Exhibit P-456

Analyzing Employment Discrimination: From the Seminar Room to the Courtroom

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In scholarly work, most economists investigate empirical questions about employment discrimination by estimating the parameters of a suitable econometric model—for example, the parameters b and d of the simple prototype equation

$$(1) \qquad P_i = \sum_j b_j X_{ji} + \sum_k d_k D_{ki} + u_i$$

where i subscripts refer to individuals; P is some employment outcome (e.g., pay); the X_j's are individuals' characteristics (e.g., education); the D_k's are demographic indicator variables for individuals' sex, race, ethnicity, and the like; and u denotes unobservables. If the coefficient d_k on variable D_k denoting group k is positive (or negative), then persons in group k receive higher (or lower) P, on average, than persons in a reference group who are the same in terms of all other factors (both X and u). In this case, and subject to the usual caveats, economists would generally say that group k benefits from (or suffers) employment discrimination, relative to otherwise similar persons in the reference group, with respect to the outcome P.

I. Problems with the Economist's Methodology

The main caveats concern the characteristics (X) taken into account when (1) is estimated. The first is the *omitted-variables problem*: data on some variables relevant to the outcome P may not be available. If so, these variables cannot be included among the X's; rather, they must be subsumed into the error term u. If persons in different demographic groups who are similar in terms of the included variables (X) are nevertheless systematically different in terms of the omitted variables, then the error term u will be correlated with the demographic variables (D), even when the included variables are held constant. In this case, conventional regression estimates of the d parameters will be statistically biased: they will not measure the true difference in the outcome P for otherwise similar persons in different demographic groups.

The second caveat about the variables used in estimating (1) is the *included-variable problem*: some of the included variables may themselves be affected by discrimination. In this case, conventional regression estimates of the d parameters face two kinds of objections (David E. Bloom and Killingsworth, 1982). The first is conceptual: if the X's are affected by discrimination, then differences in the outcome P for persons in different demographic groups who have the same characteristics (X) measure only the extent of "incremental" discrimination (i.e., only those effects of discrimination not already embodied in discrimination-induced differences in these characteristics). The second objection is statistical: if the X's are affected by discrimination—in other words, if they are determined along with the employment outcome of direct interest, P—then they are endogenous; and conventional regression estimates of the parameters of a model with endogenous right-hand-side variables may suffer from statistical bias. Thus, conventional regression methods may not even provide unbiased estimates of the extent of "incremental" discrimination.

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II. The Legal Relevance of the Economist's Methodology

Broadly speaking, in evaluating claims of employment discrimination the legal system has been remarkably receptive to studies using the economic methodology just described. Moreover, in considering how the above-noted caveats might apply to empirical studies in specific cases, the legal system has at times shown a degree of sophistication that compares not unfavorably with that found in the typical economics seminar room (see e.g., Bloom and Killingsworth, 1982; Orley Ashenfelter and Ronald Oaxaca, 1987 [especially p. 324]). However, like Oliver Twist and Samuel Gompers, the legal system not infrequently asks economists for "more"—for studies that tackle substantive questions not usually considered in the literature, and which may take the researcher into terrain that is not well marked on conventional methodological maps.

One such issue has to do with identifying the specific employment practices that may have led to discriminatory outcomes. For example, suppose an economist analyzes this week's payroll at the XYZ Company using equation (1) and obtains a negative and statistically significant coefficient on the indicator variable for female sex. In a scholarly setting, this would be quite sufficient to establish that XYZ's current salary payments discriminate against women relative to men (subject, of course, to the caveats noted previously). For legal purposes, however, it can be desirable or even essential to go beyond this simple finding to ask how it came about: Does XYZ pay different wages to equally qualified men and women doing the same job ("unequal pay for equal work")? Are women less likely than equally qualified men to be in better-paid jobs ("unequal access to better-paid work")? Is there discrimination in starting salaries? in salary increases? in promotions?

A paper by Burton G. Malkiel and Judith Malkiel (1973), one of the first contributions to the scholarly literature in this area, is noteworthy both for its insightful discussion of some of these issues and for its complete silence regarding others. Using an expression similar to (1), the Malkiels found strong evidence of sex discrimination in current salary at a particular employer. Rather than stop there, however, they went on to consider what factors might have produced this result. In effect, they generalized (1) by introducing a two-equation system of which the following is a simple prototype:

$$(2a)\quad P_{1i} = \sum_j b_{1j} X_{ji} + \sum_k d_{1k} D_{ki} + g_1 P_{2i} + u_{1i}$$

$$(2b)\quad P_{2i} = \sum_j b_{2j} X_{ji} + \sum_k d_{2k} D_{ki} + u_{2i}$$

where there are now two employment outcomes, P_1 and P_2, and thus two sets of parameters (b_1 and d_1 for P_1; and b_2 and d_2 for P_2) and two terms (u_1 and u_2) denoting unobservables. In terms of the Malkiels' analysis, P_1 refers to current salary and P_2 refers to job level. Note that (2a) implies that P_2 is a structural determinant of P_1 via the coefficient g_1.

Equation (2a) raises the included-variables issue, for P_2 ("job level") may itself be affected by discrimination (i.e., the d_2's may be nonzero). Indeed, the Malkiels' estimate of the d_1 coefficient for female sex in (2a) was essentially zero. Far from concluding that this meant that there was no "discrimination," however, they noted that this indicated only that there was no unequal pay for equal work (i.e., no sex difference in pay for otherwise similar persons in the same job level P_2). They also obtained a large negative estimate of the d_2 coefficient for female sex in (2b) and noted that this measured unequal access to better-paid work (i.e., a sex difference in job level for otherwise similar persons). Finally, the bottom-line discriminatory difference in pay is the sum of these two components—for example, $dP_1/dD_k = d_{1k} + g_1(\partial P_2/\partial D_k) = d_{1k} + g_1 d_{2k}$ for group k. Thus, the Malkiels not only showed how specific employment practices contributed to a bottom-line discriminatory pay differential; they also showed how to resolve the conceptual issues raised by the included-variables problem—by properly interpreting the results.

Unfortunately, the Malkiels had much less to say about the statistical issues, even though these may be as serious as the conceptual issues. Using ordinary least-squares regression (OLS) to estimate (2a) as the Malkiels did (and as many economists would do) may yield biased estimates of g_1 (i.e., the effect of "job level" on pay) and even of the d_1's (i.e., the extent of "unequal pay for equal work"). For example, suppose a company discriminates against women by systematically putting them in lower job levels than men, other things being equal. It follows that, for persons with the same observed characteristics X, *at the same job level*, the average woman will be better-qualified than the average man in terms of the unobserved factors u_2 that affect job level. If the unobservables u_2 are positively correlated with the unobservables u_1 that affect pay (e.g., if unobserved "motivation" affects both job level and pay within job level), then OLS estimation of (2a) may tend to imply that women are paid *more* than otherwise similar men at the same job level. Of course, such a result would not mean that men actually suffer discrimination in the form of "unequal pay for equal work"; it would merely measure the extent of statistical bias in OLS estimation.

As any good econometrician will attest, estimation with endogenous right-hand-side variables—the essential statistical issue raised by expressions such as (2a)—is not exactly a novel problem. Might it not be possible to use a standard technique already available in the literature—instrumental variables, say—to derive consistent estimates of the parameters of equations such as (2a)? In principle, yes. In practice, however, the legal system's interest in investigating the variety of distinct decisions that impinge on current salary and the complexities of each may require new techniques. For example, in the Malkiels' work, the "job level" variable P_2 is categorical rather than continuous (as in the usual instrumental-variables setup) and has ordinal but not cardinal meaning; and, in many companies, pay given one's "job level" is subject to both a minimum and a maximum. Perhaps, then, one might tackle this problem by extending the two-limit Tobit model (Richard N. Rosett and Forrest D. Nelson, 1975) to the case of a simultaneous-equation system with an ordered categorical variable. Unfortunately, this is likely to lead into some unfamiliar territory, as no such model exists, insofar as I know.

III. An Example: Analyzing Hiring Discrimination

In contrast with other employment practices, it might seem that analyzing race or sex differences in an employer's hiring decisions would be quite straightforward. Since such an analysis would be concerned with job *applicants*, who by definition are not now working for the employer, none of their characteristics X can have been influenced by the employer. Apparently then, there are no endogenous variables and no included-variables problems.

The reality can often be more complicated, however. For example, hiring may not be a simple yea-or-nay affair but rather a multistage process in which interviews, tests, and the like precede the final hiring decision. Here, as with pay, the law may either advise or require analysis of each stage as well as (or even instead of) the ultimate hiring decision. For analyses of each stage other than the first, a form of the included-variables problem may arise: the applicants considered at stage n are limited to those who survived stage $n-1$, whose outcome, like that of stage n, was ultimately determined by the employer. Thus, estimates of race and sex effects at any stage may be statistically biased due to nonrandom selection at the previous stage.

As an example, consider the following analyses of alleged race discrimination in hiring for low-level jobs based on actual litigation involving a nondurable-goods manufacturer. Each applicant was first interviewed by one of several plant officials; the survivors of this stage were then given further consideration. As implied earlier, analyzing the first or "interview" stage of this process is straightforward; in column (i)

TABLE 1—ANALYSES OF FIRST-STAGE INTERVIEW AND FINAL HIRING DECISION AT A NONDURABLE-GOODS MANUFACTURER

A. *Single-Equation Probit:*

	Dependent variable			
	Pass interview			Hired
Statistic	(i)	(ii)	(iii)	(iv)
Coefficient (SE) on indicator variable for black race	−0.841 (0.110)	−0.870 (0.112)	−0.800 (0.225)	−0.391 (0.153)
Log likelihood	−471.788	−458.651	−458.393	−295.241
Total sample:	805	805	805	485
Number succeeding:	485	485	485	309
Other variables:	(a)	(b)	(c)	(a)

B. *Two-Equation Probit*

	Dependent variable		
	Pass interview		Hired
Statistic	(v)		(vi)
Coefficient (SE) on indicator variable for black race	−0.870 (0.119)		−0.657 (0.176)
Cross-equation correlation (ρ)		0.655 (0.290)	
Log likelihood		−752.993	
Total sample:	805		485
Number succeeding:	485		309
Other variables:	(b)		(a)

[a]Indicators for female sex, age less than 18, educational attainment (4–8 years; 9–11 years; 12 years; some college), no prior work experience, and occupation category of most recent prior job; and continuous variables for years worked in immediate previous job, total prior work experience, square of total prior work experience, and years of prior work experience, by occupation and industry categories.

[b]All variables in (a), plus three indicator variables denoting interviewer.

[c]All variables in (b), plus three black-race × interviewer interaction variables.

of Table 1, I present the estimated coefficient on the indicator variable for black race in a probit analysis of an equation similar to (1) in which the dependent variable, P, denotes passing the interview stage. Even for this stage, legal considerations might suggest (or require) consideration of the effect of each interviewer. Accordingly, column (ii) of Table 1 repeats the analysis of column (i) with one difference: the analysis of column (ii) adds indicator variables to identify the plant official who interviewed each candidate. The difference in log likelihoods between columns (i) and (ii) suggests that the plant officials differed significantly in their propensity to pass applicants. However, as shown in column (iii) these differences were race-neutral: interacting the indicator for "black race" with the indicators for "interviewer" does not appreciably change the log likelihood. In other words, although some of the interviewers evaluated applicants more stringently than did others, all of them evaluated blacks relative to whites in essentially the same way.

The firm then gave further consideration to the survivors of the interview stage, hiring some and rejecting the rest. To evaluate the hiring decision per se, one might simply perform another probit analysis, using only the data for the survivors, like the one summarized in column (iv) of Table 1. Of course, this ignores the possibly nonrandom nature of the final selection induced by the first or interview stage (and, in particular, by the very strong racial differential at that first stage). For a more general approach that reflects the two-stage nature of this process, consider the model

$$\text{(3a)} \quad P_{1i} = \sum_j b_{1j} X_{ji} + \sum_k d_{1k} D_{ki} + u_{1i}$$

$$\text{(3b)} \quad P_{2i} = \sum_j b_{2j} X_{ji} + \sum_k d_{2k} D_{ki} + u_{2i}$$

where $Y_{1i} = 1$ if and only if $P_{1i} > 0$, and $Y_{1i} = 0$ otherwise; $Y_{2i} = 1$ if and only if $P_{1i} > 0$ *and* $P_{2i} > 0$, and $Y_{2i} = 0$ otherwise. Y_{1i} is an indicator for "passes the first interview," and Y_{2i} is an indicator for "is hired." (Equivalently, one might say that Y_{2i} is observed if and only if $P_{1i} > 0$; i.e., i passes the interview.) In the spirit of the univariate probit models in Table 1, let the joint distribution of the unobservables in (3) be bivariate normal with unit variances and correlation ρ. Then the log-likelihood function for this model becomes

$$\text{(3c)} \quad L = \sum_i (1 - Y_{1i}) \log\{\Phi(-a_{1i})\} + \sum_i Y_{1i}(1 - Y_{2i}) \times \log\{F(a_{1i}, -a_{2i}, -\rho)\} + \sum_i Y_{1i} Y_{2i} \log\{F(a_{1i}, a_{2i}, \rho)\}$$

where

$$a_{1i} = \sum_j b_{1j} X_{ji} + \sum_k d_{1k} D_{ki}$$

$$a_{2i} = \sum_j b_{2j} X_{ji} + \sum_k d_{2k} D_{ki}$$

and where Φ is the univariate standard normal cumulative density function and F is the bivariate standard normal cumulative density function.

Columns (v) and (vi) present maximum-likelihood estimates of the parameters for black race in the "interview" and "hiring" equations, (3a) and (3b), respectively. The cross-equation correlation, ρ, is positive, large in absolute value, and significantly different from zero at reasonable test levels. The black coefficient for hiring is about 50-percent larger in the two-equation model than it is in the single-equation model [compare the results in columns (vi) and (iv) in Table 1]. At least in this example, then, some purely statistical issues, arising from the interest in (necessity of?) looking at each stage of the selection process for legal purposes, turn out to be empirically important.

IV. Concluding Comments

Both in the news media and among members of the bar, there is considerable cynicism about so-called experts of all kinds, including economists. "Joked a Chicago trial lawyer at a recent conference, there are three kinds of liars: 'The common liar, the didactic liar, and the scientific expert'" (*Wall Street Journal*, 1989). Yet outright misconduct by economists in (or outside) the courtroom is so rare that it cannot explain the degree of skepticism about economists among the legal profession. A much more serious problem (and a more plausible explanation for such skepticism) is that the so-called expert analyses provided by economists to the courts may well produce confusion instead of enlightenment. In employment-discrimination cases as in other kinds of litigation, rival economists present analyses that lawyers (and even other economists) regard as dauntingly technical and esoteric. Predictably, the rival economists' results are usually different, but the reasons for the difference may not be obvious. Each side's lawyers then praise their own economist's analyses and cite what they view as fatal flaws in the other's work. Only rarely do they attempt to show that the alleged flaws actually explain why the results diverge, however. For example, each side may well attempt to identify coding errors in the data used by the other side's economist. However, it is less common for either side to take the logical next step: to do new analyses, with corrected data, in order to determine whether the supposed errors are in fact empirically important. More often than not, the difference in results remains largely unexplained. From the point of view of the judge in the case, this may not be a happy situation.

In fairness to the legal profession, it should be noted that lawyers are not particularly well equipped for such work, and they do not always get much help from economists, for economists are sometimes guilty of precisely the same failings in their everyday work as scholars. As a case in point, consider the widely divergent estimates of the female labor supply elasticity that have appeared in the literature: one economist may fit a Tobit model to 1980 Census data for women aged 25–44; another, using a different set of variables, may fit a selection bias-corrected regression to 1985 Current Population Survey data for women aged 35–54; and so on. Differences in the elasticity estimates may be due to differences in data, variables, statistical technique, or something else (e.g., definitional differences or even programming errors). Possible reasons such as these for differences in elasticity estimates have been much discussed, but one rarely sees an attempt to determine which of them is actually material in a given setting.

In sum, the legal system's questions about employment discrimination may sometimes raise some relatively unfamiliar conceptual and statistical issues for economists. However, as implied in the previous section, courtroom confrontations about different empirical results represent one version of an old story whose familiar but oft forgotten moral is perhaps the most important one economists can teach to lawyers and judges (and relearn for themselves). When different analyses generate different answers, one should try to determine which aspects of those analyses really matter empirically and which do not. That will make judging easier for judges; and it is excellent exercise for scholars.

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