The AIR Professional File No. 20, Fall 1984
The Association for Institutional Research

ASSESSING FACULTY SALARY EQUITY

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What is salary equity? How can one show that it does or does not exist? What statistical techniques are appropriate for negotiation or litigation? Questions such as these periodically arise in the college or university setting, particularly with regard to the salaries of continuing academic faculty, which are often determined through loosely defined policies and procedures. When university administrators demand answers, institutional research personnel suddenly find themselves enmeshed in the nontrivial task of salary equity analysis.

The complexity of the task is due in part to the diverse nature of salary inequities. Some inequities are desirable, such as the higher salaries paid to outstanding professionals and the lower salaries paid to faculty whose contributions have fallen far short of university expectations. Some inequities are divisive, such as interdepartmental differentials that cannot be explained on the basis of market factors or formal policy. Some inequities are illegal, such as low salaries historically paid to women and minority faculty at many institutions. Considering the potential legal and personnel costs that salary inequities may entail, it is simply good management to examine faculty salaries annually to determine whether the reward structure is both legal and in line with the expressed policies of the institution.

There is no single correct method for performing a faculty salary analysis. Despite the number of published guidelines, studies, and computerized statistical packages available, the researcher must always remember that equity issues are fundamentally administrative and conceptual rather than statistical in nature. The researcher should, therefore, begin the task with a thorough study of the institutional salary policies and design an analysis which reflects them. Close adherence to university salary policies may aid in the final phase of the project, which is presenting the results in a clear and straightforward manner to nontechnical (and sometimes distraught) parties. This paper presents the task as a series of questions that the researcher must answer in the course of preparing a faculty salary equity analysis.

STUDYING THE POLICIES

Who Wants the Analysis, and Why?

First and foremost, the institutional researcher must have a clear understanding as to why the study is being performed. Is the intention to discover whether salary discrimination is being practiced at the institution? Or is the purpose to discover which of the various determinants of salary carry the most weight? Is the goal of the study to explain disparities between groups or to predict the salaries of individuals? The purpose of the study must to some extent shape the specification of the model, the choice of the method, and the interpretation of the results.

The most valuable piece of advice that can be given to a researcher contemplating a salary analysis is to begin long before the results are needed. All too often, a salary analysis is undertaken as an ad hoc response to a discrimination suit, and the pressures of time prevent the researcher from properly assessing the situation in a systematic manner. The foresighted researcher will initiate a faculty salary study to ascertain whether a discrimination case could be made against the institution.

The researcher should also consider examining the salary structure of the university to determine which factors are important in the reward system and how well those factors relate to the written salary policies. Such information can prove valuable for reevaluating salary policies, redressing faculty grievances, and reallocating resources in times of retrenchment.

How Are Salaries Actually Allocated?

Faculty handbooks and policy manuals are good starting points for determining how salary decisions are made. Follow-up discussions with deans and department heads are essential. Vague language in the manuals may be symptomatic of a reward system that offers few practical guidelines for decision makers. It is as important to know how the school officially says salaries are allocated as it is to know the practical criteria upon which administrators actually base their salary decisions.

Most faculty salaries are determined on the basis of academic qualifications and professional merit. The qualifications include such attributes as formal education, field of specialty, and professional experience. Merit relates to actual job performance and productivity. Since the turnover rate among academic faculty is relatively low, the salary structure of an institution will also reflect historical factors, such as changes in policy, shifting emphasis on academic specialties, and economic conditions. The final product of the researcher's study of faculty salary policies should be a list of those criteria, and only those criteria, which guide the institution's administrators in allocating faculty salaries. This list constitutes a crude model of the institution's faculty reward system, which the researcher then refines for statistical analysis.

DESIGNING THE ANALYSIS

How Can the Criteria Be Measured?

Once the salary allocation criteria have been identified, the next step is to translate those criteria into quantifiable variables. By attempting to express the salary determination criteria in numeric terms, the researcher quickly becomes aware of one of the major weaknesses of a statistical salary equity study: good measures of many important criteria are very difficult to find. Professional experience, for example, can be represented by variables indicating years at the institution, years at current rank, years since terminal degree, and so forth. None of these variables accurately measures professional experience, however. The problem is even more pronounced for merit variables, which serve as proxies for research productivity, teaching effectiveness, and public service. The number of journal articles that a faculty member has published certainly may be one indication of research productivity, but it hardly constitutes a comprehensive measure.

Commonly used proxies for individual qualifications include type of degree, terminal degree, field of specialty, departmental affiliation, rank, appointment type, administrative experience, tenure status, years since hire, years at rank, and years in the tenure system. Proxies for merit include counts of journal articles, books, book reviews, conference presentations, grants, teaching awards, service awards, teaching evaluations, and peer reviews. A regional or national indicator of market demand for the various academic specialties is often a factor in salary decisions, particularly the decision to set starting salary.

Where Can the Data Be Found?

Much of the data needed for variables representing individual qualifications can be obtained from records maintained by the university personnel and payroll departments. Data for merit variables—those indicating output, contributions, and productivity of individual faculty members—will probably have to be collected from other sources. Definitions of merit differ across departments, and departments often keep their own records. Even when these data are gathered together in the office of an academic vice president, the task of rendering the data comparable may be a formidable one indeed. For example, counting publications to serve as a proxy for research productivity will be complicated by the fact that some disciplines stress journal articles, others stress books, and the acceptance rate for written work varies greatly among disciplines.

An annual snapshot file of pertinent personnel and payroll data, supplemented with whatever merit data are available, will be more suitable for statistical analysis than the "live" institutional files. The data should be obtained at about the same time each year—for example, shortly after faculty contracts have been finalized. Then the snapshot file must be subjected to a rigorous reliability and validity check.

How Reliable Are the Data?

Cleaning the data is a dreary but essential chore. Each variable must be systematically screened for missing values and unrealistic codes. Any data file is bound to exhibit a few peculiarities, such as 200-year-old professors with no formal education or sex codes of 'Y'. Such errors, if uncorrected, can severely compromise subsequent analysis. The courts place considerable emphasis on data reliability (Baldus and Cole, 1980, pp. 74-75), and university administrators also are likely to reject an analysis based on questionable data.

The most reliable data elements probably will be those used in ongoing administrative processes like payroll and reappointment; data stored but used infrequently are apt to be riddled with errors. Data cleaning is best accomplished with a statistical package such as SAS, SPSS, or BMDP that can also serve as the vehicle for subsequent analysis. Different screening methods should be used for categorical variables and continuous variables. The discrete values of categorical variables such as sex and rank can be checked with univariate and bivariate frequency distributions, while basic descriptive statistics such as mean, maximum, and minimum provide a better check on continuous variables such as salary and years since hire. Plots of salary against each criterion variable are also useful for spotting extreme values as well as general trends (Waters and Milliken, 1983, p. 2).

Where Should the Analysis Begin?

The analyst who has done a thorough job of data cleaning will discover that the analysis is already underway. The simple statistical procedures employed for data cleaning provide a good preliminary look at the data by describing overall characteristics of the faculty.

The researcher should begin the process of analysis by asking questions about the variables and searching for significant interrelationships as guided by the purpose of the study. Is years since hire a linear function of salary? Do minority faculty wait longer than white males for tenure? Are the mean salaries of men and women significantly different? There are many statistical procedures and tests of significance that enable the researcher to answer such questions; the more popular measures include the chi-square, t-test, correlation, and analysis of variance. A good statistics text will contain discussions of the strengths and weaknesses of these and many more, and the manuals written to accompany statistical packages usually contain short descriptions of the tests performed.

Bivariate frequency distributions (crosstabulations) allow the researcher to examine the relationship between two categorical variables, such as sex and rank. (A continuous variable may be grouped in discrete categories, of course.) The chi-square test of interaction is commonly used to determine whether a bivariate distribution indicates a systematic relationship. Measures of association, such as phi, tau, or lambda, can be used in conjunction with the chi-square test to assess the proportional strength of the relationship.

The t-test for independent groups determines whether a statistically significant difference exists between the mean values of a variable for two distinct groups, such as a difference in years of experience for males and females or a difference in salary for minorities and whites. The test is based on the group sizes, means, and variances, so the variable should be normally distributed and, for the standard t-test, the groups should demonstrate approximately equal variance. The test requires continuous dependent variables, and the level of significance most often selected by statisticians and court judges is .05.

The Pearson product moment correlation provides a measure of the relative amount of association between two variables, allowing the researcher to determine, for example, how strongly salary and years at current rank are related. Pearson correlations are most appropriate for continuous variables and categorical variables with many ordinal classes. Other correlation coefficients are available when these conditions do not exist. Because the correlation coefficients are unitless, the coefficients for several pairs of variables can be compared with each other to assess the relative strengths of association between pairs.

Graphic plots of the variables are also useful for determining whether two variables are related and, if so, in what fashion. For example, a plot of salary against years since hire will show whether the relationship is linear or curvilinear. Several statistical tests of association are based on the assumption of a strict linear relationship, so graphic representations give the researcher yet another tool for evaluating statistical association.

How Can Multivariate Relationships Be Assessed?

Investigating bivariate relationships quickly gives rise to questions involving multiple indpendent variables. Are approximately equal salaries paid to men and women of the same rank? Do men have higher salaries than minority faculty with comparable numbers of publications? These questions can be answered by repeating the procedures discussed previously for as many groups as necessary—for example, salaries of male versus female professors, male versus female associate professors, and so on. The advantage of this approach is that it is simple enough to be easily understood by both court judges and university administrators. Unfortunately, the number of tests tends to proliferate past the point of easy evaluation. Multiple tests also increase the likelihood that random occurrences will be considered significant.

Three multivariate techniques frequently used for salary studies are analysis of variance, analysis of covariance, and multiple regression analysis, all of which focus on explaining the variation in salary in terms of several variables. Of these, multiple regression has come to be the most widely used for salary analysis, both in the courtroom (Finkelstein, 1980; Fisher, 1980; Simpson and Rosenthal, 1982) and in the university setting (Scott, 1977, 1979; Prather and Posey, 1981). Some of the more advanced statistical techniques have greater appeal for institutional researchers, but they must be employed cautiously to avoid baffling the intended audience. Two multivariate alternatives to regression analysis, canonical analysis and multiple discriminant analysis, are discussed by Carter, Das, Garnello, and Charboneau (1984); Muffo and Hengstler (1983) offer additional suggestions.

The goal of regression analysis is to describe the relationship between the dependent variable, salary, and the independent variables believed to be important determinants of salary. It is an appropriate technique for salary analysis when the data meet certain assumptions upon which the procedure is based. One important assumption is that a linear relationship exists between the dependent variable, salary, and each of the explanatory variables. This assumption can be checked with plots of salary versus the explanatory variables. Where the relationship is not linear, adding a quadratic term or converting the date to logarithmic form may relieve the problem.

The other assumptions are best understood in terms of random effects or "error"—the variation in salary not attributable to the explanatory variables. There are four assumptions concerning random effects which are important for the validity of interpretations based on regression analysis (Snedecor and Cochran, 1967, p. 14; Nie, Hull, Jenkins, Steinbrenner, and Bent, 1975, p. 341):

1. The random effects must not influence any of the other explanatory variables.
2. The random effects associated with one faculty member must be unrelated to those associated with another.
3. The random effects must have a normal statistical distribution.
4. The random effects must have constant variance.

If some factors are known to be determinants of salary but are omitted from the regression model, those factors are by default included with the random effects and may cause violation of one or more of these assumptions. For example, if merit factors influence salary but merit data are unavailable, then merit is automatically included with the random effects. The results of regression analysis may be severely compromised if the guilding model violates the assumptions upon which regression is based.

The results of a regression analysis include indicators of the overall significance of the model: The adjusted R^2 estimates the proportion of variation in salary explained by the independent variables; the standard error of the estimate is essentially the standard deviation of the actual salaries from the values predicted by the regression line; and the overall F-statistic tests the hypothesis that the explanatory variables or their linear combination have no relationship to faculty salary. The results also include regression coefficients and tests of significance for each of the explanatory variables.

When written in additive equation form, these coefficients describe the relationship of these variables to salary as a mathematical function.

What Regression Techniques Are Available?

Different regression equations can be obtained from a single set of data by using different regression techniques. The researcher's choice of technique should be guided by the goals of the salary study. Kleinbaum and Kupper (1978, pp. 227-232) describe the most commonly used approaches:

1. All-possible-regressions
2. Backward elimination
3. Forward selection
4. Stepwise regression.

These techniques are available as options for the regression procedure in many of the commercially available statistical packages.

All-possible-regressions calculates a regression equation for each possible combination of independent variables (k independent variables yielding 2^k-1 equations). The analyst examines the set of equations and chooses one on the basis of preselected criteria, which may include R^2 and standard error of the estimates, and which definitely should include a personal estimation of appropriateness in terms of university policy.

The backward elimination technique begins with the fitted regression equation which contains all independent variables and then sequentially removes variables based on their marginal contribution to the equation of each step. This process continues until all variables remaining in the equation are significant explainers of salary.

The forward selection technique starts with the independent variable having the largest correlation with salary and then sequentially adds variables until those remaining do not make a significant improvement in the explanation of salary. Stepwise regression is an enhancement of the forward regression technique in that a variable included in the regression equation can be removed at any step if its contribution becomes insignificant. The process continues until no more variables can be entered or removed.

Of these procedures and their modifications, none is the "right" or "wrong" way to do a salary analysis. Each method has its proponents and detractors. All-possible-regressions is the most comprehensive technique but also the most cumbersome; it is quite unwieldy when the number of explanatory variables is large. According to Beck (1978, p. 2), forward selection tends to agree with all-possible-regressions for small subsets of the variables, and backward elimination tends to agree for large subsets. He also maintains that all-possible-regressions "can do much better than the other methods and is unlikely to do poorly," although under certain circumstances either forward or backward regression can do *slightly* better than all-possible-regressions (Beck, 1978, p. 3). All-possible-regressions is the technique of choice when variables predict poorly alone but well together, a relatively uncommon situation (Beck, 1978, p. 4).

Which Regression Technique Best Suits the Purpose?

Each of these regression techniques has certain strengths and weaknesses; the researcher should strive to capitalize on the strengths of a technique for his or her particular analysis. The purpose of the study can be a deciding factor in this choice. Three common reasons for performing a salary equity study are these:

1. To explain the salary reward system
2. To predict and monitor individual salaries
3. To check for discrimination.

These three types of studies are not mutually exclusive, of course; one regression strategy could conceivably serve all three purposes. Some of the concerns associated with each type of study are discussed below.

Explaining the Reward System. The classic regression study detailed in a good statistics text is the proper approach for determining which factors best explain the variation in faculty salaries. The final product of such a study is a regression equation containing those variables which are statistically significant explainers of salary. The beta weights associated with each regression coefficient are good indicators of the explanatory strength of each factor but must be interpreted with care. Sex and minority status may be included as dummy explanatory variables; significant coefficients for these variables imply "discrimination" in the legal sense of disparate impact. A comprehensive example of this approach is presented by Braskamp and Johnson (1978), who forced variables representing sex and race to enter the regression equation last because they felt that approach best estimated inequities.

If the goal of the salary analysis is an explanatory equation, the researcher should select a regression technique which yields an equation containing only the most significant of the variables consistent with the school's reward system. This end could be achieved with the all-possible-regressions method if the number of variables in the original model is reasonably small, or with a forward or stepwise regression technique that selects variables in their order of significance. When developing an explanatory equation, the researcher must pay particular attention to interrelationships among variables, such as interaction effects and multicollinearity, that could distort the regression coefficients.

Interaction Effects. Most salary regression equations are additive, with the weighted predictors summed to yield a value for salary. When the salary impact of one variable depends upon the value of another in a non-additive manner, a multiplicative interaction variable may be used in addition to or instead of two additive ones. For example, the researcher may decide that an interaction variable representing the multiple of research publications and grants is more appropriate than each variable used in isolation.

A decision to create an interaction variable rather than to enter both variables in an additive manner must be made on theoretical considerations (Lewis-Beck, 1980, p. 55). Allowing the variables to enter *both* additively and multiplicatively may yield unreliable regression coefficients in some cases if the two variables are themselves correlated.

Multicollinearity. The problem of multicollinearity exists when two or more independent variables are highly correlated or one is a linear combination of several others. Multicollinearity reduces the stability of the regression weights and causes difficulties in interpreting regression coefficients. If the problem is severe enough, a regression coefficient may be reported as statistically insignificant even though the predictor helps explain salary.

Lewis-Beck (1980, pp. 59-60) describes the symptoms of multicollinearity. The most suspicious signal is a high R^2 for the equation with statistically insignificant coefficients. Another indication is substantial variation in regression coefficients when variables are added or removed from the equation. Analysts often try to resolve the question of mutlicollinearity by examining the bivariate correlations between predictor variables, but this approach fails to take account of multiple interrelationships. A preferred method for assessing multicollinearity (Lewis-Beck, 1980, p. 60) is to regress each independent variable on all the other independent variables; if R^2 is near 1.0, a problem of high multicollinearity exists.

The standard remedy for overcoming the instability in regression weights caused by multicollinearity is to increase the sample size, an option not open to the institutional researcher engaged in faculty salary analysis. Muffo and Hengstler (1983) suggest that some multicollinearity problems may be overcome by using factor analysis to condense the number of predictor variables into a smaller set of factors. Belsley, Kuh, and Welsch (1980) discusses this and other alternatives.

McLaughlin, Zierkes, and Mahan (1983) discuss the problem of multicollinearity with respect to possible misinterpretation of the regression coefficient for a dummy variable representing sex. Sex is often correlated, sometimes highly, with such variables as rank or discipline. In the presence of multicollinearity, the regression coefficient for sex may be affected by the influence of sex upon other predictors of salary. The unique effect of sex upon salary can be isolated by running the regression without the sex dummy and then calculating and summing the salary residuals for males and females.

Predicting Individual Salaries. If the sole purpose of the model is to predict salaries, the analyst should include as many legitimate predictors of salary in the model as possible. Omitted factors may be much more important for individuals than for groups. The preferred regression technique is either one that will force all variables to enter the equation or a technique, such as backwards regression, that will eliminate only the least significant variables. The analyst need not be as concerned with the kinds of interrelationships between independent variables that may distort regression coefficients because, in this case, the magnitudes of the coefficients are ignored.

Even if variables such as minority status and sex are significant explainers of salary, these variables *must* be excluded from the predictive model. Predicting an individual's salary on the basis of those characteristics actually constitutes discrimination—for example, by implying that a woman *should* be paid $500 less than a man.

Predicted salary of an individual "must be used judiciously because of the large standard error" (Braskamp, Muffo, and Langston, 1978, p. 239), which may be as high as $3000 in faculty salary analyses. This error also increases as the faculty member's characteristics get further from the mean of the group (Draper and Smith, 1981). Unfortunately, administrators often seem inclined to take predicted salary values more seriously than the magnitude of the standard error would warrant.

Checking for Discrimination. A class action suit brought by plaintiffs representing a group protected by law is the type most threatening to a university. Simpson and Rosenthal (1982) provides an excellent description of the course of a typical class action discrimination suit. In order to bring a class action suit against a college or university, the plaintiffs must establish a *prima facie* case demonstrating evidence of disparate treatment or disparate impact against an entire female or minority class. This is often done using fairly simple statistics, such as univariate and bivariate frequency distributions and one or more tests of significance (Baldus and Cole, 1980).

Countering the Prima Facie Case. If the court accepts the *prima facie* evidence as suggestive of discrimination, the burden of proof shifts to the defendants. "Proof" does not mean merely discrediting the evidence presented by the plaintiffs, but also showing that if the plaintiffs' "mistakes" are corrected, the case for discrimination disappears. That is, the defense must reinterpret the plaintiffs' evidence in a fashion that does not indicate discrimination.

The university can counter the plaintiffs' evidence by showing that the revealed salary differentials can be explained using legitimate criteria, such as job qualifications; that the differentials could result by chance; or that the differentials were caused by some factor(s) external to the situation (Simpson and Rosenthal, 1982, p. 7). The university analyst may argue, for example, that a comparison of overall mean salaries for men and for women, even when distributed across academic rank, may serve as a useful point of departure for analysis but does not constitute a conclusive argument for discrimination because too many factors relevant to salary allocation decisions are ignored.

When responding to a discrimination suit, the prudent analyst will take pains to keep the counter evidence simple and to keep the analyses tightly issue oriented. In many instances, however, the salary situation will be sufficiently complex to warrant running a multivariate analysis in order to account for the simultaneous influence of a number of factors.

Discrimination in Explanatory Variables. Dealing with the question of discrimination forces the researcher to focus on associations between predictors of salary that might be due to discrimination. In many colleges and universities, men have higher mean salaries, more PhDs, more publications, more full professorships, and so forth. Are these due to legitimate selection criteria, such as years of experience, or are they actually influenced by sex or minority status? The analysis must also distinguish between associations that could indicate discrimination outside the university and those suggestive of internal discrimination. A faculty member's education, for example, is acquired before coming to the university. Although the discrepancy in the number of male and female PhDs may be due in part to discrimination against women in undergraduate and graduate education, this is not an issue in setting faculty salaries. On the other hand, the sex discrepancies in academic rank may be due to promotion discrimination within the university.

Since promotion and salary are generally part of the same reward structure, using rank to predict salary may conceal sex discrimination. (Muffo and Hengstler, 1983, p. 13; Scott, 1977, p. 8). Using rank as an explanatory variable presupposes that all academic faculty are at their "proper" ranks. If promotion policies favor white males over female or minority faculty, those faculty discriminated against in promotion may appear to be well paid for their ranks when, in truth, they should have been promoted to higher ranks with correspondingly higher salaries.

Ultimately, the decision about whether to include rank as a predictor must be based on the analyst's knowledge of university policies and practices. If the analyst is convinced (and can convince others) that fair and equitable promotion policies obtain at the institution—that promotion discrimination does not exist—then inclusion of rank as a predictor may be justified (Finkelstein, 1980, p. 742). If, however, promotion and salary decisions are made by the same individuals using the same decision criteria, rank should be highly suspect and might best be excluded from the model on those grounds. This is particularly important if the model is being used in the context of a discrimination suit.

Merit data may also be tainted by discrimination (McCabe, 1979, p. 27; Waters and Milliken, 1983, p. 3). For example, the work of female or minority faculty may be devalued on the basis of sex or race, or these faculty may be given fewer opportunities to produce work considered "meritorious." In a university environment where merit is specified by institutional policy as a crucial factor in the reward system, omitting merit variables from the analysis may prejudice the results. On the other hand, tainted or unreliable merit data will contribute little to the analysis. Most analysts will have to weigh the consequences of using tainted or unreliable data versus omitting information that may be important to the salary process.

The White Male Model. One popular strategy to check for discrimination involves running a regression analysis only for the white males at the institution and then using the resulting regression equation to predict female salaries. The difference between actual and predicted female salaries gives an indication of how well female faculty are treated with respect to their male counterparts. The rationale behind this approach is to determine whether women (or minority faculty) are receiving the salaries they would get if they were white males—that is, in the absence of salary discrimination. This strategy is covered in detail by Scott (1977).

Waters and Milliken (1983, pp. 4-5) discuss how this technique can be used to investigate salary discrimination against an individual. The process requires computing the male residuals and graphing them in the same manner as the female salary differences. On the appropriate graph, identify the individual whose salary is in question and then overlay the two graphs to see how the individual is situated relative to other faculty.

The greatest disadvantage with the male model strategy is the lack of a formal test to indicate whether the salary differences are statistically significant. An advantage is that it works well in the situation where there are many male faculty but few females.

The Two-Sex Model. Waters and Milliken (1983, p. 5) also discuss a more elaborate strategy that allows the researcher to retain data for all cases in the same model. The two-sex regression model, which can be executed with SAS's GLM procedure, allows for a different slope for each sex for each continuous variable and a different intercept for each sex for each categorical variable. This model permits significance tests of the various slopes and intercepts for both sexes. Plots of the regression lines for both sexes can then be presented visually on a single graph. One disadvantage of this approach is that multicollinearity may mask sex inequities. Another is that if a large disparity exists between the number of males and females in the model, some of the categories for grouping may be too small.

CONFRONTING THE RESULTS

How Should the Results Be Interpreted?

The analyst must always bear in mind that the interpretation of any statistical results is heavily dependent upon the specification of the model defining the analysis and the reliability of the data used. Several factors should be used to judge the suitability of an analysis (among them R^2), the standard error of the estimate, the stability of regression weights, a residual analysis, and the relationship of the results to the theoretical considerations behind them.

Court justices and administrators place considerable emphasis on the magnitude of R^2; not all statisticians share their enthusiasm for this measure, however. Cook (1977) observed:

> It is perhaps a universally held opinion that the overall summary statistics (e.g., R^2, B) arising from data analysis based on full rank linear regression models can present a distorted and misleading picture. (p. 15)

As Achen (1982, p. 59) points out, R^2 characterizes the geometric shape of the regression points; it does not directly measure goodness of fit or strength of relationship because the variances are a function of the particular individuals being analyzed rather than the relationship of the variables. R^2 should not be the sole criterion for evaluating a regression analysis. The prediction errors, or residuals, give a better picture, particularly for a predictive model where R^2 may be artificially elevated due to multicollinearity.

Residual analysis, a procedure that has gained considerable popularity in recent years, focuses on identifying systematic patterns in the prediction errors that might indicate problems with the fit of the regression equation. In a properly fitted regression model, a plot of the residuals should appear as a random scatter of points approximately equally distributed above and below the regression line (Lewis-Beck, 1980, pp. 38-39). The scatterplot of the residuals may reveal other patterns, such as outliers with residuals that are very high in absolute value; a curvilinear pattern indicating that the independent variables do not have a linear relationship to salary; heteroscedasticity, where the variance of the residuals depends upon the value of one or more independent variables; or a linear relationship between the predictors and salary, indicating that some relevant variable has been omitted from the regression equation.

If the researcher has been thorough in data cleaning and preliminary analysis, these problems are less likely to occur. Residual analysis does provide a good check on the fitness of the regression, however, and is highly recommended.

How Should the Results Be Presented?

As Norris (1983) so wisely points out, the entire analysis may be wasted if it is presented in an arcane or unintelligible manner. Readers are referred to his excellent article for guidance. Despite the reams of computer printouts that may have been generated in the quest for a fair equity assessment, the figures that actually influence a cynical judge or a harried administrator will prove to be few indeed. A thirty-page report may be valuable for documenting the entire analytic process, but it is likely to go unread by anyone in a position of authority.

Recognition of this simple fact should sensitize the researcher to focus on the vital elements of the analysis and plan the most effective methods of presenting them, which in most cases means simple tables and graphs. Failure to produce these simple summaries may drive a judge or administrator to lift some ideas wholesale from the hefty report, perhaps woefully out of context. The researcher must recognize that he or she simply will be unable to share with any decision maker the entire wealth of information gleaned from a salary equity study.

When the analysis is finally complete, the institutional researcher may ruefully conclude that his or her chosen solution to the problem is only the best of a number of poor alternatives. This realization should be presented along with the statistical evidence, because too often the numbers are reified while the human factors behind them are overlooked. Statistical studies represent a good point of departure for asking questions about salary equity and making policy decisions. But the questions are too complex to be resolved in terms of numbers alone.

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The AIR Professional File

Intended as a presentation of papers which synthesize and interpret issues, operations, and research of interest in the field of institutional research. Authors are responsible for material presented.

Published up to four times per year by the Association for Institutional Research, 314 Stone Building, Florida State University, Tallahassee, FL 32306.

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