Use of Latent Variable Models for Detecting Discrimination in Salaries

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A major criticism of the direct regression approach to detecting employment discrimination has been that when qualifications are not perfectly measured, one could be misled by the well-known bias associated with using fallible covariates with nonequivalent groups—sometimes called the "errors in variables" problem. With regard to salary discrimination, a number of solutions to this "problem" have been proposed. I argue that this bias should be treated as irrelevant and that the proposed solutions are misleading. In order to sustain the argument against direct regression (or its nonparametric analogue), one must be willing to assume that true quality of performance influences salary over and above the influence of measures of performance. This involves postulating a latent variable, often labeled "qualifications," that has a direct effect on salary. For several reasons it may be undesirable to make this assumption. Other problems with the regression approach, however, do require serious consideration.

Statistical comparisons for detecting inequities in salary and employment practices are common in the courts and in empirical investigations aimed at examining social equity. As a result, considerable discussion and controversy have been aroused over the appropriateness of various statistical methods and diagnostic tests for making these comparisons.

Probably the most common diagnostic technique is a direct regression analysis (or, equivalently, analysis of covariance) in which salary is regressed simultaneously on a measure of merit (for academic positions this might be some composite of number of publications, years of experience, etc.) and a dichotomous variable indicating group membership (e.g., sex or race). A nonzero effect of group membership on salary with merit partialed is taken as evidence of bias. A number of criticisms of this direct regression approach have been raised, and alternative procedures have been proposed to deal with its difficulties.

In this article I describe these criticisms and the proposed alternative procedures for detecting inequities. I conclude that despite the claims of much recent literature, the most commonly cited criticism of the direct regression approach—namely the probable presence of measurement errors in the indices of merit—is basically inappropriate, and that existing procedures designed to correct this "problem" are ill-conceived. Moreover, under reasonable assumptions about the organization's decision-making process, the fact that measured merit is not a perfect indicator of true quality (but includes well-behaved measurement error), will not itself cause the direct regression diagnostic test to yield misleading conclusions. In fact, social policy considerations of the kinds of claims that employers ought to be allowed to make about their salary decisions are crucial in evaluating the adequacy of alternative statistical techniques. One sensible social policy leads to models that favor direct regression over alternatives that correct for measurement error. Other major criticisms of direct regression, however, are more substantial and deserve careful consideration.

It is important first, however, to define discrimination. I use the example of sex discrimination throughout, but the argument applies equally to discrimination based on group membership (race, sex, age, etc.) in general.

Definition of Sex Discrimination

The problem of how to define sex discrimination so as to permit empirical investigation is not trivial. I adopt a definition that seems to entail most of what is usually meant by discrimination. *Sex discrimination* is here defined as the differential treatment of employees of equal true qualifications on the basis of their sex. True qualifications are assumed to incorporate all legitimate factors including seniority, merit, experience, productivity, type of job, and so on. In statistical terms, I interpret this definition to mean that the distribution of salaries for men with a given set of qualifications is the same as that for women with the same set of qualifications. In most instances, the means of these conditional distributions are of primary interest; hence, in what follows I restrict my attention to mean salary differences. Furthermore, the argument is made using population values. The conclusions do not change when sampling variability is considered.

If one makes the following simplifying assumptions, the definition of discrimination can be expressed statistically very concisely.

1. All relations are linear, perhaps because they were linearized by appropriate transformations.
2. The regression functions of salary conditional on qualifications for men and women are parallel; that is, they have the same slope.
3. The conditional distributions of salary for given qualifications and sex all have the same variance and shape.

If these assumptions are met, the definition can be expressed

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as follows: Discrimination will be said to occur if and only if the partial correlation between salary (S) and sex (X), with true qualifications (Q) partialed out, is different from zero. That is,

$$\rho_{SX \cdot Q} \neq 0.$$

If it were possible to obtain actual values of Q, then evaluating whether this discrimination condition is met would be fairly straightforward. However, because Q typically cannot be measured perfectly, it becomes necessary to construct a model incorporating additional assumptions that specify the nature of relations among Q, S, X, and the available measures of Q. The validity of these additional assumptions cannot usually be assessed by a purely statistical examination of the data. Consequently, questions about the employer's actual decision-making process often become relevant in examining the plausibility of a particular statistical assumption simply because that assumption's validity cannot be directly checked in the data due to the fact that Q is unobserved. Moreover, if some aspects of the employer's decision-making process are known, they can often be shown to have predictable consequences for the validity of the model's statistical assumptions. The predictable statistical consequences of common decision-making processes can thus be very important in evaluating whether a particular model is adequate for analyzing whether discrimination as defined previously has occurred (cf. Dempster, 1984, p. 318).

The abovementioned definition of discrimination is, of course, not the only one possible. Gollob (1983, 1984a, 1984b), for example, proposes a definition based on an examination of differences between what employees are paid and what their qualifications are "worth," as explicitly or implicitly defined by relevant decision makers. Gollob (1984b) examines a number of discrimination indices from the standpoint of his definition and explains the implicit assumptions of each about the worth of qualifications once his definition is adopted. The question of whether worth of qualifications ought to be a part of an adequate definition of discrimination is complex and open to debate. I follow the Equal Pay Act of 1963 (see, e.g., Koch & Chizmar, 1976, p. 129) and many court decisions in avoiding any consideration of worth of qualifications.

Problems With Direct Regression

A major criticism of the direct regression approach has been that when qualifications are not perfectly measured one could be misled by the well-known bias associated with using fallible covariates with nonequivalent groups—sometimes known as the "errors in variables" problem. As regards salary discrimination, this criticism has been made most strongly by Birnbaum (1979, 1981) and Roberts (1980). Basically, the argument goes as follows. Suppose that an organization pays its employees strictly according to their true qualifications or true productivity except for random (unrelated to sex) variations in salary. Suppose further that there is a relation between sex and true qualifications, say, with men being more qualified on the average. Finally, suppose that an investigator, attempting to determine whether there is sex bias in salaries, uses some measure of merit as a "proxy" or less than perfect indicator of true qualifications in a regression analysis predicting salary from merit and sex. If we assume that all relations are linear and that salary residuals and measurement errors in merit have zero means and are uncorrelated with sex, true qualifications, and each other, we can represent the situation by the path diagram shown in Figure 1.

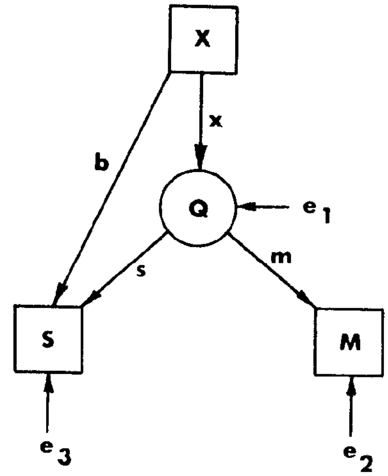

Figure 1. Model with salary directly influenced by true qualifications. (M: measured merit; Q: true qualifications; S: salary; and X: sex. e_1: error variable; e_2 and e_3: random errors. b, m, s, and x are structural regression parameters; b represents sex bias.)

The structural equations that describe this situation for the ith employee are as follows (without loss of generality all variables are assumed to have means of zero):

$$Q_i = xX_i + e_{i1},$$

$$M_i = mQ_i + e_{i2},$$

and

$$S_i = sQ_i + bX_i + e_{i3}, \tag{1}$$

where M_i represents measured merit (for academic positions, perhaps some composite of experience, publication record, teaching effectiveness, etc.), which is assumed to be an imperfect indicator[1] of Q_i, the true quality of performance. S_i represents salary; X_i is a dummy variable coding sex, giving men the higher number; and e_{i2} and e_{i3} are random errors assumed to be uncorrelated with Q_i and with one another. The error variable e_{i1} is assumed to be uncorrelated with X_i and the other errors. The coefficients x, m, s, and b are structural regression parameters. The parameter b represents sex bias, that is, the direct effect of sex on salary, and would be zero in this situation.

Now an investigator performing an ordinary regression analysis predicting salary from merit and sex, assuming for simplicity that he or she has observations on the entire population, would find the regresion weight for sex to be

$$\beta_{SX \cdot M} = \frac{\sigma_{SX}\sigma_{MM} - \sigma_{SM}\sigma_{MX}}{\sigma_{MM}\sigma_{XX} - \sigma_{MX}^2}, \tag{2}$$

[1] For simplicity's sake, the models that follow contain only a single imperfect indicator of true qualifications, M, although in most applications there would likely be several such indicators. The arguments are not fundamentally affected if one allows several indicators instead of just one. Thus M can be thought of as a block of less-than-perfect indicators of true qualifications, if so desired.

where σ_{SX}, for example, is the covariance between salary and sex.

It is straightforward to show (by substituting the covariances among S, X, and M implied by Equation Set 1 into Equation 2) that this regression weight for sex would be

$$\beta_{SX \cdot M} = b + \frac{sx\sigma_{22}}{m^2\sigma_{11} + \sigma_{22}},$$

where σ_{11} is the variance of e_1 and σ_{22} is the variance of e_2.

It is clear from this that if s, x, and σ_{22} are greater than zero, the regression weight for sex in an equation predicting salary from merit and sex will overestimate the true sex bias, b. If salaries are directly influenced by employees' qualifications, then s will be greater than zero; if men are more qualified on average than women, then x will be greater than zero; and unless the merit measures are perfect indicators of qualifications, σ_{22} will be greater than zero. Under these assumptions, then, a direct regression analysis could lead one to conclude that women were being paid less than equally qualified men when in fact there was no sex bias at all.

This "underadjustment bias" in ordinary regression led Birnbaum (1979, 1981), Roberts (1980), and others to recommend alternative statistical procedures to detect salary inequities. Roberts (1980) recommends "reverse regression," that is, regressing merit on salary and sex, and using the coefficient for sex in this equation as an index of discrimination. Birnbaum (1979, 1981) calls the abovementioned model the "one-mediator" model and argues that it is only when both the direct regression coefficient for sex and the reverse regression coefficient for sex agree in the direction of sex bias they suggest that one should reject a no-bias hypothesis.

These alternative procedures have been criticized on a number of grounds. Madden (1982) and Kahn (1982) have argued that the reverse regression solution to the problem of imperfect measurement of qualifications requires that salary be the true reward variable of interest in sex discrimination and that it be measured perfectly. If "total compensation" (including things like fringe benefits and nonmonetary compensation) is the true reward variable, for which salary is only a proxy, they argue that reverse regression will be subject to essentially the same objection as direct regression.

Others (Ferber & Green, 1982; McLaughlin, 1980; Weisberg & Tomberlin, 1983) have argued that because sex discrepancies in salaries for similar qualifications are the kind of unfairness that interests us, rather than differences in qualifications for similar salaries, the reverse regression approach is conceptually inappropriate because it tests the wrong null hypothesis (however, see Conway & Roberts, 1983, for an argument that both kinds of fairness are important).

Goldberger (1984) and Solon (1983) have demonstrated that even if the model in Figure 1 is adopted, estimates of the effects of discrimination obtained using reverse regression will also be biased (unless $\sigma_{33} = 0$), albeit in the opposite direction from estimates obtained using direct regression. Goldberger (1984) gives a very useful and detailed analysis of a number of models that might be used in analyzing discrimination. He argues that the only known model (at present) for which reverse regression provides a valid estimator of sex bias is the one in Figure 1 (or its multivariate generalization; see Footnote 1) with σ_{33} required to be zero. Goldberger provides a statistical test of the restrictions implied by the model and concludes that unless the data can be shown to adequately fit the model, reverse regression results should not be taken seriously.

Although these are important criticisms, there is a more fundamental objection against the reverse regression approach and the one-mediator model. Both reverse regression and Birnbaum's test were designed to deal with the underadjustment bias described previously. It is important to see, however, that the underadjustment bias occurs only as a result of a crucial feature of the model in Figure 1 or Equation Set 1. This crucial feature is that the model makes the statistical assumption that salary is a linear function solely of true qualifications plus random noise unrelated to measured merit. To put it another way, it is assumed that the conditional relation between salary and imperfectly measured merit, holding true qualifications constant, is zero.

It is important to consider what is necessary for this assumption to hold. The most important condition is that salary decisions must have been totally uninfluenced by whatever imperfections or measurement errors existed in the measures of merit at the organization's disposal. If any imperfections in these measures influenced salary, the conditional relation between salary and imperfectly measured merit, holding true qualifications constant, would not be zero, and the model would be misspecified.

Adopting this model thus seems to require that courts and other interested parties be willing to assume that the organization had access to the true qualifications of each employee and based its salary decisions solely (except for random noise) on them, while ignoring any less than perfect measures of merit (e.g., performance evaluations, experience, or productivity measures) that might have been available. At the very least the model assumes that the employer is somehow able to separate the "true" and "error" components of the merit measures from one another and rely only on the true part. This scarcely seems reasonable, yet the rationale for reverse regression and the one-mediator model depends heavily on precisely this postulate.

McFatter (1982) pointed out the implausibility of this assumption and showed that if one modifies the model to allow the possibility that salary is influenced by both true qualifications *and* measured merit, it is impossible without further constraints on the model to determine whether sex bias is occurring or not. Moreover, under this circumstance reverse regression and the related one-mediator model test could result in overadjustment, underadjustment, or no bias at all, depending on the specific relations among salary, qualifications, and merit.

I argue that a very sensible constraint to impose on the model is to disallow any direct influence of the latent variable, true qualifications, on salaries.

True Qualifications as a Latent Variable

As indicated previously, true qualifications must be treated as a latent or unobservable variable in most actual situations. Perfect measures of employees' qualifications are usually simply not available even to employers, much less to outside analysts attempting to statistically detect sex discrimination. This fact itself, however, is insufficient to justify constructing a model like Figure 1 and imagining it to be an improvement over an ordinary regression model simply because it contains a latent variable (reassuringly designated "qualifications").

In the first place, as Weisberg and Tomberlin (1983) point out, the classical measurement error model that is assumed in Equation Set 1 to describe the relation between qualifications and measured merit may not be very appropriate. They argue as follows. "Suppose, for example, we are using education as a proxy for productivity. Should education be regarded as productivity plus random error . . . or is the reverse model . . . , in which productivity is regarded as education plus error, more appropriate?" (1983, p. 400). To Weisberg and Tomberlin's argument we may add that for some proxies one model might seem more reasonable, whereas for others, gathered on the same employees, the opposite would. With respect to Figure 1, the issue may be cast as the question of whether the arrow should point from Q to M or from M to Q. This is not a trivial consideration in this model, as whether one expects bias in regression esimates, and the direction of any such biases, depends on the actual relation between qualifications and its proxies (Goldberger, 1984; Reichardt, 1979; Weisberg, 1979). In the model I shall propose, in which there is no direct path from Q to S, the direct regression analysis provides an unbiased estimate of the discrimination effect regardless of which way the arrow between Q and M points.

Second, in order to take seriously, as a null hypothesis, a no-bias model with a single latent variable, we ought to have some grounds for thinking that the latent variable has something to do with true qualifications. Testing the adequacy of the one-mediator, no-bias model (Birnbaum, 1979, 1981; Goldberger, 1984) only answers the question of whether we can account for the observed covariances by postulating a single underlying factor. It does not specify the nature of that factor. Even if the model fits, the one mediator could as well be personal prejudice as true qualifications. The courts might with good reason be reluctant to allow employers to use a no-bias null hypothesis that has this possible interpretation. Now if a reasonable number of good indicators of merit were available, it might be possible to make an argument on factor analytic grounds that the latent variable was more like true qualifications than anything else. However, whether this could be done convincingly in many real situations remains an open question.

Third, as I argued in the previous section, even if we could be sure that the latent variable was really true qualifications and that the classical measurement error model was appropriate, it is probably unreasonable to assume that employers base their salary decisions on unobservable true qualifications while remaining uninfluenced by any imperfections in the fallible measures of merit actually available to them.

For these three reasons, then, it may be best for the courts to discount statistical analyses of discrimination that explicitly postulate (or depend for their rationale on the assumption) that salaries are directly influenced by the unobservable variable, true qualifications, rather than observable measures of those qualifications. This would rule out the reverse regression and the one-mediator model approaches (at least as strategies for eliminating the "underadjustment bias"). Would adopting this course imply an assumption that qualifications were measured perfectly? Not at all. Figure 2 shows a model that includes the idea that measured merit is only an imperfect indicator of qualifications, but excludes a direct path from Q to S. It is easy to show that as long as there is no direct path from X to M, the coefficient for X in the direct regression of S on M and X will correctly reflect whether the nondiscrimination condition, $\rho_{SX \cdot Q} = 0$, is met or not. The reverse regression and one-mediator model tests would not correctly reflect this. The crucial point here from a policy perspective is that requiring the model to have no direct path from Q to S is equivalent to saying to the employer, "If you have sex differences in salary, you must be able to justify those differences with explicit, *observed* measures of qualifications that can account for the differences." This does not require that qualifications be measured perfectly, but simply prevents employers from justifying sex differences by claiming to have made their decisions based on unobserved true qualifications while remaining uninfluenced by any "noise" in the actual observed measures of merit available to them.

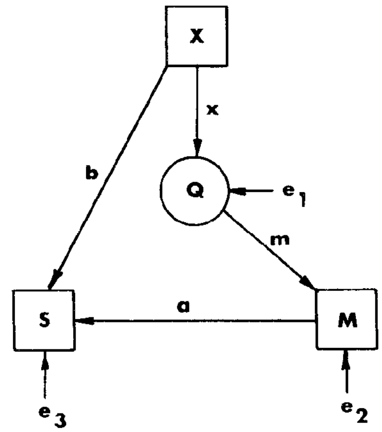

Figure 2. Model with salary only indirectly influenced by true qualifications. (M: measured merit; Q: true qualifications; S: salary; and X: sex. e_1: error variable; e_2 and e_3: random errors. a, b, m, and x are structural regression parameters; b represents sex bias.)

Some might object to the approach I have outlined on the grounds that it is only reasonable to assume that the employer may have access to more information about qualifications than is contained in the measures of merit available to the statistician (see, e.g., Dempster, 1984; Roberts, 1980). If so, the argument might go, should not the model used to assess discrimination take this possibility into account and include a latent variable that is unobserved to the statistician, but that has a direct effect on the employer's salary decisions?

It may sometimes be reasonable to think that employers have access to additional information about qualifications and use that information in setting salaries, but the important question is "What is the relation of any such additional information to sex?" If the additional information the employer uses is uncorrelated with sex (i.e., all sex differences in true qualifications are captured by the merit measures available to the statistician), then the direct regression analysis will still yield an unbiased estimate of sex discrimination, whereas reverse regression will be biased (cf. Goldberger's, 1984, "multiple causes" model; Wesiberg & Tomberlin, 1983, p. 403). If the additional information is sex related, then it is true that direct regression will be biased, but only to the extent that the additional information is sex related. Thus, direct regression is biased here only if one allows the employer to claim that additional information about qualifications that is both *unobserved* (to the statistician, courts, etc.) and *sex related* has directly influenced the employer's salary decisions. Whether this kind of claim should be allowed is, of course, the key question. Furthermore, it highlights the fact that the statistical method or model used to detect discrimination cannot be justified purely on statistical or even scientific grounds. Policy considerations, such as the nature of the claims employers ought to be allowed to make about unobserved factors in salary decisions, determine at least in part the kind of statistical method that should be used.

It is also important to realize, in considering the models of both Figures 1 and 2, that the assumption that there is no *direct* path from X to M is a strong assumption. It requires that any sex differences in the measure of merit be due solely to sex differences in true qualifications; that is, the measure of merit must be unbiased. If it is not unbiased in this sense then *none* of the statistical approaches in common use will be trustworthy. Measures of merit that cannot be assumed to be free of sex bias themselves are called *tainted* variables (Finkelstein, 1980), and in a number of cases the courts have not supported their inclusion in a regression analysis (Baldus & Cole, 1980). Examples of variables that may be challenged on these grounds are job rank and supervisory merit ratings, both of which, it is sometimes argued, are subject themselves to discrimination. Whether such variables will be allowed usually depends on the case that can be made for their being free of bias themselves.

More Serious Problems With Regression

I have argued that the so-called underadjustment bias, because of imperfectly measured qualifications, is not really a viable objection to regression studies of discrimination. However, other more serious difficulties may arise in regression analyses of discrimination. Many of these difficulties arise from the failure of data sets in actual discrimination cases to conform to the assumptions underlying regression analysis. Assumptions of linearity, homoscedasticity, and similarity of regression functions among the groups are almost certain to be violated in real cases. Sometimes these violations can be handled satisfactorily through the use of transformations or more sophisticated estimation techniques, but in order to do so, the analyst must examine the data thoroughly and explicitly with regard to these assumptions. For example, controlling for seniority effects on salary almost always requires that nonlinearity be taken account of in some way, perhaps by transforming variables to obtain linearity.

Hoffman and Quade (1983) have argued that over and above possible violations of statistical assumptions and issues concerned with measurement errors, the regression approach suffers from conceptual problems when used to diagnose discrimination. They distinguish between two different approaches to "controlling for" or "taking account of" variables in an analysis: (a) adjustment for the variables, which underlies the regression or general linear model approach; and (b) holding constant the variables, which underlies analyses based on blocking or matching. Hoffmann and Quade argue that the second approach more appropriately assesses what the courts are really interested in, because it compares individuals in different groups who are actually similar on the variables in question rather than "hypothetically similar groups produced by statistical adjustment" (1983, p. 430). They suggest a nonparametric analysis of covariance technique, developed by Quade (1982), for comparing all possible pairs of individuals matched within a specified tolerance, and argue that it allows an analysis more sensitive than regression analysis to the actual processes that produce salary differences in an organization.

Whether this is the case or not, the rationale and conceptualization of discrimination that underlie the nonparametric matching approach are quite compatible with my arguments. In fact, if the underadjustment bias due to measurement error were to be accepted as a valid objection to direct regression, it would also be a valid objection to the nonparametric matching approach.

In sum, it seems clear that there are circumstances under which direct regression analysis may not be an appropriate method for detecting discrimination. It could be that under these circumstances a matching approach such as Hoffmann and Quade's will prove most reasonable. However, the mere presence of measurement errors in available indicators of qualifications is not a sufficient reason for rejecting direct regression in favor of alternatives like reverse regression or the one-mediator model. Moreover, in order to evaluate alternative statistical methods for detecting discrimination, extrastatistical decisions must be made about the kinds of claims that employers should be allowed to make about employees' unobserved qualifications and their influence on salaries.

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