FACULTY SALARY: ISSUES IN MULTIPLE REGRESSIONS

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Equity in faculty salaries has always been a controversial issue facing institutions of higher education. As a bastion of academic freedom where faculty and students purse knowledge, it is almost anti-intellectual to find a gender gap in salaries. More importantly, there are laws, which ensure gender equity in salaries. Thus, salary equity has evolved from a moral issue to a legal issue. A judicial salary decision has become all the more important when faculty discrimination can be brought to court.

In order to fend off any legal challenges in court, an institution of higher education has to first decide whether or not there is a salary disparity among faculty on campus. There are various ways of pursuing this inquiry. First, descriptive statistics are informative, yet they lack inferential power. Then, the use of inferential statistics such as regression analysis provides more probative values yet poses some difficult statistical problems. The nature of these statistical problems is rather different if one views it statistically or substantially. The purpose of this paper is to discuss some major statistical issues involved in the court system, and to explore solutions to such problems. Actual data was used in presenting the problems and solutions.

Law with Regard to Gender Discrimination

There are two major statutes available for seeking remedy in employment sex discrimination. The Equal Pay Act and Title VII of the 1964 Civil Rights Act. The essence of The Equal Pay Act refers to the condition that employers have to pay equal wages to employees when the job requires equal skill and responsibility. Merit increase, seniority, and production are the only exceptions where pay differentials are allowed. The second law is much broader in scope. Title VII prohibits discrimination in either private or public institutions of higher education, and is the most widely used statute in litigation. Title VII stipulates that employment practices should not discriminate against employees on the grounds of religion, race, color or sex. In *Griggs v. Duke Power Co.* (1971), the Supreme Court decided that the discriminatory impact of an employment decision is a major concern - even if the policy is neutral in nature. This is important because a gender disparity in faculty rank could become an issue of contention even when the average salaries of both sexes are the same.

The decision to allow the use of statistics in court could trace back to *International Brotherhood of Teamsters v. U.S.* (1977) when the U.S. Supreme decided that statistics were probative of discrimination. Since then, most legal cases involve statistics, particularly the use of multiple regressions.

Procedure

A sample of 357 faculty members was selected from a Catholic institution of higher education in the Midwest. Variables included salaries, rank, tenured status, performance measures, gender, race, colleges and departments. The actual salary study was performed in 2004. Illustration of the statistical issues in the paper used the actual data from the 2004 faculty salary study.

Issues of Standardized and Un-standardized Regression Coefficients

Related to the impact of variable groupings, an issue emerges as the individuals in a group may change the relative variances among variables (Langbein & Lichtman, 1978). Aggregation bias will be included in the standardized measures, such as correlation and standardized regression coefficients, but not in un-standardized regression coefficients.

Issues in usage of standardized versus un-standardized regression coefficients received great attention when path analysis was introduced in the social sciences. When path models were presented, immediate questions were raised as to whether standardized regression coefficients or un-standardized regression coefficients should be used in a comparison. Aggregation bias and appropriate comparison are two facets of one issue, both relating to the variance ratio of s(x) and s(y).

The symbol for a standardized regression coefficient, usually called a beta coefficient *B*, which is computed by converting both x and y to Z-scores and then estimating the regression equation. Thus, an un-standardized regression could change into *B* by multiplying the un-standardized regression coefficients by the standard deviation of the independent variable, then dividing it by the standard deviation of the dependent variable.

B yx=(byx)(sx/sy).

Much discussion on the usage of un-standardized regression coefficients and *B* were published in the path analysis literature. Blalock (1971) argued that *B* was appropriate for describing the relationship in a single sample; un-standardized regressions should be used for comparing samples or stating general laws. Most sociologists tend to agree with this statement.(Duncan, 1966; Boudon, 1965; Turkey, 1954) *B* yx is a standardized regression coefficient indicating the amount of change the dependent variable for an independent variable change of one standard deviation (in standard deviation units).

On the other hand, byx is an un-standardized regression coefficient indicating the amount of change in any unit of measurements of the dependent variable for an independent variable change (in any unit of measurement). Thus, byx has an invariant property from sample to sample. For example, if the unit measurement is in dollars or meters, it will remain the same. The magnitudes of sx/sy are the real variations in a particular sample, and are therefore subject to change across samples. It then becomes misleading to compare the value of Byx in two different samples when the values of byx or sx/sy are uncertain. Schoenberg (1972) analyzed Bayer's data and presented the following table.

Bayer's study (1969) was one of several major studies focusing on educational aspiration, social and economic status, peer influence upon aspiration and their correlates. In the sociology of education, the hypotheses that intelligence and family SES are appreciable influences on aspiration, and that the influence of a friend's aspiration on a respondent's aspiration are also appreciable, have generated much debate on the meaningful comparison of sociological data.

The un-standardized regression coefficients indicated that SES affected a significant others' influence in large cities three times more than on farms, yet standardized regression coefficients indicated that SES had the *same influence* on significant others' influence in large cities and on farms. The reason for this discrepancy is due to the standard deviation of SES varying greatly among the different regions (see column 4, table 1). A faulty conclusion could have been avoided if one used un-standardized regression coefficients in the comparison, as Schoenberg suggested (1972).

Table 1

Comparison of the Behavior of Standardized Regression Coefficients and Un-Standardized Regression Coefficients across Residence Categories

1	2	3	4	5	6	7	8
Farm		3	6.048	1.677	0.174	0.048	5.854
Village	Under 2,500	3.2	9.851	1.666	0.247	0.042	6.159
Small city	2500-25,000	3.9	11.267	1.752	0.236	0.036	6.336
Medium city	25,000-100,000	4.7	11.505	1,665	0.232	0.034	6.371
Large city	over 100,000	5.5	12.226	1.612	0.145	0.019	6.89

1-Residence
2-Population

3-Mean log of population
4-Standard deviations of SES
5-Standard deviations of significant others' influence
6-Standardized regression coefficients of SES on significant others influence
7-Unstandardized Regression coefficients of SES on significant others' influence
8-Intercept

Correct use of standardized and un–standardized regression coefficients has a tremendous influence on the conclusion of salary studies. Unless a meaningful comparison is being made, one can never be sure if a gender-bias exists—affecting rank, tenure and salaries. Since both rank and tenure are measured in same units, un-standardized regression coefficients should be used in the comparison.

Table 2 was computed on a female sample of 130 faculty members and a male sample of 227. Tenure status is a dummy variable coded either as 1—tenured, or 0—not tenured. The standardized regression coefficients *B* and un-standardized regression coefficients, along with other pertinent information were presented in Table 2. Examining the standardized regression coefficients, one would conclude that the effect of tenure status was more important upon salary levels for the female faculty (.216) than for the male faculty (.191). However, when one looked at the un-standardized coefficients, the effect of tenure status was far more important upon salary for male faculty (9497) than female faculty (6693), reversing the conclusion found from standardized regression coefficients. If one applied the numbers into the equation *B*yx=(byx)(sx/sy), one would have immediately realized that the standard deviation of the male faculty salary varied greatly (22,591), while comparatively speaking, the standard deviation of female faculty varied far less (15,199) Thus, when both standardized deviations of tenured status remained the same (.491 versus .455), the effect of sx/sy could neutralize the effects of byx, and reverse the conclusion of un-standardized regression coefficients. The computations were presented as followed:

.216=6693*.49/15,199

.191=9497*.45/22,591

Table 2

Comparison of Tenure Status upon Salary across Gender

V13	Model		Un-standardized Coefficients		Standardized Coefficients	t	Sig.
			B	Std. Error	Beta		
Female	1	(Constant)	55450.784	2086.253		26.579	.000
		V5A	6693.076	2676.240	.216	2.501	.014
Male	1	(Constant)	61555.152	2735.550		22.502	.000
		V5A	9497.519	3248.214	.191	2.924	.004

a Dependent Variable: V6, Independent variable: Tenure Status 0 = Not Tenured, 1 =Tenured.

Descriptive statistics for Salary & Tenure Status

V13		N	Minimum	Maximum	Mean	Std. Deviation
Female	V5A	130	.00	1.00	.6077	.49015
	V6	130	$39,390	$128,500	$59,518.12	$15,199.239
	Valid N (listwise)	130				
Male	V5A	227	.00	1.00	.7093	.45511
	V6	227	$36,260	$185,810	$68,291.28	$22,591.845
	Valid N (listwise)	227				

A similar approach was adopted by Duncan (1969), who adamantly advocated the use of un-standardized regression coefficients in his interpretation of the stratification process in White and Non-White populations. Personal income measured in dollars was the variable used in the comparison. The invariable nature of the measurement of dollars avoids unnecessary problems accompanying the use of standardized regression coefficients.

Multi-Collinearity

Interaction effect and multi-collinearity present special problems in analyzing salary data. Tenure, rank and merit increase all tend to go together. In *Bakewell v. Stephen F. Austin State University* (1996) case, the court found that the plaintiff's models suffer from multi-collinearity because experience, degree, and gender are all highly related to each other. Even so, the court stated that the problems were not significant enough to negate the results of probative value. The lesson from this decision is to decide the nature of multi-collinearity. If it is a problem of computation then one has to drop a variable in order to estimate the other one. When two variables are perfectly correlated or nearly perfectly correlated so that the inversion of matrix could not be found, the regression coefficients of the variables cannot be computed. A perfect collinearity is extremely difficult to find empirically.

Less than a perfect multi-collinearity among the variables poses estimation problems. Ordinary Least Square parameters remain reliable and un-biased, but the standard errors for the regression coefficients become large and imprecise. Furthermore, simple correlation among the variables is not a necessary condition for multi-collinearity. Multi-collinearity arises when the individual coefficients indicate that the null hypothesis (where the coefficients were zero) cannot be rejected, yet the combined set of regression coefficients were significantly jointed in the F-test. Furthermore, the values of regression coefficients changed dramatically from sample to sample.

Multi-collinearity referred to a problem in the regression equation when two independent variables were highly correlated. In social sciences and economics, variables were generally correlated. Income, education, ACT scores, grades, and social status were highly correlated. If one treated a variable such as wealth as a dependent variable, one would expect a high correlation with an independent variable like education. The question emerged when both wealth and education were included in the equation as independent variables, of which their high correlation obfuscated the individual effect of each of the variables upon the dependent variable of prestige. In a severe case, wealth was found significant while education became insignificant or vice versa solely depending upon the order of variables entered in the equation. A more subtle problem emerged when a different sample was chosen. Although the regression coefficients of the correlated variable remained unbiased, its standard errors were far larger than they would have been in absence of multi-collinearity. As the standard errors of regression coefficients were used to construct the confidence level around the sample point estimates of regression parameters, the larger the standard errors, the wider the confidence intervals and the less precise the regression coefficients (Knoke, Bohrnstedt and Mee, 2002).

There are two ways of solving the problem of which either is acceptable in an appropriate setting to the social scientists. One strategy is to drop a highly correlated variable in the sample and the other is to combine the variables into an index. The Duncan Socioeconomic Index (SEI) is a combination of income, education, and occupational prestige (Reiss, Duncan, Hatt and North 1961).

Lewis and Beck (1980) cited a study to illustrate the issue of multi-collinearity by dropping a variable from the model. In order to assess the support, Peron garnered from workers and internal migrants in the 1946 Argentina Presidential election, sociologist Gino Germain included the following variables in the equation. “Y” represented the percentage of the country’s vote for Peron, x_1 represented urban blue-collar workers (as a percentage of the economically active population in the county), x_2, rural blue-collar workers (as a percentage of the economically active population in the county), x_3, urban white-collar workers (as percentage of the economically active population in the county), x_4, rural white-collar workers, and $x_{5,}$ internal migrants (as a percentage of Argentinean-born males). The result of the analysis with five independent variables was as follows:

$$Y=.52 +.18x_1 -.10x_2 -.57\ x_3 - 3.5\ x_4 +.29x_5$$

The only significant regression coefficient was .29 and none of the workers were influential in the election of Peron support. However, when each independent variable regressed with the remaining variables, the astounding results were revealed: R_2x_2=.99, R_2x_3=.98, R_2x_1=.98, R_2x_4=.75 and R_2x_5=.32. Such high correlation (.99) indicated multi-collinearity existed. Removal of the x_2 from the equation brought about a new analysis and thus an entirely new perspective to the data.

$$Y=.42+.28\ x_1 -.47\ x_3 - 3.07\ x_4 +.30x_5$$

With the exception of the intercept, all the variables in the equation were significant at .05. The conclusion that workers have played a major role in Peron's election was valid. This is an example where dropping a variable to solve the problem of multi-collinearity was successful.

In salary studies, the problem of multi-collinearity arises when one finds that tenured status and rank are tangled. It is customary in an institution of higher education to grant tenure to an assistant professor along with a promotion to rank of associate professor. Therefore, rank and tenure status almost goes hand in hand. However, dropping either rank or tenure status would present tremendous difficulties in presenting the data to the jury in court. In *Sobel v. Yeshivam* case, (1988). The court found that the regression model should include rank as a variable, and any other variable included in the model has to show relevance to the variable of rank. In *Presseisen v. Swarthmore College* (1977), the court rejected the regression model presented by the plaintiff because the model did not include the variable of rank.

If dropping the variable of rank is not advisable, then some other alternatives have to be sought. As one would expect, the prior knowledge between tenure status and rank is readily available. Previous salary data were also available to assess the quantitative ratio between tenure status and rank. The regression coefficient of tenure status on rank in the sample was 1.12 in year 2002, 1.13 in year 2001, and 1.11 in year 2000. It is entirely reasonable to assume that the ratio between tenure status and rank is somewhere between .36 and .35 within the population, which can be utilized to alleviate the problem of multi-collinearity.

$Y = a + b_1x_1 + b_2x_2 + e$

$b_2 = 1.13b_1$ (b)

let x_2 = rank; and x_1= tenure status

rankten=1.13*tenure + rank

salary = a + rankten + e (a)

Table 3 Coefficients(a)

Model		Un-standardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	39,005.794	3,145.477		12.401	.000
	RANKTEN	7,092.908	811.488	.421	8.741	.000

a Dependent Variable: v_6 Salary

The variable of rankten is a composite variable of tenured status and rank. One can now use ordinary least regressions to compute the regression coefficients in the equation (a) where the calculation of rankten yielded the un-standardized regression of 7092. This was also the estimate of effect of tenured status. The estimate of rank was derived from the equation (b), 7092*1.13=8013.

Issues of Interaction

One of the most serious problems with multi-collinearity is the use of multiplicative terms in the regression analysis. Blalock (1972) indicated that if one defines $x_3=x_1x_2$, then x_3 is an exact nonlinear function of x_1 and x_2. Thus, his findings concluded that the correlations of x_3 with both x_1 and x_2 were typically very high. Gordon (1968) identified that both the number of variables and the correlations among the variables have substantial impact upon the interpretation of the data. The redundancy of the variables referred to the high correlation among the variables and repetitiveness referred to the number of variables. The sizes of the regression coefficient were depressed for a larger set of variables and enlarged for a smaller set of variables.

With equal repetitiveness, variables with less redundancy had larger regression coefficients and smaller standard errors than variable with more redundancy. Further analysis of Gordon's work indicated that the more interaction allowed in the equation, the more serious the problem of multi-collinearity became (Althauser, 1971). The size of interaction related to the regression coefficient became smaller relative to the coefficient of the individual terms. Cronbach (1987) suggested centering the variables by subtracting the mean score from each individual score. The slope remained the same while intercept became the mean of the independent variable. This approach tended to produce smaller correlations between the individual variables and their interaction variables, yet a complete treatment of the complex issues raised by Gordon remained unanswered.

The problem of multi-collinearity should be placed in perspective. The seriousness of the multi-collinearity issue can be reflected by the Coefficient Variance Inflation, a measure of multiple correlations of independent variables. VIF=1/(1-R^2ij) where R^2ij stands for the multiple correlation of the J variable with other independent variables (i) in the equation (Johnston, 1972). Moderate correlation (less than .50) among the independent variable "S" was of no great theoretical significance in the study, especially when one is careful with the interpretation of inflated standard errors.

The sample data was used to compute the interaction effect of rank and tenured status on salary. The un-standardized regression coefficients (-1818.33) of the interaction term was not significant (.595). Thus, the issue of interaction of tenured status and rank is not an issue of concern in this sample.

Table 4 Coefficients(a)

Model		Un-standardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	20373.848	6419.941		3.174	.002
	V5A	-5138.081	8895.336	-.117	-.578	.564
	V4A	17884.483	2883.434	.698	6.202	.000
	V45A	-1818.330	3419.664	-.144	-.532	.595

a Dependent Variable: V6, v45a=v4a*v5a, interaction effect.

Variables Entering the Regression Model

Variables entering into the regression model were generally determined by theory in economics. This was especially true in econometric literatures. For example he Cobb-Douglas function, $Q=b_0L^{b1}k^{b2}e^u$, where Q represented output, L the labor input in work hours, C, capital input in machine-hours, and ln L and ln K were highly correlated yet, states that capital and labor should be included in the equation (Johnston, 1972). In faculty salary studies, there was no such well-ground theory to specify which variable should be included in the equation. Institutions have specific personnel policies to accommodate their needs. Doctoral research institutions may have different promotion policies from community colleges. A survey of literatures however, would provide some common background for the variable selected in the regression models. Rank, discipline, merit, tenured status, gender, and minority status were all variables recorded in the faculty personnel system and were widely used in the salary studies on campus. Discussion on the appropriate use of these variables has consequently entered the debate in court.

Rank. One of the most polemic discussions on the variable selection in the regression analysis is rank. In *Mecklenburg v. Montana Board of Regents of Higher Education* (1976), the court rejected the use of rank because the court believed that rank was related to promotion, which was discriminatory in nature. This argument has been widely shared by various researchers (Ferber and Green, 1982, Scott 1977, Gray, 1990). Confusion arose here because the discriminatory meaning of rank had two interpretations. Rank was discriminatory because it was awarded in a fashion that the individuals or committees on campus discriminated against female faculty either in the promotional process or in the outcome. In this case, this is morally wrong and should be ameliorated. The second meaning of discriminatory in rank was morally sound because rank was implied to refer to promotion, which was objectively part of an evaluation. In light of this debate, objections to the use of rank in the regression analysis centered the argument that the discriminatory nature of rank will obscure the result of the salary disparity of gender.

Recent court cases however, asked that rank be included in the salary study. (Sansonetti, 1988; Fogel, 1986). Fogel (1986) believed that rank should be included because gender discrimination in pay could be appealed only within the same level of job category. Thus, salaries for full professors should be higher than for associate professors. If there are disproportionate male faculty members within a higher rank category, a separate study on the rank appointment should be addressed, as Title VI indicates that discrimination in rank is prohibited. In *Sobel v. Yeshiva University* (1988), the court stipulated that rank should be included in any regression analysis.

Whether or not the variable of rank should be included in a regression analysis is an empirical query. If rank is related to salary, then it should be included in the model. Omission of the variable of rank from the regression model does not remove the influence of rank upon salary from the model, but simply leaves its influence in the residual variable or other correlated variables, such as tenured status in the model. When one uses an un-standardized regression analysis, the constant term connotes all the unexplained variances. The influence of rank would be left in the constant term if rank is left out of the model. A separate regression analysis would detect any tremendous differences in the constant terms between the equation with the variable of rank and the equation without said variable. The estimates of the regression coefficients for the variables in model become either underestimated or overestimated depending on either the positive or the negative relationship among rank and the variables in the model.

Race. Race, like gender, is also a variable of contention. The question raised in salary studies is whether or not to combine different minority races into one. The advantage of combining different races is that it avoids the danger of leaving small cases into racial categories. Depending on the size of the institution, one may end up with fewer than five cases in a particular category such as Native American. Prior examination of the racial data before combining them is an idea to be worth studying. Asian faculty in the engineering department may not be at a disadvantageous position relative the European faculty, and combining them with other minorities may bias the results. The general consensus seems to be that if there are enough cases, breaking each category out would be desirable. Caution comes when there are not enough cases for a particular racial category. The racial categories in the 1993 salary study at the State University of New York (SUNY) were African-American, Latino and Asian (Haignere, Lin and Eusenber 1993). The separation of Asian from other minority groups was deemed necessary because of the existing salary differentials among the different minority groups.

The difference among college, discipline, and department. Less controversial is the issue of including discipline or departmental differences in faculty salary studies. In *Coser v. Collvier* (1984), the court agreed to the institution's analysis that it included departments in the analysis. Along the same line, the court ruled against the plaintiffs' analysis because it did not include the variable of department or discipline in the regression model in *Wilkins v. University of Houston* (1981). In *Soble v. Yeshiva* (1988), the court asked the plaintiff to account for the differences in salaries between departments.

If the past court decisions provide any clue to the future trend, the variable of discipline or department will be included in the study. This approach tacitly agreed with the basic assumption that disciplinary differences in salaries were legitimate since they reflected the market forces, specifically the law of supply and demand. However, some researchers were dubious as to whether or not the negative association between salary levels and the percentage of women in academic discipline could be attributed to market forces. Academic disciplines with higher proportions of women had the lowest growth in salary over time (Bellas, 1997, Semelroth, 1987). The same negative relationship was also found between the proportions of women in academic disciplines and average entry-level salaries (Staub, 1987). These studies suggested that salary differentials between genders were at least partially due to sex discrimination and not entirely dependent on market forces. The issue of comparing the value of different disciplines on campus seems to be embroiled into the larger issue of comparing the value of or worth of dissimilar work whereby a practice of a comparable worth salary remains elusive.

The pertinent question is: will entering the “department” impair the quality of data analysis? Using either the hierarchical models or dummy variables in an ordinary regression will significantly decrease the degrees of freedom because of the number of departments. In a department with fewer than five faculty members, the number of the faculty members would be less than the number of the variables in the equation where an inverse matrix in regression analysis could not be computed. Less dramatic is the situation where the significance test loses its power because of small size of the departments. Comparison by colleges seems to be a desirable alternative, especially when there is not much of a salary difference among the departments within a college.

An empirical quandary facing research is the impact departmental separation versus discipline separation would make on the sample size of each disciplines or departments so small that renders meaningful comparison impossible.

Hierarchical Linear Models

Hierarchical models were specifically designed to find meaningful comparisons in terms of the different disciplines and colleges. The ecological fallacy has long been noticed by social scientists when one inferred individual relationships from aggregate data. As Robinson (1950) has long indicated, one would choose the wrong level to analyze the data when it is the only data available. Hannan (1970) further stated that a general inability to construct a macro-measure to reflect the meaning of the general theory was the real problem. A necessary correspondence between the micro-level and macro-level is needed in testing a theory. Robinson (1950) found an individual correlation of .22 between race and literacy, a state marginal correlation of .77 and a census district marginal of .94. Correlation increased as the level of aggregation changed. The aggregation and dis-aggregation effects detailed in the analysis evidenced the difficulties associated with the synthesized results from different level of constructs. The implication of the Robinson study was that when areas correlations increase from within, the numbers of areas increased.

The bounds of individual correlations inferred from the grouped data were studied by Duncan and Davis (1953). Only one cell needed to be determined in order to estimate the correlation of the table cells. As each row and column of the tables was constrained by the marginal totals, the maximum and minimum values of a particular cell were determined. The values of Phi-coefficients, an indication of correlation were bounded by the marginal of a contingency table (Liu, 1980). The correlation dynamics became more evident when Cartwright presented the conclusion that small groups having negative group correlations when combined into large groups would increase the correlations of the large groups (1969). This analysis presented mathematical proof of Robinson's line of reasoning.

Although conceptually the inflation problem has long been recognized and widely discussed among social scientists, the solutions were regarded technically impossible until in the 1990's (Raudenbush and Bryk 2002). Hierarchical linear models, which were an extension of general regression analyses, were specifically introduced to address this problem of the assumption of independence being violated in regression analysis.

Institutional researchers are well versed in the concept of the dependent and independent variables in the general model of regression analysis. The independent variable of Socio-economic status and the dependent variable of College Matriculation are tested to see if there exists any relationship between them. A null hypothesis is formulated and an F-test is used against the alternative hypothesis. When Socio-economic status was measured by Duncan's socioeconomic index (Blau & Duncan, 1967) and matriculation rate is measured by an age cohort, the reliability and validity of the measurements are impeccable. As most of the Office of Institutional Research would be asked to incorporate home addresses into the study for recruiting, the assumption of independence in regression analysis is violated. Neighborhood information such as zip code is highly correlated with social economic status. When observations are not independent, hierarchical model should be used in lieu of ordinary regression.

When the information of the correlated sample is not used in the study, the principle of constant variance in multiple regressions is violated. Hierarchical models were designed to alleviate this problem statistically. Furthermore, the use of the model would draw on the estimation of variance and covariance components with imbalanced, nested data (Raudenbush and Bryk, 2002). This is quite conceivable in faculty salary analyses that different colleges have different views about the reward structures. Law school faculty members generally have higher salary demands than liberal arts faculty members. The salaries in the same college are more likely to be similar than those salaries of faculty in different colleges because of distinct academic market demands. In other words, colleges are a random factor, and thus, not a fixed factor—as the fixed-effects analysis of variance models assumes.

The results of an Unconditional Random-Effects Model were presented in Table 5-Estimates of Covariance Parameters (a). It indicates variance estimates for the two components: the college effect and the residual terms.

Table 5 - Estimates of Covariance Parameters (a)

Parameter	Estimate	Std. Error	Weld Z	Sig.	95% Confidence Interval

						Lower Bound	Upper Bound
Residual		210,277,883	15,828,206	13.285	.000	181,435,083	24,370,583
college	Variance	669,054,389	555,234,021	1.205	.228	131,542,881	34,029,494

a Dependent Variable: v6.

The residual variance was 210,277,883 revealing how much salary differences vary within a college. The college variance was 669,054,389—three times as large as the residual variance indicated that the extent of faculty salary varied in the population of colleges. The intra-class correlation coefficient, 75.8 %, is known the variance could be attributed to differences between colleges. The intra-class is close to 1 when the entire salary difference could be attributed to the colleges.

Total variance = residual variance + college variance

Intra-class coefficient = college variance/total variance

However, the column entitled “Sig.” indicated that college variance was not significant at .05 (.228). Hence, the null hypothesis that variance components are 0 could not be rejected. In this study, the different colleges have not indicated differential salary structures among male and female faculty members.

Validity of inferences is more superior in hierarchical models than in ordinary regression models. When data were completely balanced, a small sample theory for inferences holds because the value of standard errors was distributed as a t variety (Raudenbush and Bryk, 2002). However, balanced data, unlike in an experimental design, were almost impossible to find in survey research. In imbalanced cases, a large sample theory was employed in estimating the fixed effects and their stand errors. Variance components generally depend upon the sample sizes to justify its large sample normality approximation. Extensions beyond the basic two levels were straightforward in logic, but would encounter difficulties in meeting the sample size requirement.

Conclusion

Issues of equity by gender require ongoing reviews, and detailed information is generally available on campus. Regression analysis may not be solely appropriate in deciding whether a *prima facie* case of discrimination exists. Sample size is one major factor, which could influence the results significantly yet researchers in most cases can only rely on the available cases on hand. In some instances, some of the statistical techniques become unavailable because of insufficient sample size. Hierarchical Linear models are extremely powerful in data analysis when data structures are hierarchical. Modern statistical techniques and computer programs make fitting such models relatively easy. Insufficient cases in the sample often render this technique useless. This obstacle certainly should not preclude the usage of regression analysis in salary equity studies but caution the researcher to be more careful with the analysis of data.

The inferential power of regression analysis has been proven in court, and one can reasonably assume its usage will be more prevalent in the future. Still, researchers should take precautions when using statistics to sift through delicate, salient topics such as gender equality in the higher education workforce. It is crucial that the investigators take great strides to ensure that the method and manner they pursue gender pay equity or any such topic is both politically feasible and logically coherent.

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