	Difference from Mean ($)	Liability Distribution ($)
1	$12.00	$1.00	
2	$11.00	$0.00	
3	$9.00	-$2.00	$2.00
4	$16.00	$5.00	
5	$7.00	-$4.00	$2.00

Note: Total Group Mean = $11.00

When applied to the example:

1. Overall group mean = $11.00
2. Compute the difference from mean for each individual (see Table 3).
3. Count the number of individuals below the mean: $n_{\text{Below Mean}} = 2$
4. Compute the even distribution for individuals below the mean: $4.00 / 2 = $2.00.

While an improvement over the *Even Distribution for All* model, the authors do not recommend this method because it does not take into account *individual* employee differences and may require liability payments to employees already paid more than their predicted salary.

Liability Distribution—Proportionate Distribution

Although *Even Distribution for Individuals Below the Mean* is an improvement over the first model, there is a noticeable weakness—the distribution is not proportional to individual pay disparity (*i.e.*, the difference between what each underpaid employee is actually paid, and what they should be paid, based upon the regression model). In this example, Person #5 is twice as far from the mean as Person #3 ($4.00 vs. $2.00, respectively), but both received the same amount ($2.00). In addition, similar to the *Even Distribution* method, it does not take into account individual employee differences in job-related factors.

One variant of the third distribution model, *Proportionate Distribution*, serves to address these concerns. We believe that this method is ideal in most circumstances because it simultaneously considers both group- and individual-level pay disparities. At the group level, this method focuses on reducing the significant coefficient (*b*) for the group variable (*e.g.*, men/women, white/minority) to the specified level (*e.g.*, 0 for parity, to 1 standard deviation [SD]). In this way, the amount of the regression model that is directly attributable to race or gender (after controlling for differences in job-related variables) is addressed in the most direct manner possible. And, on the individual level, rather than splitting the liability evenly for those paid less than the mean, the *Proportionate Distribution* model considers individual differences when determining liability distribution. This is accomplished by first creating a regression model *without* the protected variable (*e.g.*, dummy-coded men/women, whites/minorities). By leaving out the protected group variable, an overall model of compensation is created without any potential discrimination based on gender and/or race affiliation. By applying this approach, it is possible to obtain a predicted compensation for each individual based on their unique job-related attributes (*i.e.*, explanatory variables) only.

The mechanics of this method are detailed below:

■ **Step 1:** Compute the *Predicted Compensation* ($\hat{Y}$) for each employee:[3]

Eq. 1.

$$\hat{Y}\text{predicted} = \alpha + b1X1 + b2X2 + \ldots + biXi$$

Apply this model in computing the predicted compensation ($\hat{Y}_{predicted}$) for each individual, given their unique attributes (*i.e.*, explanatory variables). When no explanatory variables are specified in the model, the regression model simplifies to $\hat{Y}_{predicted} = \alpha$, which is the average compensation for all members (Focal and Reference together).

■ **Step 2:** Compute the *Difference from the Model* for each underpaid employee. For members in the negatively-impacted group, compute the difference between observed compensation ($Y_{observed}$) and predicted ($\hat{Y}_{predicted}$):

Eq. 2.

$$\text{Difference from Model} = Y_{observed} - \hat{Y}_{predicted}$$

■ **Step 3:** Identify those employees paid less than the model predicts. For members in the negatively-impacted group, select only those who are paid below their predicted salary ($Y_{observed} < \hat{Y}_{predicted}$), (*i.e.*, negative *Difference from the Model*).

■ Step 4: Compute the *Total Model Shortfall*. For members in the negatively-impacted group who fall below their predicted salary ($Y_{observed} < \hat{Y}_{predicted}$), sum the *Difference from the Model* (item 2, above). This is the *Total Model Shortfall*—the total amount that is under the predicted model.

■ Step 5: Compute the *Proportion of Impact*. For each member in the negatively-impacted group who fall below predicted, compute their *Proportion Impact* using:

Eq. 3.

Proportion of Impact = $(Y_{observed} - \hat{Y}_{predicted})$ / Total Model Shortfall

■ Step 6: Compute *Proportionate Distribution*. For each member in the negatively-impacted group who fall below the predicted value, compute their *Proportion of Distribution* using:

Eq. 4.

Prop. Dist. = $(Y_{observed} - \hat{Y}_{predicted})$ / (Total Model Shortfall X Total Liability)

This formula computes the proportion of the *Total Liability* that each individual should receive as a function of their individual attributes ($\hat{Y}_{predicted}$) and how far their observed compensation is from their predicted compensation ($Y_{observed}$ - $\hat{Y}_{predicted}$) relative to all members who fall below their predicted compensation.

A detailed (and realistic) case study of the *Proportionate Distribution* method is provided below.

Case Study: An Example of the Proportionate Distribution Method

Company Z conducts a proactive compensation analysis that is not in response to litigation or government enforcement agency investigations. Company Z has 100 employees in the at-issue Similarly Situated Employee Groups (SSEG) (*i.e.*, job title): 50 women and 50 men. The average compensation for men is $52,260 and $48,520 for women (a $3,740 mean difference, or about 7.16%). Tenure is the only explanatory variable included in the model, and no interactions are found between tenure, pay, and gender.

After conducting the regression analysis, both tenure and gender are statistically significant, with tenure having a correlation of .56 to pay and a corresponding coefficient (*b*1) of $1,631.96 and the gender variable having a .34 correlation to pay and a coefficient (*b*2) of $2,205.95. The *t*-values are 5.83 ($p < .01$) and 2.36 ($p = .02$) respectively; indicating that tenure is highly significant and that evidence of possible pay discrimination exists because the gender *t*-value exceeds 2.0 (indicating that $p < .05$) after controlling for tenure.

The tenure coefficient indicates that for every single-unit increase in tenure (*i.e.*, for every year), the expected pay of each employee in the model goes up by $1,631.96. Because men are coded as 1 and women as 0, the gender coefficient indicates that the effect of being a man (after controlling for tenure) adds $2,205.95 to an individual's predicted pay. Adding the constant (a = $42,514.37) to the model allows for pay predictions to be made for each employee in the SSEG.

These coefficients can readily be used to predict pay using the following standard regression formula ($\hat{Y}_{predicted} = a + b_{tenure}X_{tenure} + b_{tenure}X_{tenure}$). For example, a woman (dummy-coded 0) with five years experience has a predicted pay of: $42,514.37 + ($1,631.96 x 5 = $8,159.80) + 0 = $50,674.17. A man (dummy-coded 1) with the same five years experience has a predicted pay level that is exactly $2,205.95

higher ($52,880.12) because the 0 would be replaced by $2,205.95 x 1, which adds $2,205.95 to the pay prediction.

Because the tenure coefficient is still significant after controlling for job qualification factors, Company Z desires to utilize the information from the regression model to eradicate the possible pay discrimination using the *Proportionate Distribution* method. Company Z has already completed an extensive cohort analysis including manager interviews to determine whether the statistical evidence of possible pay discrimination that has been identified by the regression study would be confirmed with additional evidence. As a result, they are choosing to correct the pay differences from the current *t*-value of 2.36 (with a corresponding *p*-value of .02) down to a *t*-value of 1.0 (with a corresponding *p*-value of .0.317, obtained by using the formula: =2*(1-NORMSDIST(1)) in Excel. (Remember, *t*-values are about the same conceptually as "standard deviations" referred to in the OFCCP regulations when interpreting the probability levels of the analysis results, with *t*-values exceeding values of 2.0 as statistically significant).

Company Z then generates a regression model *without gender* (including the tenure variable only) to compute predicted pay values for each employee, and subtracts each employee's actual pay from their predicted pay. Because there are 50 women in the at-issue group and the coefficient associated with gender is $2,205.95, the *maximum* liability amount is $110,297.67 (50 women x $2,205.95 each). In other words, the $2,205.95 effect associated with gender multiplied by the total number of women equates to the *total gender effect* identified by the regression model—*after giving each employee credit for their tenure*. If Company Z desired to reduce this gender effect to 0, this total amount ($110,297.67) would be allocated to the subgroup of women in the job title who were under-paid based upon the regression model—in proportion to how far each was away from their predicted salary (in this case 29 of the 50 women—see Table 3).

Important Note: *In ideal situations, liability computations should be made for employees for whom complete data exists for the variables in the model. However, in practical settings, this is not always possible. In these situations, data can be* imputed *for the missing variables using the average from the regression model. Without imputing data values for subjects who have missing data, the liability computations would simply compute 0 values for each—working detrimentally to the employees. In other words, without imputing data, the impact of not having the data for a certain variable—say job performance score—will actually treat the employee as if their score was 0.*

However, because Company Z desires to correct the pay disparity down to a *t*-value of 1.0 (and not make the assumption that 100% of the pay gap is due to possible discrimination), they will use the *p*-value that corresponds to a *t*-value of 1.0 (p = 0.317, using the formula above) and compute the associated gender coefficient: $t = b / SE_b$, which translates to $2,205.95 / $934.44 = $1,266.72. Multiplying this value by the total number of class members ($1,266.72 x 50) results in a modified total liability value of $63,336.02. This amount is then proportionately distributed to each of the (29) women whose actual pay ($Y_{observed}$) is below their predicted pay ($\hat{Y}_{predicted}$), by dividing each "Difference" value by the liability total (see values provided in Table 4 in the column titled, "Pay Adjustment to 1.0 *t*-value").

To confirm the validity of these adjustments, a "what-if" simulation analysis can be performed. In such an analysis, calculated adjustments are added hypothetically to the appropriate employees in the database and the pay disparity between focal and reference members is reevaluated. If the results of the statistical test match the desired pay disparity (*e.g.*, 0, 1, 2 standard deviations), then the computed liability is valid. However, unless the sample sizes are very large and the regression model is perfect (or nearly perfect—which, of course, is never the case), the desired *t*-value will not be exactly obtained.

TABLE 3: Identifying Compensation Liability Adjustments

ID #	Tenure	Curr. Pay ($Y_{observed}$)	Pred. Pay ($\hat{Y}_{predicted}$)	Diff.[a]	Weigh Prop.[b]	Pay Adjust. to 0 *t*-value[c]	Pay Adjust. to 1.0 *t*-value[d]
51	2	$36,000	$46,481	$-10,481	9.03%	$9,955	$5,716
53	4	$41,000	$50,117	$-9,117	7.85%	$8,659	$4,972
52	2	$38,000	$46,481	$-8,481	7.30%	$8,055	$4,626
72	4	$42,000	$50,117	$-8,117	6.99%	$7,710	$4,427
94	4	$42,000	$50,117	$-8,117	6.99%	$7,710	$4,427
56	4	$44,000	$50,117	$-6,117	5.27%	$5,810	$3,336
73	4	$44,000	$50,117	$-6,117	5.27%	$5,810	$3,336
83	4	$44,000	$50,117	$-6,117	5.27%	$5,810	$3,336
58	5	$46,000	$51,935	$-5,935	5.11%	$5,637	$3,237
55	3	$43,000	$48,299	$-5,299	4.56%	$5,033	$2,890
54	2	$42,000	$46,481	$-4,481	3.86%	$4,256	$2,444
95	3	$44,000	$48,299	$-4,299	3.70%	$4,083	$2,345
91	7	$52,000	$55,571	$-3,571	3.08%	$3,392	$1,948
77	5	$49,000	$51,935	$-2,935	2.53%	$2,788	$1,601
90	6	$51,000	$53,753	$-2,753	2.37%	$2,615	$1,502
66	7	$53,000	$55,571	$-2,571	2.21%	$2,442	$1,402
74	3	$46,000	$48,299	$-2,299	1.98%	$2,184	$1,254
85	3	$46,000	$48,299	$-2,299	1.98%	$2,184	$1,254
96	3	$46,000	$48,299	$-2,299	1.98%	$2,184	$1,254
76	4	$48,000	$50,117	$-2,117	1.82%	$2,011	$1,155
97	4	$48,000	$50,117	$-2,117	1.82%	$2,011	$1,155
89	5	$50,000	$51,935	$-1,935	1.67%	$1,838	$1,055
57	2	$45,000	$46,481	$-1,481	1.28%	$1,407	$808
84	2	$45,000	$46,481	$-1,481	1.28%	$1,407	$808
75	3	$47,000	$48,299	$-1,299	1.12%	$1,234	$709
86	3	$47,000	$48,299	$-1,299	1.12%	$1,234	$709
63	4	$49,000	$50,117	$-1,117	0.96%	$1,061	$609
88	4	$49,000	$50,117	$-1,117	0.96%	$1,061	$609
65	6	$53,000	$53,753	$-753	0.65%	$715	$411

Notes: aThese values are computed by subtracting each employee's actual pay from their predicted pay. bThese values are computed by dividing each employee's Difference value by the total of all values in the Difference column. cThese values are computed by multiplying each employee's Weighted Proportion value by the total amount of liability identified by the regression model (computed by multiplying the gender coefficient by the total number of impacted class members). dThis column is identical to the "Pay Adjustment to 0 t-value" column, but is set to correct pay to a t-value of 1.0 (computed using Eq. 2), then multiplying this value by the total number of impacted class members.

Liability Distribution—Dual Regression Models

A "dual" regression model for calculating liabilities simply implies developing one regression model to identify the existence of an unexplained statistically significant disparity between two groups, and another regression model to calculate the liability. The dual regression model is also commonly referred to as the "Peters-Belson" (P-B) method named after the two authors.[4] The P-B method (also sometimes referred to as the "Blinder–Oaxaca" method[5]) simply builds the liability model using only the reference group members, then applies the model to the focal group members. The resulting pay differences are said to constitute the "difference due to discrimination" (at least in the context of compensation analysis where the facts would support this conclusion). For example, a male-only regression model could be developed using the relevant job qualification factors, the resulting constant and regression variable weights could be used to compute predicted pay values for each of the women, and the resulting differences between their actual and predicted pay treated as the liability amounts.

While this method has been used in some litigation settings[6] it has not been met without criticism.[7] Perhaps the most significant limitation with the P-B method is that it substantially reduces the sample size used in the analysis. Because the regression model is developed using only the reference group members, the resulting model is less "conditioned"—and therefore possibly less accurate—than a regression model developed using the entire sample. Unless the strong assumption that "the focal group members can offer no useful information for building an accurate regression model" can be met, the predictive accuracy of the model will typically be reduced by using only part of the sample to build it.

This is especially true when conducting regression analyses on smaller samples which will typically result in a wider Standard Errors of Estimate (*SEE*). Wider SEEs result in decreased accuracy when using the model to make predictions regarding pay. While techniques do exist (*e.g.*, "jackknifing" and "bootstrapping") to help accommodate for these limitations,[8] we view this particular limitation as a serious one that applies to many regression situations.

An additional limitation that pertains to the P-B method has to do with the *statistical distributions* of the job qualification factors used in the model. For the P-B method to work accurately and reliably, both the *range* and the *variance* of the job qualification factors should be similar between the two at-issue groups. For example, if the regression liability model (*i.e.*, the model used in the dual regression approach to identify the dollar liability amount) is developed using a male-only model, and most of the men in the model have mid- to high-levels of the job qualification factors, the model might not predict well when applied to the females if they only have low- to mid-levels of the same factors. This is because the regression model may not be able to make accurate predictions for individuals in the focal group (*e.g.*, women), who may have lower levels of the job qualification factors, if there is a meaningful floor in the job qualification factor where the correlations were observed in the reference group (*e.g.*, men only) model.

If there are no major range differences between the groups on job qualification factors, then the variance between the two groups should be similar enough so that building the model on the reference group will provide regression weights that can be validly applied to the focal group members. If one group's variance on a job qualification factor is wide (shown by a large SD), while the other group's variance is narrow (shown by a small SD), the regression weights may not translate accurately between models.

While the extent of these limitations can be evaluated on a case-by-case basis, we do not view the P-B method as a typical *starting place* to use when computing liabilities. Rather, we recommend the single regression model (using the Proportionate Distribution Method) described above because it does not have these limitations. In addition, the preferred method typically *increases* the robustness of the model (*i.e.*, by increasing R^2) after pay corrections are made, whereas the P-B method lowers the same. Given these limitations, the P-B method may still be an effective way of computing the "upper bound limit" of liability in some circumstances (because the liability amounts will almost always be higher when using the P-B method as compared to others).

EVALUATING THE LEGAL DEFENSIBILITY OF REGRESSION MODELS DESIGNED TO INVESTIGATE PAY DISPARITIES

Employers that make pay adjustments to certain group members by relying on weak or flawed statistical evidence can open themselves to legal challenge. One of the most widely-cited cases dealing with this issue is *Rudebusch v. Hughes*.[9] In *Rudebusch*, the employer made $278,966 in corrective pay adjustments to women and minorities based on a limited (and flawed) regression study. After several years of litigation and a review (and remand) by the Ninth Circuit Court of Appeals, the Federal District Court ultimately ordered the defendants to pay $2 million to the whites and men who were adversely impacted by the earlier decision to increase the pay of women and minorities based on the limited and flawed regression study. On remand, the District Court made a careful review of the original regression study that was used to make the pay increases to women and minorities and identified several issues that undermined the validity of the regression model—making the resulting pay changes to women and minorities unjustified.

When looking back over the last 30 years of pay disparity cases, it becomes quite clear that the most fundamental requirement for substantiating pay discrimination (and therefore making changes to the disadvantaged group) is a showing of *statistical significance* associated with the gender/race variable. This is precisely where the employer went awry in *Rudebusch*—they made changes to the salaries of minorities and women without first clearly proving that a *statistically significant* pay disparity existed between groups. When evaluating whether making pay adjustments to disadvantaged group members is justified, the courts first typically evaluate whether a *manifest imbalance* exists in the pay between groups. Absent clear evidence of disparate treatment, demonstrating that a manifest imbalance exists in the pay between two groups *requires* a statistically significant finding. In the context of regression analysis, this means that the gender or race variable must be statistically significant *after* controlling for job qualification factors. This was not the situation in *Rudebusch*, and was one of the reasons that the employer ultimately had to redress their decision to make pay changes to the minorities and women in the case.

In fact, both the defense and plaintiff regression studies reviewed by the Court in *Rudebusch* revealed that the differences in pay were not statistically significant. The defendant's regression revealed that the difference attributable to ethnicity was only $87 and was not statistically significant. The difference between men and women was also not statistically significant.[10] The plaintiff expert's regression analysis found that the differences between men and women "would not even remotely be statistically significant" and both "gender and minority status do not come close to being statistically significant."[11] The District Court further clarified that "if 'manifest imbalance' requires a 'statistically significant disparity,' then there is no 'manifest imbalance' in this case."[12]

In addition to not demonstrating that a manifest imbalance existed between groups (through a showing of statistical significance), the opposing expert analysis and the court noted several internal flaws with the original regression analysis that was used as a basis for making pay changes.

There are two major lessons that can be learned from the *Rudebusch* case. First, before making pay adjustments to a group, be sure the regression model clearly shows that the gender or race variable is statistically significant after controlling for job qualification factors. Second, make sure that the regression model is sound, accurate, and reliable. To help employers address these key requirements, as well as the core requirements from other related pay discrimination cases, we offer the following guidelines:

1. Do not make pay adjustments unless multiple regression analyses are used (opposed to other techniques) to control for realistic differences in job-related factors that may exist between groups. In most situations, using multiple regression is the only clearly acceptable way to model compensation

decisions, and has decades of support in the federal courts and recent endorsement from both federal enforcement agencies that investigate and enforce pay equity cases.[13]

2. Do not make pay adjustments unless the gender or race variable is statistically significant after controlling for job qualification factors.

3. Be sure that the pay equity analysis was designed to identify significant pay disparities that may exist for *any* group (whites and men included). In addition, determine (preferably in advance) how pay disparities will be addressed if discovered to insure that the criteria and rules will be *uniformly applied* across all gender and race/ethnic groups.

4. Do not make pay adjustments unless *the regression model itself is statistically significant*. This can be accomplished by evaluating the ANOVA associated with the model.

5. Insure that the *strength* of the regression model is adequate for making reliable predictions. The strength of the regression model can be evaluated by referencing the Adjusted R^2 value, with Adjusted R^2 values that are statistically significant passing a minimum threshold.[14] In addition, the degree of multicollinearity among the variables should be evaluated (high multicollinearity tends to inflate standard errors associated with predictions, which can make predictions less reliable).

6. Do not make pay adjustments until after performing a "*cohort*" analysis whereby additional variables (*i.e.*, those not included within the regression analysis) are investigated.

7. Be sure that the *fundamental factors* relevant to compensation have been included in the regression analysis or evaluated in the cohort analysis. This has been one of the key factors reviewed when regression studies are contested in litigation settings. In *Bazemore v. Friday*,[15] the U.S. Supreme Court addressed this issue by evaluating the validity of statistical evidence that is necessary to support an inference of discrimination, but fails to consider *all possible variables*. In *Bazemore*, the Court reversed the lower court's refusal to accept the plaintiff's regression analysis as proof of pay discrimination, noting that "discrimination need not be proved with scientific certainty." The Court rejected the lower court's conclusion that "an appropriate regression analysis should include *all measurable variables thought to have an effect*" (478 U.S. at 399, 400) (emphasis added). Thus, in *Bazemore*, the Court ruled that statistical evidence may prove discrimination provided that it accounts for the major measurable factors causing the disparity. Rather than requiring the "perfect regression model," the courts typically require the opposing party to prove that the omitted variables would have *substantially changed the outcome of the study*, and they typically do not allow an inference of discrimination (based on statistical evidence) to be rebutted by simply pointing out unaccounted variables that might have affected the analysis.[16]

8. Be sure that the compensations adjustments made to the disadvantaged group are no more than necessary to attain a balance. As noted in *Rudebusch*:

> *"In addition to existence of a manifest imbalance, the pay equity plan must not unnecessarily trammel the rights of others, and it must be designed to do no more than 'attain a balance' (citing Johnson v. Transportation Agency, 480 U. S. at 637-39, 1987). It is logical that, since pay equity plans are, at least theoretically, implemented to eliminate a pre-existing manifest imbalance, Title VII requires that they must not be designed to go beyond correcting the imbalance, or unnecessarily trammel the rights of others."*[17]

When dealing with the important issue of "attaining balance" and "not trammeling the rights" of other groups not part of the pay adjustments, the Ninth Circuit noted in *Rudebusch* that "while pay equity plans resemble affirmative action, they are not concerned (as affirmative action usually is) with providing an ultimate advantage, such as providing preferences in hiring and promotion plans. Though sometimes labeled as affirmative action, "a pay equity plan such as that implemented by [the defendants] seeks to eliminate *existing* salary disparities for *particular individuals* due to race and sex (emphasis added)."[18] The Federal District Court also clarified this matter by stating: "In other words, where salary is already skewed due to discrimination (as prohibited by Title VII, on account of race and sex equalization results in the *elimination* of the preferences—it does not create a preference."

9. Thoroughly discuss with legal counsel and executive staff how adjustments to compensation will be made (*e.g.*, incrementally, lump-sum, as part of a yearly compensation/performance review).

SUMMARY

Based upon the limited discussion of the three above distribution methods, it should be apparent that liability calculations and the distribution of those monies is a dynamic and complex issue. It is important for employers to remember that regression analyses are only as good as the data they include. Given this, it is important for employers to also realize that, to the degree a regression analysis is lacking due to small sample sizes, missing data, or a myriad of other factors, the liability calculations and the distribution of those monies should be used only as a guide. Regression analyses and statistical liability calculations should never be used as the sole determinant for compensation adjustments.

Lastly, employers are cautioned against making compensation adjustments based upon weak, incomplete, or flawed regression analyses.

Important Note: *It is important for employers to remember that* all *employees are protected from unlawful discrimination. Making unjustified salary adjustments only for certain groups may lead to findings of unlawful compensation discrimination elsewhere. It is highly recommended that* all *significant disparities, regardless of impacted group, be thoroughly investigated, documented, and addressed.*

ENDNOTES

1 For example, Colquitt, J., Conlon, D.E., Wesson, M. J., Porter, C., & Ng K. Y. (2001). Justice at the millennium: A meta-analytic review of 25 years of organizational justice research. *Journal of Applied Psychology, 86*(3), 425–445.

2 Average salary computation includes individuals from both the Focal and Reference groups.

3 Exclude the grouping variable (*i.e.*, Men/Women, Whites/Minority).

4 Peters, C. C. (1941). A method of matching groups for experiment with no loss of population. *Educational Research, 34*, 60; Belson, W. A. (1956). A technique for studying the effects of a television broadcast. *Applied Statistics, 5*, 195.

5 Blinder, A. S. (1973). Wage discrimination reduced form and structural variables. *Journal of Human Resources*, 8, 436–455; Oaxac, R. (1973) Male-female differentials in urban markets. *International Economic Review*, 14, 693–709.

6 Sinclair, M. D. & Pan, Q. (2009) Using the Peters-Belson method in equal employment opportunity personnel evaluations. *Law, Probability and Risk, 8*, 95–117.

7 Greiner, J. D. (2008). Causal inferences in civil rights litigation. *The Harvard Law Review, 122* (2), 540–597.

8 Sinclair, M. D. & Pan, Q. (2009) Using the Peters-Belson method in equal employment opportunity personnel evaluations. *Law, Probability and Risk, 8,* 95–117; Efron, B. & Tibshirani, R. J. (1993). *An introduction to the bootstrap*. Chapman and Hall, New York.

9 *Rudebusch v. Hughes*, No. 95-CV-1313-PCT-RCB, No. CV-1077-PCT-RCB (D. Ariz. 2007).

10 Plaintiffs/Appellants Reply Brief, Exhibit 46, p. 2-3, T. 130). Rudebusch v. Hughes, 313 F.3d 506 (9th Cir. 2002). See also Rudebusch v. Hughes, No. 95-CV-1313-PCT-RCB, No. CV-1077-PCT-RCB (D. Ariz.). Judgment entered June 28, 2004.

11 Plaintiffs/Appellants Reply Brief (Appendix 1 to Opening Brief, p. 8; 2 T. 84.). *Rudebusch v. Hughes*, 313 F.3d 506 (9th Cir. 2002).

12 Plaintiffs/Appellants Reply Brief (Citing Excerpt of Record, 147, pp. 25–26). *Rudebusch v. Hughes*, 313 F.3d 506 (9th Cir. 2002).

13 U.S. Department of Labor (DOL), Employment Standards Administration, Office of Federal Contract Compliance Programs (June 16, 2006). Voluntary Guidelines for Self-Evaluation of Compensation Practices for Compliance With Nondiscrimination Requirements of Executive Order 11246 With Respect to Systemic Compensation Discrimination; *Federal Register*, Vol. 71, No. 116. See also EEOC Compliance Manual, Section 10-III A.3.c. (*http://www.eeoc.gov/policy/docs/compensation.html#3*).

14 For example, if the R^2 of a given regression is 0.28 and the corresponding p-value is .03, one would also desire the Adjusted R^2 (*e.g.*, 0.24) to be statistically significant (< .05).

15 *Bazemore v. Friday*, 478 U. S. 385 (1986).

16 See for example, *Contractors Association v. Philadelphia*, 6 F.3d 990, 1007 (3d Cir. 1993); *EEOC v. General Tel. Co.*, 885 F.2d 575, 582 (9th Cir.), cert. denied, 498 U.S. 950 (1989); *Sobel v. Yeshiva Univ.*, 839 F.2d 18, 34 (2d Cir. 1988), cert. denied, 490 U.S. 1105 (1989); *Catlett v. Missouri Highway and Transp. Comm'n*, 828 F.2d 1260 (8th Cir. 1987), cert. denied, 485 U.S. 1021 (1988); *Palmer v. Shultz*, 815 F.2d 84, 101 (D.C. Cir. 1987).

17 *Rudebusch v. Hughes*, No. 95-CV-1313-PCT-RCB, No. CV-1077-PCT-RCB (D. Ariz.). Judgment entered June 28, 2004 (p. 16).

18 *Rudebusch v. Hughes*, 313 F.3d 506 (9th Cir. 2002) (at 520).