Summer 1992

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Statistics for Wage Discrimination Cases: Why the Statistical Models Used Cannot Prove or Disprove Sex Discrimination

JAMES T. MCKEOWN*

In 1977, in *International Brotherhood of Teamsters v. United States*, the United States Supreme Court held that gross statistical disparities can provide prima facie proof of discrimination.¹ Since then, statistical evidence, most commonly multiple regression analysis, has become the primary means of establishing wage discrimination in disparate treatment cases.² Nearly every plaintiff offers a regression analysis to prove the employer's pattern or practice of discriminating; the employer then relies on regression analyses to criticize the plaintiff's regressions as incomplete and to rebut the prima facie case.

Although plaintiffs and defendants stress the numerical results of their regressions, these results provide probative evidence of discrimination only if all parts—theory, model, and statistical method—are sound. Too often, however, courts analyzing multiple regression evidence concentrate on the statistical method, for example by checking for statistically significant coefficients or an appropriate sample.³ The model receives some attention when one party claims that an equation contains too few or the "wrong" variables, but the economic theory underlying the model tends to be assumed without inspection or critical analysis.⁴

A court should look first to the economic theory to ensure that the theory, and not statistical results or methods, provides the basis for the model. Turning next to the model, courts need to check not only whether the model follows from the theory, but also whether the model enables the researcher to draw inferences about the disputed fact. Since the hypothesis

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that an employer discriminates in salary is a hypothesis that an employer has different demand curves for the preferred and nonpreferred groups,\(^5\) a statistical model offered to prove or disprove the existence of discrimination should permit inferences about the employer’s demand curve. If the model cannot isolate the effect of demand on wages, the coefficients do not measure the effect of discrimination, regardless of any measures of statistical significance.\(^6\) Finally, only after evaluating the theory and the model should courts consider any alleged errors in statistical method and evaluate the probative value of the statistical evidence.

This Article examines the interrelated theory, models, and statistical methods to demonstrate why the statistics commonly offered can neither prove nor disprove sex discrimination. This observation should not be considered a benefit to either plaintiffs or defendants. Rather, it evidences the need to develop fuller models or, when that is not possible, to examine statistical evidence more critically and to weigh the probative value of the statistics and the need for complementary, nonstatistical evidence.

I. MOVING FROM THE STATUS QUO TO A COMPREHENSIVE APPROACH FOR EVALUATING STATISTICAL PROOF OF DISCRIMINATION

While recognizing the usefulness of statistical proof, such as regression analysis, courts will not accept such evidence uncritically.\(^7\) The Supreme Court has held that statistics, like all other proof, can be rebutted and that “their usefulness depends on all of the surrounding facts and circumstances.”\(^8\) Some lower courts express their concern in more jaundiced terms, warning that statistical evidence has an “inherently slippery nature.”\(^9\)

The Supreme Court’s decision in Bazemore v. Friday\(^10\) best frames the current evidentiary status of statistical proof of wage discrimination. In Bazemore, black employees of the North Carolina extension service alleged

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5. Discrimination occurs when an employer treats an individual or group differently due to race, sex, religion, or some other improper basis. See Watson v. Fort Worth Bank & Trust, 487 U.S. 977, 986 (1988). Since the employer’s demand curve reflects what the employer is willing to pay for certain quantities of labor, an intent or decision to pay less for women than for men, for example, indicates a separate, lower demand curve for women. See infra notes 21-23 and accompanying text.

6. See infra notes 52-63 and accompanying text.


8. See Spaulding, 740 F.2d at 703 (quoting Wilkins v. University of Houston, 654 F.2d 388, 395 (5th Cir. 1981), vacated and remanded, 459 U.S. 809 (1982), aff’d on remand, 695 F.2d 134 (5th Cir. 1983)); see also Sears, Roebuck & Co., 839 F.2d at 348 (District court had “a healthy distrust of the ability of regression analyses to explain the factors involved in management salary decisions.”).

that the state agency discriminated against blacks, with the result that black extension agents were paid less than equally qualified white employees. At trial, the plaintiffs relied heavily on a multiple regression analysis that purported to explain differences in salary resulting from race, education, tenure, job title, and job performance. The district court held, and the court of appeals agreed, that the plaintiffs' statistics were inadmissible because the statistical model had not included a number of variables that the court considered significant. Without that proof, the district court and court of appeals held that no discrimination was proved.

The Supreme Court reversed, holding that "it is clear that a regression analysis that includes less than 'all measurable variables' may serve to prove a plaintiff's case." Instead, as long as an analysis accounts for the major factors, the failure to include other variables normally affects only the probative value of the statistics, and not the admissibility. Furthermore, once the plaintiffs' statistics were admitted, they would be sufficient to permit the plaintiff to prevail, and it would become incumbent on the defendant to impeach or rebut the resulting inference of discrimination.

Although Bazemore instructed lower courts that the limitations of statistical studies of discrimination go only to the probative value of the study, the decision failed to provide a framework for analyzing regression studies and for weighing their probative value. As a result, courts have tackled some sophisticated, or some would say sophistic, regression analyses and have attempted to parse out the probative value of equations that omit variables or that meet some minimum level of statistical significance. This approach may impart upon courts an unwanted education on such statistical concepts as the Chow test, multicollinearity, and statistical significance. It does not, however, create a consistent, comprehensive approach to analyzing the types of regression analyses that are routinely offered as proof of discrimination.

11. Id. at 398-99.
12. Id. at 399-400.
13. Id. at 400.
14. Id.
15. Id. at 403 n.14 (noting that there was "very little evidence to show that there was in fact no disparity in salaries" and disapproving of the district court's use of nonstatistical evidence).
A rather simplistic point—but one that is sometimes lost—is that regression, by itself, reveals little about causation. Regression analysis is a tool for manipulating data, a mindless computer exercise whose results gain meaning only when interpreted in light of a theory of causation. Consider, for example, a regression that included a baseball player's 1981 batting average as the dependent (or explained) variable and his 1982 salary as the independent variable. The regression would probably yield a statistically significant coefficient on the "salary" variable, but no one would believe that the regression proved that a higher salary in 1982 caused the player to have had a better batting average in 1981. Note, however, that the rejection of the regression results comes not from a flaw in performing the statistical technique but from common sense about causation or, in other words, a theory of how the market works.

The importance of a theory in evaluating regression results also underlies the problem with gathering data on every conceivable explanatory variable, entering that data into a computer, and then relying on stepwise regression or a similar computer program to identify which variables should be in the model. Such programs include or exclude variables according to each variable's explanatory power in that particular sample—regardless of the variable's theoretical merit. As one commentator has noted, "a study that casts about for a good-looking relationship by trying all sorts of possibilities is very likely to come up with relationships where none exist."

Developing statistical proof of discrimination requires not just a computer regressing data but an affirmative study that:

(1) starts with a theory, both as to how the market works and how certain factors (including discrimination) affect wages;
(2) develops a statistical model that permits a measurement of the statistical significance of the effect of sex (or race) on the demand curve for employees;
(3) includes in the model all relevant variables, measured in a meaningful way; and
(4) after accomplishing the first three steps, determines the statistical significance of the results.

Each step builds on the preceding one. Just as regression results require statistical significance before they have probative value, they must also come

18. See M. Lewis-Beck, APPLIED REGRESSION: AN INTRODUCTION 18-19 (1980); see also K. Fox, INTERMEDIATE ECONOMIC STATISTICS 81-83 (1968); R. Wonnacott & T. Wonnacott, ECONOMETRICS 173 (1979); cf. Tagatz v. Marquette Univ., 861 F.2d 1040, 1044 (7th Cir. 1988) (Correlation is not causation.).
19. See S. Chang, PRACTITIONERS' GUIDE TO ECONOMETRICS 62 (1984). The most common stepwise regression instructs the computer to add independent variables to the equation one at a time in the order of which variables explain the most variation in the dependent variable. Consequently, a poor measure of a variable or the vagaries of the sample might cause the computer to drop a theoretically justified variable. Id.
WAGE DISCRIMINATION STATISTICS

from properly measured variables in a model conforming to the economic theory. If the regression results have no basis in theory or if the model fails to measure what theory indicates is determinative, the probative value is vastly diminished.

II. AN ECONOMIC THEORY OF DISCRIMINATION

Under disparate treatment analysis, an employer discriminates when it treats an employee differently because of that employee's race, sex, religion, or age.\(^2\) Plaintiffs alleging sex discrimination, therefore, offer evidence of a wage differential between men and women to show that the employer treats women differently. As an examination of the labor market will demonstrate, however, a wage differential does not, by itself, prove discrimination.

A common difficulty in using statistics to isolate discriminatory effect lies in the qualitative nature of an employee's performance.\(^2\) If everyone worked on an individual basis canning peas and was paid according to the number of cans produced, a difference in price per can for men and women would reflect discrimination. As we move away from piecework or commissions, factors such as quality of work, managerial ability, and efficiency make discrimination harder both to prove and to disprove. To highlight how these factors fit within an economic theory of discrimination and how they affect the statistical model, the market for college professors will be used as an example. This market is particularly useful because it permits some (perhaps illusory) quantification of output and it is a frequent subject of sex-discrimination litigation.

A. Wage Differentials Caused by Discrimination

Like other markets, the market for college professors has a demand for teachers and a supply of them. Moreover, because the equilibrium price reflects the intersection of the demand and supply curves, a shift in either curve can change the equilibrium price. Assume that we have a hypothetical, nondiscriminating college that bases each professor's salary wholly upon the number of articles that professor published in the prior year. In Figure

\(^2\) See Penk v. Oregon State Bd. of Higher Educ., 816 F.2d 458, 465 (9th Cir. 1987) (Important decision-making variables were either missing or inadequately represented.); EEOC v. Sears, Roebuck & Co., 628 F. Supp. 1264, 1288 (N.D. Ill. 1986), aff'd, 839 F.2d 302, 350 (7th Cir. 1988), cert. denied, 111 S. Ct. 370 (1990) (The more qualifications and subjective factors required, the less mathematical models can accurately analyze the decision-making process.).
1, the demand curve, $D$, reflects the price that the school is willing to pay for varying quantities of articles published by its faculty. The supply curve, $S$, aggregates the individual supply curves of all professors and thus illustrates how many articles the faculty as a whole will supply at each price. Under this analysis, point $A$ is the equilibrium outcome, indicating that the university would pay $P_1$. Multiplying $P_1$ by the number of articles a professor wrote would yield the professor's salary.

Now suppose that the university discriminated against women by paying them less money per article. As Figure 2 shows, the demand curve for articles written by women would lie below that for articles by men.

Assuming that the supply curve is the same for men and women, the price per article for women is $P_2$ and a wage differential exists. Moreover, by rewarding men at a higher rate, the discrimination would cause men to
produce more articles and appear more productive—even though both men
and women are assumed to have the same supply curve.

Of course, colleges do not set salaries solely by publications. Colleges
usually also consider teaching ability, administrative responsibility, public
service, and other factors. Nevertheless, the basic idea remains: a college
discriminates when it is willing to pay more to a man than to a woman
with the same publishing, teaching, and other qualifications. In terms of
the supply and demand curves, a discriminating employer has a separate,
lower demand curve for women.

In theory, some colleges paying women teachers less than men teachers
would be only a short-run result as long as most colleges do not discriminate.
The women faculty at the discriminatory schools would transfer to nondis-
criminatory ones, thereby increasing the supply of teachers to these schools
and lowering the salary level. As salaries fall, the men teaching at the
nondiscriminatory schools would notice that they could earn more by
teaching at a discriminatory school. Some male teachers would therefore
move to discriminatory schools, decreasing the supply and raising the salaries
at nondiscriminating schools while increasing the supply and lowering the
salaries at the discriminatory ones. This transfer of women to nondiscrimi-
matory schools and men to discriminatory schools would continue either
until the salary level was the same at both schools or until the discriminating
schools realized the futile nature of their discrimination. Under these
assumptions, segregation might result, but women and men would receive
equal salaries.

This equalization of salaries would not result if all, or nearly all, univer-
sities discriminate against women or if other barriers or limitations dis-
courage transfer from one school to another. If all colleges discriminate
on the basis of sex, women cannot transfer to nondiscriminating schools
and receive the same salaries as males. To the extent that the nondiscrimi-
inating schools would have limited openings, they similarly would be
prevented from bidding for the services of any underpaid women faculty at
other universities.

Structural barriers may limit the number of opportunities or otherwise
discourage mobility even if a substantial number of universities did not

23. See Tagatz v. Marquette Univ., 861 F.2d 1040, 1043 (7th Cir. 1988); Willner v.
University of Kan., 848 F.2d 1023, 1031 (10th Cir. 1988).
24. Lindsay & Shanor, County of Washington v. Gunther: Economic and Legal Consid-
erations for Resolving Sex-Based Wage Discrimination Cases, 1 Sup. Ct. Econ. Rev. 185, 207
(1982).
25. Id.
26. See Stiglitz, Approaches to the Economics of Discrimination, 63 Am. Econ. Rev. 287
(1973).
27. See Lindsay & Shanor, supra note 24, at 208.
28. See id. at 208-10.
discriminate. For example, a female professor who has finished three years on a tenure track at a discriminating school may prefer to keep that position rather than transfer to a higher paying position with less seniority. Similar restraints would face those men at nondiscriminating schools who, under the perfect competition model, would transfer to discriminating schools. Imperfections in the market would thus allow some colleges to have two demand curves: one for men and a second for women.

B. Wage Differentials Caused by Supply Factors

Thus far, I have assumed a wage differential caused by discrimination. But a wage differential could also occur if there are differences in supply. For example, assume once again that all universities pay their faculty members according to the number of articles published in the prior year, with each article being worth the same amount. Assume further that all university teachers possess equal research skills and that, therefore, they produce articles of the same quality in the same amount of time. Figures 3a and 3b illustrate this hypothetical market for articles.

In Figure 3a, the supply curves $S_c$ and $S_o$ are individual supply curves for two professors. For any given price, Professor O will devote more time to research and, consequently, produce more articles than Professor C; thus Professor O's supply curve $S_o$ lies to the right of Professor C's curve $S_c$. Summing up the number of articles published by all professors at each price, we obtain the aggregate supply curve ($SS$) shown in Figure 3b. The intersection of the aggregate supply curve with the aggregate demand curve ($DD$) in Figure 3b results in an equilibrium output of $Q_1$ articles being produced with each university paying faculty members $P_1$ for every article. Returning to Figure 3a, at a price of $P_1$ per article, Professor C will produce...
$q_e$ articles and receive a salary of $P_f \times q_e$, while Professor O will write $q_o$ articles and receive a salary of $P_f \times q_o$.

Figures 3a and 3b illustrate how differences in supply, and not discrimination, might explain a wage differential between male and female faculty members. It is possible that women faculty members with young children at home have more inelastic supply curves for articles ($S_e$) than those professors who are not responsible for child care ($S_o$). In other words, as the price of articles rises, teachers without young children may spend more time researching and writing than teachers who must devote at least part of each day to child care. If this hypothesis proved true, a university could pay all professors $P_f$ per article and, assuming there are no other distinctions between teachers, a wage differential of $P_f (q_o - q_e)$ would exist between professors caring for young children and all other professors. Many, if not most, female professors could fall within the group not caring for children, but—if the hypothesis were accurate—the lower salaries for women with child care responsibilities would lower the average salary for women as a group. Thus a wage differential, even if statistically significant, could reflect not discrimination but instead more inelastic supply curves for women with small children.

A supply-caused wage differential could also occur if some wives sacrifice career opportunities in order to maximize their husbands' career opportunities or family income. 29 Suppose, for example, that Dr. Smith, a female biologist, is overqualified for her teaching position at College A, but her husband has a high-paying professional job in the same city. If that city does not have any other colleges needing biology teachers, Smith might accept the lower wages in order to stay where her husband can best further his career. 30 Similarly, maximizing their household income does not necessarily result in maximizing Dr. Smith's personal income. 31 Even if the couple is willing to move, they may decide that the job search and moving costs associated with finding acceptable jobs for both in the same city exceed the difference between her salary at College A and what she could earn in a more suitable position. 32 In short, Dr. Smith may accept the job at College A even though she earns less there than what her qualifications would ordinarily command in the market. She also would appear, on the basis of

30. See id.; Reagan, Two Supply Curves for Economists? Implications of Mobility and Career Attachment of Women, 65 Am. Econ. Rev. 100, 102 (1975) (Sixty percent of female economists said spouse's job or immobility had been a major or minor problem to their career development.).
31. See Frank, supra note 29, at 361.
32. Presumably, a couple would move only if the transfer maximized their discounted lifetime earnings. If the moving and job search costs exceed the discounted value of the increase in the salary at the new jobs, the couple would elect to keep their present jobs.
her paper credentials, to be underpaid as compared to less qualified men teaching at College A.33

A third supply influence, differences in human capital, could also cause a wage differential between men and women. The human capital theory views an individual's decision to acquire additional schooling or on-the-job training as an investment in oneself that makes the individual more valuable to an employer.34 Publishing or otherwise increasing one's research skills and reputation increases the value of a teacher's human capital and, therefore, may allow the teacher to command a larger salary. The rational employee, or future employee, will invest in himself—through schooling, experience, or otherwise—with a view toward maximizing discounted lifetime earnings.35 Put differently, the decision-making rule for any individual is to undertake those capital-enhancing activities that maximize the difference between discounted earnings and costs.

Because human capital continues to accumulate over time, two professors may begin with the same human capital but accumulate additional amounts at different rates. For example, if one history teacher is an avid runner and spends a good deal of time training for and competing in marathons, he will have less time to devote to research and consequently may not accumulate human capital as rapidly as a colleague with a less time-consuming hobby.36 Similarly, taking a year off to "see the world" would cause a
professor’s human capital to remain the same or perhaps depreciate. Time spent on other jobs, such as an accounting professor who also practices as a CPA, also decreases the time available for capital-enhancing activities. If a professor’s value to a university is a function of the human capital supplied, professors who devote a good deal of their time to outside activities would have less human capital, would be of less value to the school, and consequently would receive lower salaries.

Applying this human capital analysis to sex discrimination cases suggests a possible reason for separate supply curves. A female faculty member expecting to interrupt her career for childbearing has a shorter time to recoup her investment in herself and may therefore invest in less human capital than a male with the same initial human capital. She might also have less incentive to publish or conduct extensive research. Even if the woman made an equal investment in education and publication, the value of her human capital would remain constant, or might even decline, while she took a few years off or worked part time. Meanwhile, her counterparts (both male and female) who did not interrupt their careers would increase their human capital and, consequently, their value to a university.

III. DEVELOPING A MODEL CAPABLE OF PROVING DISCRIMINATION

With theory in hand, an economist or statistician can devise an equation on which to run a regression. It is here, however, that most statistical proof misses the mark and settles for models that do not isolate the effects of supply factors from the effects of demand factors.

A. The Traditional Models for Proving Discrimination

The regressions offered to prove sex discrimination generally follow the forms suggested by a 1975 *Harvard Law Review* Note:

(1) Regressing the dependent variable (wages, promotions, or hires) on legitimate factors affecting the decision (e.g., experience, education) and on a dummy variable for the worker’s sex; or

(2) separating the sample into males and females and then regressing

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37. See Corcoran, Duncan & Panza, *A Longitudinal Analysis of White Women’s Wages*, 18 J. HUM. RESOURCES 497, 513 (1983); Johnson & Stafford, *supra* note 35, at 890, 897. Judge Richard Posner has suggested that women’s current wages are depressed because many women working today did not have that expectation when they were young. Thus, they did not invest in human capital through schooling or otherwise to the extent that they would have had they expected to be working. See Posner, *An Economic Analysis of Sex Discrimination Laws*, 56 U. CHI. L. REV. 1311, 1315-16 (1989).

38. See *supra* note 35.

the dependent variable on the independent ones (without a dummy variable) for each subset.40

Under the first method, the regression is of the form:

\[ W = a + b(T) + c(E) + d(S) + e \]

where \( W \) represents wages, \( T \) is years of tenure, \( E \) is years of graduate education, \( S \) equals 1 for females and 0 for males, and \( e \) is the error term.41 The regression would also include any other variable that affected wages. If the sample is adequate and the t-score indicates a statistically significant negative coefficient on the sex variable, a plaintiff would claim to have proven sex discrimination in wages.42

A similar form was used in the regression at issue in Bazemore v. Friday.43 In that case, the plaintiffs regressed salary on four independent variables: race, education, tenure, and job title.44 The coefficient for the race variable indicated that black employees earned an average of $331 less than similarly qualified white employees in 1974 and $395 less in 1975.45 As noted above, the Supreme Court held that this sufficiently established a prima facie case of discrimination.

The traditional model has received some criticism. Because it uses wages as the dependent variable and years of tenure, education, and sex as the independent variables, the model assumes that differences in seniority and education have the same effect on men's and women's wages. In other words, at every level of seniority and education, men's earnings exceed those of women by the same amount.46 One commentator therefore suggested that if one believes that the difference between men's and women's wages increases or decreases at higher levels, an appropriate study would either use the logarithm of wages as the dependent variable or include two regressions, one for each sex, with wages the dependent variable and years of tenure and education the independent ones.47 Additionally, including an

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41. See Note, Beyond the Prima Facie Case, supra note 40, at 404.
42. Id. at 402-04.
43. 478 U.S. 385 (1986).
44. Id. at 398-99 (Brennan, J., concurring in part).
45. Id. at 399.
47. Id. at 724; see also Campbell, Regression Analysis in Title VII Cases: Minimum Standards, Comparable Worth, and Other Issues Where Law and Statistics Meet, 36 STAN. L. REV. 1299, 1312-19 (1984) (saying that a single equation model with a dummy variable for sex is inappropriate).
interaction term could also reveal if the difference in salaries is greater at higher levels.48

A second critique of the traditional regression model concerns the effect of mistaken functional form. Functional form, in simplest terms, refers to a model's mathematical formula that describes the relationship between an independent variable and a dependent one.49 By examining linear, loglinear, quadratic, and other functional forms, one can test the regression's "close-ness of fit" to a number of geometric curves.50 Using an inaccurate functional form, or merely assuming that a form is correct, might mistakenly suggest that an employer discriminates.51

B. The Identification Problem

A return to our theory of discrimination reveals a more fundamental problem with these models. The theory indicated that there would be separate demand curves if there was discrimination, but the equations typically used—which are called "reduced form equations"—do not separate the demand effect from any supply effect. A negative coefficient on the sex variable does indicate that women earn less on average than men, and it may accurately predict the salary differential.52 What it cannot do, however, is explain the cause of the differential.

A brief explanation of reduced form equations illustrates their inherent limitations. Returning to our hypothetical university, assume the following equations are the true, but unknowable, supply and demand functions for teachers:

\[
Q_s = A + B(P) + C(K) + E_s
\]

\[
Q_d = F + G(P) + H(S) + E_d
\]

where

\[
Q_s = \text{quantity of services supplied (including teaching, publications, etc.)}
\]

48. See Fisher, supra note 20, at 711-12 & n.20. An interaction effect exists when the effect of one independent variable on the dependent variable depends on the value of another independent variable. M. Lewis-Beck, supra note 18, at 54. For example, if one suspected that a university paid women less than men for each article published, one would want to include an interaction term (reflecting the joint effect of the articles and sex variables) in the model. See id.


50. Id. at 162-67; see also Fisher, supra note 20, at 711-12 & n.20.

51. See EEOC v. Sears, Roebuck & Co., 628 F. Supp. 1264, 1287-88 (N.D. Ill. 1986), aff'd, 839 F.2d 302, 350 (7th Cir. 1988), cert. denied, 111 S. Ct. 370 (1990) (Courts need not accept the results of regression when the model does not have a sufficiently good "fit.").

\( Q_d = \) quantity of services demanded (including teaching, publications, etc.)

\( P = \) salary

\( K = 1 \) if a person is a spouse primarily responsible for care of children;
0 if not

\( S = 0 \) if male, 1 if female

\( E_s \) and \( E_t = \) error terms

The reduced form of these equations,\(^{53}\) the equivalent of the equations used to estimate sex discrimination in the faculty salary cases, would be

\[
P = \frac{f - a}{b - g} + \frac{h(S)}{b - g} - \frac{c(K)}{b - g} + \frac{e_s}{b - g} - \frac{e_t}{b - g}
\]

This model permits estimates of the effect of sex \((S)\) on salary since regressing \( P \) on \( S \) and \( K \) would yield an estimate for \( h/(b - g) \), the net effect of sex on salary.\(^{54}\) Suppose, however, that the plaintiff wants to estimate the effect of a teacher’s sex on the university’s willingness to pay, or, in other words, whether the university discriminates. Then the researcher would need a model that could isolate and estimate \( h \), the coefficient for sex in the demand equation. As demonstrated above, a regression on the reduced form equation yields not an estimate of \( h \), but an estimate of \( h/(b - g) \). If \( (b - g) \) has a large value, it could mask a substantial \( h \); conversely, a small value for \( (b - g) \) would magnify the apparent effect of sex.

In the model outlined, it may be possible to make realistic assumptions about supply and demand that permit some inferences about \( h \). Since we know that \( B \), the effect of price on quantity supplied, is positive, and that \( G \), the effect of price on quantity demanded, is negative, the denominator \( (b - g) \) will be a positive number. Furthermore, unless both supply and demand are fairly inelastic, the denominator \( (b - g) \) will be greater than one.\(^{55}\) This suggests that, although the reduced form equation may accurately estimate the correlation between sex and salary, the reduced form coefficient

\[53. \text{The math underlying the reduced form equation is fairly simple. In equilibrium, } Q_s = Q_d. \text{ Therefore,}
\]

\[ a + b(P) + c(K) + e_s = f + g(P) + h(S) + e_t
\]

Solving for \( P \), we obtain

\[ b(P) - g(P) = f - a + h(S) - c(K) + e_s - e_t
\]

\[
P = \frac{f - a}{b - g} + \frac{h(S)}{b - g} - \frac{c(K)}{b - g} + \frac{e_s}{b - g} - \frac{e_t}{b - g}
\]

\[54. \text{See H. THEL, supra note 52, at 321-22.}
\]

\[55. \text{The coefficient reflects the slope of the line in a bivariate regression, or the slope of the plane in the example given. Thus, the coefficient } b \text{ indicates the increase in quantity supplied in response to a one unit increase in price. Similarly, the coefficient } g \text{ reflects the change in the quantity demanded in response to a one unit change in price. Since a 45 degree line has a slope of one, the denominator } (b - g) \text{ would have a value of two if both supply and demand were 45 degree lines in the relevant range. For the total of } b \text{ and } g \text{ to be one or less, both demand and supply would need to be fairly inelastic.}
\]
on the sex variable is less than the true \( h \) (the effect of a teacher's sex on quantity demanded).\(^{56}\)

A further complication with this example is that it assumes that any effect of sex on price is the result of a change in demand, or discrimination. As discussed in Part II, however, sex can also influence supply, even absent discrimination, if women on average supply less output than men on average in the relevant salary range. To the extent that one could isolate and accurately measure potential supply influences such as responsibility for child care, desire to maximize household income, or lower investment in human capital, there would be more comfort in the assumption that a sex variable reflects only demand factors. If, as is probably more realistic, the model fails to account for such supply factors or fails to reflect fully their qualitative nature,\(^{57}\) the coefficient for sex is not merely an estimate of \( h/(b - g) \), but instead reflects the effect of the sex variable plus the net effect of the omitted correlated variables.\(^{58}\) The residual effect of such factors that are correlated with sex would cause the reduced form coefficient to capture both supply and demand effects on price.

Thus, the fundamental problem with using a reduced form equation to estimate sex discrimination is that the reduced form regression estimates the net effect of sex on salary and does not isolate the supply and demand curves for university professors. Since the proposed theory underlying sex discrimination is that universities have separate demand curves for men and women, discrimination can only be proven (as a matter of econometrics) if the statistics demonstrate that two demand curves exist. A multiple regression on a reduced form equation neither demonstrates that two demand curves exist nor refutes the theory of two supply curves.\(^{59}\) It cannot, therefore, prove discrimination.

56. One can hypothesize situations where the supply or demand is inelastic. For example, although a competitive market clearly determines the salaries for the top professors in their fields (since competing universities bid for their services), some professors may realistically have only one option (their current university) and may therefore be bid takers. Thus, over the relative range of salaries, they would not change their services considerably in response to a change in salary.

57. The problem with measuring quality or otherwise capturing the full effect of a variable may result despite the best attempts to include all relevant variables in the model. For example, the quality of publications is certainly a factor that will affect faculty salaries, but measuring quality can be a difficult, if not impossible, task. See Moore, The Relative Quality of Graduate Programs in Economics, 1958-72: Who Published and Who Perished, 11 W. Econ. J. 1, 3-12 (1973). Similarly, quality of teaching and value of administrative service may be difficult to quantify. Moreover, it may be difficult to locate data on the sample that reflects any differences in human capital, any implicit or explicit decision to maximize household rather than personal income, and any child care responsibilities. Even after the relevant theoretical factors have been chosen, the regression is limited by the data available to serve as a sample.

58. See infra Part IV.B. (discussion of the statistical effect of omitting a variable or not accounting for its qualitative nature).

One might think that this limitation of reduced form equations may be overcome simply by running regressions on the supply and demand equations. For example, one could set up the following model:

\[
\begin{align*}
Q_s &= a + b(P) + c(K) + e_s \\
Q_d &= f + g(P) + h(S) + e_d
\end{align*}
\]

Furthermore, assuming data exists for each of the variables, a statistician could run a regression and obtain estimates of \(a\), \(b\), \(c\), \(f\), \(g\), and \(h\). Unfortunately, because this approach does not resolve the identification problem, the estimates would be useless. Rather than estimating the true supply and demand functions, the estimates would approximate a line representing a combination of supply and demand.

The identification problem can be understood both intuitively and in terms of regression theory. For intuitive purposes, assume the following diagram shows the true supply curves \((S_1, S_2, S_3)\) and the true demand curves \((D_1, D_2, D_3)\) for a perfectly competitive market.

![Figure 4](image)

Also assume that the subscript refers to a time period so that, for example, \(S_i\) and \(D_i\) reflect the supply and demand curves in time period 1. Of course, a statistician wanting to estimate the demand function does not know what any of these curves look like; in the real world the only data available are the price and quantity sold in period 1, in period 2, and in period 3. Accordingly, a statistician would know the points where the corresponding supply and demand curves intersect, but points, by themselves, reveal nothing about the slopes of the intersecting lines. The regression would estimate neither supply nor demand, but instead, some combination of the two (reflected in the diagram by the line \(Z^*\)).

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60. See K. Fox, supra note 18, at 376-77; R. Wonnacott & T. Wonnacott, supra note 18, at 274-77.
The identification problem can also be explained in terms of the regression model. The standard linear regression model assumes that a dependent variable is a function of a number of predetermined, or exogenous, explanatory variables. For example, to estimate the effect of rainfall on wheat production, one could regress wheat production in a given year on rainfall for that year. Rainfall is clearly not affected by wheat production, so the amount of rainfall is determined outside the model or, in other words, is an exogenous variable. By contrast, basic microeconomic theory teaches that the price and quantity of a good are determined by the market forces of demand and supply. Neither price nor quantity has a predetermined value completely independent of the value of the other; instead price and quantity are interdependent. A model describing a market must therefore contain not one equation with all exogenous explanatory variables, but two equations with the values of price and quantity being determined simultaneously within the system. In statistical terms, both price and quantity are endogenous variables, and this simultaneous interdependence between the dependent variable and one of the explanatory variables presents the identification problem.

IV. RESOLVING THE IDENTIFICATION PROBLEM

As the forgoing discussion demonstrates, the statistical models routinely used to prove discrimination in wages fail to distinguish illegal demand considerations (discrimination) from supply-caused differences. Having described the problem, the next step is to consider the possible statistical and legal solutions. Unfortunately, because the statistical solutions are often unavailable or impractical, courts will ultimately need to consider the identification problem as one other factor that goes to the weight, but not necessarily the admissibility, of regression analyses.

A. Potential Statistical Solutions to the Identification Problem

Economists have suggested several ways to identify a supply or demand curve. First, if one knows that the demand curve is constant but the supply curve varies, the corresponding values of quantity and price reflect the

61. See S. Chang, supra note 19, at 117; H. Theil, supra note 52, at 319. In statistical terms, a variable is exogenous if its value is stochastically independent of the disturbance (error) term. H. Theil, supra note 52, at 321.
62. See S. Chang, supra note 19, at 117; H. Theil, supra note 52, at 320-21; R. Wonnacott & T. Wonnacott, supra note 18, at 257-58, 274-75.
63. See S. Chang, supra note 19, at 117-18.
64. See generally R. Wonnacott & T. Wonnacott, supra note 18, at 277-85.
intersection of many supply curves with one demand curve. A regression of quantity on price would therefore yield an estimate of the demand curve.\textsuperscript{65} Conversely, if supply was constant but demand varied, a regression would yield an accurate estimate of supply.\textsuperscript{66} Thus, if one could assume (or otherwise prove) no difference in supply by men and women, the coefficient would represent a pure demand effect, namely discrimination. The shortcoming of this solution to the identification problem, of course, is that supply and demand are rarely constant in the real world.

The identification problem is also avoided if the theory indicates that a sufficient number of factors affect supply but not demand, while others do the opposite.\textsuperscript{67} In statistical terms, an equation (supply or demand) is identified if the number of exogenous variables excluded from the equation is at least as great as the number of endogenous variables included on the right side of the equation.\textsuperscript{68} For example, it seems reasonable to assume

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{supply_demand_diagram.png}
\caption{Diagram illustrating the intersection of supply and demand curves.}
\end{figure}

\textsuperscript{65} See K. Fox, \textit{supra} note 18, at 375-76. The following diagram illustrates how the intersection of many supply curves with one demand curve would identify the demand curve by providing a number of points falling on the demand curve. Note, however, that these points do not yield information about the slope of the supply curves.

\textsuperscript{66} \textit{Id.}

\textsuperscript{67} Such variables, referred to as exogenous variables, are taken as given for the purpose of determining the value of the endogenous variables. In some circumstances, the lagged values of endogenous variables can also serve this purpose. See A. Walters, \textit{supra} note 52, at 180-81; \textit{see also} Hoenack & Weiler, \textit{A Structural Model of Murder Behavior and the Criminal Justice System}, 70 \textit{Am. Econ. Rev.} 327, 333-37 (1980) (tests of overidentifying restrictions).

\textsuperscript{68} See R. Wonnacott & T. Wonnacott, \textit{supra} note 18, at 282. More specifically, an equation is exactly identified if the number of exogenous variables excluded from the equation equals the number of endogenous variables on the right side of the equation. If the number of exogenous variables exceeds the number of endogenous ones, the equation is overidentified. Overidentification presents no great problem since one can use a statistical technique such as two-stage least squares to estimate the structural equation. \textit{See id.} at 287-90, 292-94. Exogenous variables cannot merely be picked out of the air. Each exogenous variable used to identify the supply curve must be found to have a statistically significant effect on demand. Those used to identify the demand curve must affect supply but not demand.
that rainfall affects the supply of, but not the demand for, wheat. If $P$ is price and $R$ is rainfall, the supply and demand equations would then look like this:

$$Q_s = a + b(P) + c(R) + e_s$$
$$Q_d = f + g(P) + e_d$$

Since rainfall is an exogenous variable included in the model but not affecting the demand for wheat, rainfall can be used as an instrumental variable in the demand curve, thereby allowing estimates of that curve. Similarly, an exogenous variable that affected demand, but not supply, could serve as an instrumental variable in the supply curve and allow estimates of that curve's coefficients. Through the use of these exogenous variables, both equations are identified and one can estimate the actual supply and demand curves.

Although this example is useful to explain identification, it differs from the supply and demand for college teachers in that wheat is a fungible good while college instructors are neither interchangeable nor equivalent. Each individual has different research, teaching, and administrative skills, and universities usually adjust salaries to compensate for these differences in human capital. In short, the quantity of teachers does not fix a uniform price for all teachers; salaries vary according to experience, publications, and—to the extent that discrimination occurs—sex or race. To measure the effect of employer discrimination on faculty salaries, one must use a model that not only identifies the supply and demand functions, but that also reflects the effects of the varying characteristics of teachers.

The hedonic model presents one possible way of identifying the demand curve when employees bring a cluster of attributes rather than a single measurable contribution. Under hedonic price theory, products consist of bundles of attributes or characteristics that vary among products. The theory further assumes that one can estimate the value that consumers put on each characteristic by measuring the total value paid for products with differing

69. See A. Walters, supra note 52, at 164-68. Exogenous variables that affect only supply are sometimes referred to as "supply shifters." Those that affect only demand are referred to as "demand shifters."

70. An instrumental variable is a variable that is uncorrelated with the error term but correlated with the variable for which it will substitute. An exogenous variable not in the demand function is not correlated with the error term in that equation. But if the exogenous variable is in the supply equation, it is correlated with price. Therefore, it can serve as an instrumental variable in the demand equation, and that equation is identified. See R. Wonnacott & T. Wonnacott, supra note 18, at 255-62, 280-83.

amounts of the characteristics. Thus, in the market for college teachers, one would attempt to place an implicit value on each attribute. Accordingly, the university might be willing to pay $400 per article, $1200 per year of seniority, and so forth. In this respect, the hedonic theory is similar to the results from a multiple regression on publications, seniority, sex, and other characteristics. Unlike the normal regression results, however, the hedonic theory analyzes each characteristic in terms of the "demand" and "supply" for that characteristic.

The difficulty with a hedonic theory approach is that adding independent variables, or characteristics, makes it harder to "identify" the supply or demand equation. Since a professor would presumably devote more time to research, training, and university service if the university increased the amounts paid for such services, these characteristics reflect the quantity of output supplied for a given price. If the value placed by the university on publications increases while the value on the other characteristics remains constant, teachers will shift more effort toward publications. Consequently, the amount of publications, experience, and service supplied by teachers is not a "given" but is determined by the interaction of the "demand" and "supply" of each characteristic. In statistical terms, they are endogenous variables because their values are determined within the market.

The identification problem becomes more difficult with a hedonic model. A supply or demand curve can be identified only if there are at least as many exogenous variables excluded from the equation as there are endogenous variables included on the right side of the equation.\(^2\) Thus, if a model included publications, quality of teaching, and community service as endogenous variables that helped explain demand, the model would also need to include at least three exogenous variables that affected supply but did not affect demand.\(^3\) Although some factors would appear to meet this criterion,\(^4\) it will probably be difficult to obtain a sample that contains

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\(^2\) Some economists have suggested that, even with a sufficient number of exogenous variables, a hedonic model cannot identify the underlying "supply" and "demand" for characteristics without using many detailed and often rather arbitrary assumptions and specifications. See S. Rosen, The Theory of Equalizing Differences 75 n.12 (1985); Brown & Rosen, On the Estimation of Structural Hedonic Price Models, 50 Econometrica 765, 767-68 (1982). The appropriateness of such assumptions would create yet another issue as to the appropriate weight to be given a regression analysis.

\(^3\) See R. Wonacott & T. Wonacott, supra note 18, at 282.

\(^4\) For example, the school's location and prestige are factors that (if they could be measured) may affect supply but not demand. Location would be a supply factor if teachers were willing to accept less monetary compensation from schools with favorable location characteristics (for example, low income taxes, favorable weather, good schools). See Bayless, The Influence of Location on Faculty Salaries at Major Universities, 21 Neb. J. Econ. & Bus., Spring 1982, at 39. A teacher's nonuniversity consulting business or time-consuming hobby also might affect supply but not demand and present possible exogenous variables. From the demand perspective, factors such as predicted freshman enrollment and number of graduate students may affect demand but not supply (thus making them possible exogenous variables that can be used to identify the supply curve).
enough independent, exogenous variables to identify the demand and supply curves for university teachers.

B. Problems with the Potential Statistical Solutions to the Identification Problem

Despite the possible statistical methods of resolving the identification problem, there remain considerable practical difficulties with isolating demand and supply effects. One obvious problem is that the necessary data will often be unavailable or too expensive to obtain. In other cases, there may simply be no way to locate or include enough exogenous variables to identify the supply or the demand curve. In this respect, the identification problem becomes more difficult to solve as the equation adds independent variables that may affect the salaries at issue.

1. The Need to Include Numerous Exogenous Variables

As noted previously, a regression can produce an identified demand curve (and thus show that the difference in salaries results from discrimination) only if the model includes at least as many exogenous factors that affect supply (but not demand) as there are endogenous variables in the demand equation. This concept, known as the "order condition for identification," creates a tension between limiting the number of endogenous variables (in order to facilitate identification) and including all variables that potentially affect supply or demand.

Implicit in the Supreme Court's decision in Bazemore is the notion that the more variables that are included in the model, the more likely that the model accurately reflects the effect of each.75 Similarly, the Ninth Circuit has suggested that the "more sophisticated the method of algebraic adjustment that is used, such as multivariate regression analysis, the more likely an illicit discriminatory factor can be ferreted out."76 Other courts have stressed the importance of including all relevant nontainted variables, even if those factors affect salaries only jointly with other included variables.77

The inclusion of additional variables is often necessary to provide accurate predictors even within a reduced form equation. If a variable is omitted, the regression analysis attributes the effect of that variable to any correlated, included variables.78 Tagatz v. Marquette University79 illustrates this

75. Bazemore, 478 U.S. at 400.
78. See M. Lewis-Beck, supra note 18, at 29. This is a form of multicollinearity that is sometimes called a specification error. Id. at 57-58.
79. 861 F.2d 1040 (7th Cir. 1988).
problem. In that case, a non-Catholic teacher claimed a Catholic university discriminated against non-Catholic teachers and paid them lower salaries. Tagatz supported this claim with statistics showing that non-Catholics in his department were paid less, on average, than Catholics. As noted by both the district court and the Seventh Circuit, however, this "discrimination" disappeared when publications were considered. The plaintiff's poor publication record dragged down the average for non-Catholics in the department and suggested discrimination where none existed. Accordingly, without a variable for publications, a regression would have attributed the salary difference to religion, which was correlated with salary for the sample in the Tagatz case but was not the cause of the salary differential. If an economist had run a regression with a publications variable, the omitted variable problem would have been solved and the claim of discrimination rebutted.

The danger of the "more-variables-the-better" approach espoused by some courts is that its blind application increases the difficulty of proving discrimination. As a pure statistical matter, adding variables makes it more difficult to obtain statistically significant results. The inclusion of too many variables that do not significantly affect the dependent variable can distort the results and, in fact, report no statistically significant relationships even where some actually exist. Moreover, if the model includes variables that are highly correlated, the model will yield less precise estimates of the coefficients (for either the structural or the reduced form equation) and the estimates are less likely to be statistically significant. Each of these statistical effects makes discrimination more difficult to prove as the number of variables increases.

Balancing the need to include all relevant variables and to exclude all superfluous variables is a difficult task. If the regression excludes a variable that affects demand or supply and is correlated with sex, the effects will be attributed to the sex variable and overstate or understate the effect of the sex variable on salary. Moreover, this attribution may occur even if

80. Id. at 1043-44.
81. Id. at 1044-45.
83. See A. Walters, supra note 52, at 180 (Although there is no limit on the number of exogenous variables, a large number of variables "complicates the theory, reduces its sharpness, and reduces the degrees of freedom.").
84. Id.; see also Sears, Roebuck & Co., 628 F. Supp. at 1287.
85. See S. Chang, supra note 19, at 59-63; H. Kelejian & W. Oates, supra note 82, at 186-87; A. Walters, supra note 52, at 127-29.
86. This problem is particularly acute when the variable at issue allegedly reflects the effects of past discrimination. See, e.g., Sobel v. Yeshiva Univ., 839 F.2d 18, 35 (2d Cir. 1988), cert. denied, 490 U.S. 1105 (1989). For example, if it is more difficult for women to have articles
the regression would not yield a statistically significant coefficient for the omitted variable. By contrast, requiring the regression to include every conceivable variable—regardless of theoretical or empirical merit—unfairly favors the defense. 87

The decision to include or exclude a variable must be based on the economic theory of the particular labor market. In supporting a statistical model, the proponent should explain why a factor influences the supply or demand for labor, why the proxy chosen to measure this attribute was chosen, and what the regression results indicate as to the explanatory power of the variable for the given sample. If there is no sufficient theoretical justification for the variable or if the model fails to measure the factor meaningfully, the variable should be excluded.

Producing probative identified supply and/or demand regression analyses requires not only including all relevant variables but also assuring that the model includes enough statistically significant exogenous variables. Again, the theory must provide the justification for both the endogenous variables (publications, service) and exogenous variables (department, average salary in nonteaching alternatives) to be included in the model. Furthermore, for identified equations, the theoretical justification dictates whether a factor is included in the supply or the demand equation. If the theory suggests that a factor should affect only demand, it should not be included in the supply equation—even if the particular sample suggests some correlation.

2. The Difficulty of Measuring Quality

A similar practical difficulty in obtaining identified structural equations (or assessing the probative value of unidentified equations) is the problem of measuring quality. Like the omission of an influential variable, inaccurately measuring quality causes the regression to attribute part of the effect of that variable to an included variable that is correlated. 88 For example, if accepted than it is for men, a difference in publication rates may, at least in part, reflect that discrimination rather than explain a salary differential. See Ferber & Green, Traditional or Reverse Sex Discrimination? A Case Study of a Large Public University, 35 INDUS. & LAB. REL. REV. 550, 552 & n.9 (1982). If that assertion were true, including publications would include a tainted explanatory variable. On the other hand, if some differences in publications would be correlated with sex even without any discrimination, excluding publications would cause the nondiscriminatory aspect to be attributed to the sex variable.

87. The inclusion of every conceivable variable also could unfairly favor the plaintiff if the defendant was offering a regression showing that a supply factor provided a statistically significant explanation of a wage differential.

88. See Moore, supra note 57, at 3-12 (counting the number of articles published or books written misses the important quality differences in the research performed); see also Behrman & Birdsall, The Quality of Schooling: Quantity Alone Is Misleading, 73 AMER. ECON. REV. 928, 928-29 (1983) (suggesting that quality of schooling affects productivity and therefore earnings).
women included in the sample tend to write better articles than the included men and the quality of articles affects salary, a regression including only the number of articles published would be incomplete. Such an analysis would underestimate the effect of publications on a woman's salary and would instead attribute that influence to a correlated factor, the teacher's sex. The suggested equation would thus have a multicollinearity problem.\textsuperscript{89}

The inherent limitation of regression analysis, even if all of the statistical assumptions are satisfied, is that it assumes that the intricacies of human decision making can be reduced to mathematical formulae.\textsuperscript{90} As courts have recognized, however, academic and professional employment and advancement decisions include a high regard for subjective personal qualities and characteristics.\textsuperscript{91} Measuring teaching quality, prestige, publication quality, and similar variables is admittedly difficult, but the use of exogenous variables to identify supply and demand curves assumes that the statistician has accurately measured both the exogenous and endogenous variables.\textsuperscript{92} Absent good proxies for the variables, both the reduced form equation and any identified equations will not provide unbiased estimators of the true market effect.

C. Treating the Identification Problem as Affecting the Probative Value of Multiple Regressions

In a perfect world, the relevant variables would include enough exogenous variables to identify both the demand and the supply curves for labor. Given the practical difficulties in obtaining identified supply and demand curves in statistical models, however, the more practical question is what probative value multiple regression studies should be given in evaluating discrimination claims.

The Supreme Court has consistently held that the probative value of statistical proof "depends on all of the surrounding facts and circum-

\textsuperscript{89} See Smith & Abram, \emph{supra} note 82, at 69-70. When quality of publications is omitted, its effect is included in the error term. Thus, if quality is correlated with sex, the sex variable is correlated with the error term, violating one of the basic assumptions of regression analysis and resulting in biased estimators. M. Lewis-Beck, \emph{supra} note 18, at 26-30 (listing assumptions of regression analysis); see also Sobel, 839 F.2d at 35 (requiring defendant to show that omitted variables are not multicollinear with other included variables and not tainted by sex discrimination).

\textsuperscript{90} See Sears, Roebuck & Co., 628 F. Supp. at 1288.


\textsuperscript{92} The difficult issue of quality might be approached by considering the quality of the journal in which the professor publishes or by counting the number of publications in top journals. See, e.g., Gordon & Purvis, \emph{Journal Publication Records as a Measure of Research Performance}, 45 INDUS. & LAB. REL. REV. 194, 199 (1991).
stances." Since the Court held in Bazemore that the exclusion of variables normally goes to the weight and not to the admissibility of the statistical study, the Court should treat the identification problem in a similar manner. The serious weakness of such studies, however, should be considered in evaluating the probative value of the statistics and the need for other evidence.

1. The Plaintiff's Initial Burden

From the plaintiff's perspective, the identification problem should have little effect on the initial burden of establishing a prima facie case of sex discrimination. Although a model that identifies separate demand curves for men and women would obviously establish a prima facie case, the Supreme Court has held that a plaintiff need not prove discrimination with scientific certainty, but instead by a preponderance of the evidence.  

The reduced form equation, if it includes the most relevant variables (properly measured) and produces statistically significant coefficients for the race or the sex variable, evidences a difference in salary. The reduced form equation will not prove whether the differential resulted from supply or demand factors, but because it shows that a difference exists, the unidentified reduced form equation should be admissible under the Bazemore standard.

The plaintiff can buttress the limited probative value of the reduced form regression with nonregression evidence. Rather than relying solely on aggregated statistics, the plaintiff should offer several side-by-side individual comparisons of the salaries of comparable male and female teachers. If the plaintiff has excluded a variable on the grounds that the variable reflects past discrimination, she should offer anecdotal or other evidence to support the exclusion of that variable. The plaintiff should also explain her economic theory of how the market works and support that theory as much as possible with direct testimony. By laying a nonstatistical groundwork in the direct evidence, the plaintiff will provide concrete examples that will assist the court to weigh the significance of an omitted or included variable in the multiple regression analysis.

2. Rebutting the Prima Facie Case

Just as it is unrealistic to require the plaintiff to produce an identified model to satisfy the prima facie burden, so too is it unfair to impose such

94. See Bazemore, 478 U.S. at 400.
95. See supra note 86 and accompanying text.
96. See Griffin v. Board of Regents of Regency Univs., 795 F.2d 1281, 1292 (7th Cir. 1986) ("Certainly, examples of individual discrimination are not always required, but we think the lack of such proof reinforces the doubt arising from the questions about the validity of the statistical evidence.")
a burden on the defendant. Depending on the available data, the size of
the sample, and the number of theoretically justified exogenous variables,
neither party may be able to provide a regression study that isolates the
effects of demand and supply and either proves or disproves discrimination.
A defendant would have an incentive to produce an identified regression
model if it could explain any salary differential that was correlated with
sex, but the identified model should not be necessary to rebut the reduced
form prima facie case made by the plaintiff.

Courts should permit the defendant to challenge the probative value of
unidentified regression analyses, more specifically their inability to separate
the effects of demand and supply. This is contrary to the approach of at
least some circuits, where the courts have held that theoretical criticisms of
regression studies are insufficient to rebut an inference of discrimination.97
Thus, if a defendant claims that the regression does not prove discrimination
because it omitted a critical variable, those courts require the defendant to
produce a regression analysis showing that there exists no statistically
significant disparity when that variable is included.98 But whatever merit
that approach may have for omitted variables,99 it is inappropriate when
the plaintiff offers an unidentified regression model and, due to the sample
size or available data, it is impossible or impractical for the defendant to
supply an identified model.

Rather than bar either defendants or plaintiffs from criticizing a study
as unidentified, the identification issue should reduce the probative value
of the unidentified statistical results and force a further analysis into why
any salary differential exists. The parties would then need to return to their
theory of the market and offer other statistical or anecdotal evidence to
prove why the court should find that the differential was or was not caused
by discrimination.100

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1105 (1989); see also Palmer v. Schultz, 815 F.2d 84, 101 (D.C. Cir. 1987) (“Implicit in the
Bazemore holding is the principle that a mere conjecture or assertion on the defendant’s part
that some missing factor would explain the existing disparities ... generally cannot defeat the
inference of discrimination created by plaintiffs’ statistics.”).
98. See Sobel, 839 F.2d at 34; Palmer, 815 F.2d at 101.
99. This requirement is also subject to question with respect to challenging the ability of
proxies to measure attributes such as quality and teaching ability. The fact that no better
measures are available in the sample should not prevent either party from challenging the
probative value of the other’s proxy for a qualitative attribute. Compare Penk v. Oregon State
Bd. of Educ., 816 F.2d 458, 464-65 (9th Cir. 1984) (district court properly discounted probative
value of statistical evidence in light of missing and inadequately represented variables) with
Sobel, 839 F.2d at 34-35 (defendant cannot rely on assumptions about imperfections in proxies
but must demonstrate that the failure to include a variable caused an actual underadjustment).
100. For example, if the defendant suggested that a supply factor (such as the need to care
for young children) explains a wage differential, the defendant should need to offer numerical
or anecdotal proof of that proposition.
3. Weighing the Probative Value of Statistics

Some courts clearly view statistics skeptically and question the "unbiased" results of regression analysis. As one judge commented, "[t]he most apparent consistency between the two experts' testimony was their insistence that the other's study contained serious statistical flaws." Nonetheless, in weighing the probative value of identified and unidentified regression analyses, several guidelines seem appropriate.

First, the court should recognize, and require the parties to explain, what the regression study can and cannot show. In this regard, the parties can state whether the models they are offering can isolate the effects of demand and supply or whether they rely on reduced form equations, which indicate the net effect of demand and supply.

Second, a statistical study with identified equations (either proving or disproving the existence of a separate curve by sex or race) should automatically trump an unidentified regression on a reduced form equation. Since the ultimate question is whether the defendant discriminated, the most probative statistical evidence is that which shows whether any salary differential was caused by the employer having separate demand curves for men and women. The identification of separate demand curves for men and women proves discrimination; by contrast, a statistically insignificant coefficient on the sex variable in an identified demand curve refutes a discrimination claim.

Similarly, an identified supply curve that explains the salary differential should defeat regression studies on unidentified equations. Suppose, for example, the unidentified reduced form equation suggested a $1000 difference in salary according to the sex of the teacher. If an identified supply curve shows at least a $1000 difference caused by supply factors, the difference has been explained in nondiscriminatory terms, and any inference raised by the unidentified results should be conclusively rebutted.

Third, the parties should be required to address the issue of omitted or difficult to quantify variables not only in terms of the effect on the differential but also whether those factors affect supply, demand, or both. This analysis is important whether the parties rely on identified or reduced form equations. By focusing on how well the variables and proxies conform

102. Obviously, if the identified study were ripe with error or contained other errors that went to the validity of the results, the fact finder would need to decide the sufficiency of the study. The fact finder should be charged, however, with the instruction that an identified study, if properly done, necessarily defeats an unidentified regression.
103. A study with identified equations and no statistical significance for the sex variable satisfies even the most stringent requirements of what a defendant must show to rebut a prima facie case. See Sobel, 839 F.2d at 34.
104. Again, this assumes that the regression was properly run on the identified equation.
to the economic theory, the analysis is sharpened to go beyond the question of whether additional variables should be included to an analysis of whether one expects the variable to affect supply or demand and whether the omission is likely to affect the coefficient on the sex variable.

Finally, under the Civil Rights Act of 1991,105 Title VII plaintiffs will have a right to a jury trial on the discrimination issues. Previously, there was no right to a jury trial on sex discrimination claims, and district courts served as the finders of fact.106 In trials to the bench, district courts not only can review the statistical proof but also can review the transcript of testimony and have the parties provide post-trial briefs citing to the critical statistical evidence. The courts also can consult statistics texts as necessary to evaluate the regression analyses.107 Further contributing to a careful and reasoned study of the statistical issues is the requirement that a district court issue written findings of fact sufficient to permit a meaningful review by the court of appeals.108

If juries are to evaluate and weigh statistical “proof” of discrimination, the courts will need to provide detailed instructions, and perhaps warnings, about the statistical evidence. In the typical case, where both sides rely on statistical models with reduced form equations, the court should specifically instruct the jury not only that discrimination occurs when an employer is willing to pay more for a male employee than for an equally qualified female but also that the models offered by the parties do not conclusively provide whether the employer discriminates. The jury then needs to consider how well the parties explain the supply and demand aspects of any salary differential and how well the economic models match the proffered theories and the jury’s common sense.109


106. Most courts agree that a plaintiff has no right to a jury trial on a discrimination claim brought under Title VII (which would include sex discrimination claims). See Sherman v. Burke Contracting, 891 F.2d 1257, 1259 n.4 (11th Cir.), cert. denied, 111 S. Ct. 353 (1990); Keller v. Prince George’s County, 827 F.2d 952, 955 (4th Cir. 1987); Shah v. Mt. Zion Hospital and Medical Center, 642 F.2d 268, 272 (9th Cir. 1981); Grayson v. Wickes Corp., 607 F.2d 1194, 1196 (7th Cir. 1979). But see Lytle v. Household Mfg., Inc., 110 S. Ct. 1331, 1335 n.1 (1990) (“This Court has not ruled on the question whether a plaintiff seeking relief under Title VII has a right to a jury trial.”).


109. The jury should also be given some specific, clear, and simple instructions (preferably in writing so that the jury can take the instructions to the jury room) about the undisputed statistical principles. For example, the instructions may include the meaning of statistical significance and how the regression coefficients do not determine the precise differential but only permit a determination of the confidence interval within which there is a 90-95% probability that the true value lies. The court should also provide (or have the parties jointly provide) the jury with a glossary of statistical terms included in the expert exhibits or raised in testimony.
Courts should recognize, and help juries recognize, the inherent limitations of multiple regression analysis and the importance of the model and underlying theory. By itself, an identification problem should not bar the admissibility of statistical evidence concerning alleged discrimination. The flaw in the models is a serious one, however, and courts (and now juries) should consider the limited probative value of reduced form equations and look to other direct, anecdotal, or statistical proof that confirms or rebuts the plaintiff's and defendant's regressions.

CONCLUSION

As courts demonstrate increasing sophistication in analyzing statistical techniques, they also need to require the parties to justify their theories and statistical models. Litigants are routinely using regressions on unidentified equations and claiming that the results prove or disprove a discrimination claim. In fact, such unidentified models can do neither, and, absent regressions on identified equations, the courts need to increase their skepticism of the probative value of the statistical proof.