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DO WOMEN AND MINORITIES EARN LESS DUE TO OCCUPATIONAL SEGREGATION, LOWER WAGES, OR FEWER HOURS?

by

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Do Women and Minorities Earn Less Due to Occupational Segregation, Lower Wages, or Fewer Hours?

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Abstract

Using consistently estimated occupational, wage, and hours equations, we calculate earnings differentials by gender, race, and ethnicity. For example, if the market treated women like men, the average women would have earned $133 more per week so that American women would have earned $338 billion more per year. We decompose the earnings differential into wage, hours, and occupational effects. Occupational segregation explains little of the earnings differential for women, but roughly a fifth of the differential for black and Hispanic men. For all groups, within-occupation wage discrimination is responsible for most of the earnings differential.

Do Women and Minorities Earn Less Due to

Occupational Segregation, Lower Wages, or Fewer Hours?

I. Introduction

Do women and minorities earn less than white males with similar characteristics due to wage discrimination, hours discrimination, or occupational discrimination? To answer these questions, we decompose the overall earnings differential into wage, hours, and occupational effects, controlling for possible sample selection in choice of occupation when estimating occupational wage and hours equations.

This decomposition of gender and racial earning differentials into within-occupation wage differences, within-occupation hours differences, and differences in occupational distributions is important for developing effective policies for eliminating discrimination. For example, if wage discrimination is the primary cause of earnings differentials, society should focus resources on enforcing "equal pay for equal work" laws that are designed to equalize wages within an occupation. If hours discrimination is a prime factor, "equal pay for equal work" laws will not be fully effective.[1] If occupational discrimination is largely responsible for the earnings disparity, society might try to knock down barriers to entry into high-wage occupations.

We believe that this study is the first to systematically consider occupational, wage, hours, and earnings discrimination simultaneously. Until recently, virtually all discrimination studies examined only wage or earnings differentials. They ignored the role of occupational distributions and hours differentials in explaining total earnings differentials.

Hours and occupational distributions, however, may play an important role in determining earnings differences. For example, Goldin (1990) finds that, because women work fewer hours than men, their earnings as a fraction of men's is smaller than their wages as a fraction of men's.

Recently, some economists, sociologists, and comparable-worth advocates have argued that women (and presumably minorities as well) are segregated into certain occupations by institutional barriers, prejudice, or socialization processes that influence an individual's taste for work. Beller (1984) estimates that, in 1981, over 60 percent of the female labor force would have had to change jobs in order for the two genders to have the same detailed occupational distribution. Polachek (1987) finds, however, that the occupational distribution explained only 20 to 21 percent of the 1970's earning gap using 195 occupations. Similarly, Treiman and Hartmann (1981) find that occupational segregation explained only 11 to 19 percent of the differential for 222 occupations.

Most existing studies of the role of occupational-crowding regress wages or earnings on individual workers' productivity-related characteristics and a measure of the occupation's gender composition. This approach has three potential flaws. First, using a single, additive measure may not explain all the occupational effects. Second, using only aggregate measures may be misleading if there are substantial variations in decisions by individuals within a demographic group. Third, gender composition within an occupation may be endogenously determined, so that ordinary least squares estimates of wage or earnings equations have inconsistent parameter estimates.

Thus, we believe that studies of the role of occupational distributions on earnings should be based on a model of endogenous, individual decision making. So far as we know, only two studies explicitly estimate occupational wage or earnings equations controlling for possible occupational-based sample selection.

Sorensen (1989) estimates wage equations that control for both a woman's decision whether or not to work and the choice of occupation. In a clever article, she finds that possible selectivity bias from the decision to work or not does not have a significant effect on earnings whereas the selectivity bias due to occupational choice does. In her model, worker make a dichotomous choice between selecting a female-dominated job and a non-female-dominated job. To avoid the possibility of circularity in our estimation, we use five broad, commonly-used categories of occupation — rather than occupational categories created on the basis of the share of women in them.

Reilly (1991), using a methodology similar to ours, examines five occupational groups and corrects for sample selection in estimating wage equations based on Irish data. He finds that sample selection is significant for clerical and skilled workers, and that intra-occupational wage differentials are more important than occupational distribution.

Although both these studies are very well-done, we believe our study makes two additional contributions. First, these studies only estimate occupation and wage equations, so they cannot examine the relative importance of hours discrimination. Second, these studies concentrate on gender discrimination, whereas we also examine discrimination on the basis of race and ethnicity.

We now describe our statistical model and then describe the data. Next, we discuss the estimates of our occupation, wage, and hours equations. We then use these estimates to determine the earnings differences by gender, race, and ethnicity, and decompose these total earnings effects by wage, hours, and occupation effects.

II. Statistic Model and Estimation

In the absence of discriminatory barriers, workers choose their occupations by weighing the pecuniary and nonpecuniary costs and benefits of each. Workers take into account the differences in costs and benefits across occupations that vary by skill level and demographic characteristics. After controlling for these demographic characteristics such as education and experience, we attribute any remaining differences associated with gender, race, or ethnicity to discrimination or taste differences. Because of the possibility of systematic taste differences by gender, race, or ethnicity, one might interpret the estimated differences due to gender, race, and ethnicity as bounds on the degree of discrimination.

We divide workers into five broad occupational classes. We then estimate a "reduced-form" multinomial logit equation to predict occupation. This equation is a reduced-form in the sense that we do not include wages as explanatory variables. We only include demographic and other variables that explain wages or occupational choice directly.

Next, adjusting for occupational choice based on the logistic equation, we estimate five wage and five hours equations.[2] Whether a particular individual i (= 1, . . . , N) works in occupation j (= 0, . . . , 4) depends on individual choice, discrimination, and chance. In service occupations, the base category, j equals 0; in blue collar, $j = 1$; in clerical, $j = 2$; in technical or sales, $j = 3$; in administration or professional occupations, $j = 4$.

Let J_i be the occupation-selection variable for individual i that takes on the values 0, . . . , 4. Using the logistic model, the equation that determines the probability that individual i is in occupation j is

$$p_j \equiv \text{Prob}[J_i = j] = \frac{e^{\gamma_j' Z_i}}{1 + \sum_{k=1}^{4} e^{\gamma_k' Z_i}}, \tag{1}$$

where γ_0 is normalized to be 0 and Z_i is a vector of exogenous characteristics of individual i including gender, education, education squared, experience, experience squared, race, ethnicity, veteran status, city size, and geographical region as well as many variables interacted with female.

We estimate separate logarithmic wage and hours equations for each occupation. Individual i's wage in an occupation, w_{ij}, or hours worked, h_{ij}, is only observed if individual i is in occupation j. We now drop the i subscript for notational simplicity and focus on the wage equations (as the hours equations are estimated in the same manner). For a particular occupation j, we estimate over the individuals who are in that occupation

$$\ln w_j = X_j \beta_j + \sigma_j u_j, \tag{2}$$

where σ_j is the standard deviation for the logistic distribution, X_j is a vector of exogenous individual characteristics including gender, education, education squared, experience, experience squared, race, ethnicity, veteran status, geographical region, city size, and union membership; $E(u_j \mid X, Z) = 0$ and $E(\eta_j \mid X, Z) = 0$, where η_j are independent and identically Gumbel distributed error terms from the multinomial logit equation.

Unless occupations are assigned randomly, the error terms of the occupation, wage, and hours equations may be correlated, leading to a sample selection bias if the wage and hours equations are estimated by ordinary least squares. Instead, we use Lee's extension of Heckman's two-step procedure to obtain consistent estimates. The regression equation derived by Lee is

$$\begin{aligned} \ln w_j &= \beta' X + \rho_j \sigma_j \frac{\phi\left(H_j(\gamma_j' Z)\right)}{\Phi\left(H_j(\gamma_j' Z)\right)} + \eta_j \\ &\equiv \beta' X + \rho_j \sigma_j \lambda_j + \eta_j \\ &\equiv \beta' X + \theta_j \lambda_j + \eta_j, \end{aligned} \tag{3}$$

where H_j is the inverse of the standard normal cumulative density function, Φ, and ϕ is the corresponding normal density.

First, we estimate the multinomial logit model by maximum likelihood. Then we select all the individuals within a given occupation *j*. For the individuals in this occupation, we calculate the predicted probability, p_j, using Equation (1), calculating $H_j = \Phi^{-1}(p_j)$, and then compute $\lambda_j = \phi(H_j)/\Phi(H_j)$. We then estimate Equation (3) to obtain consistent estimates of β_j and θ_j by regressing $\ln w_j$ or h_j on X and λ_j. The formula for the asymptotic covariance matrix is given in Greene (1991).

III. Data

The model is estimated using the 7,460 usable observations from a one-in-twenty random sample of civilian, nonfarm workers in the 1988 Current Population Survey (CPS) who worked at least ten hours a week.[3] Means and standard deviations are reported in Table 1.

Race is divided into three categories: whites (87 percent of the sample, residual category), blacks (10 percent), and other non-whites (3 percent). There are two ethnic categories: Hispanics (five percent of the sample) and others (95 percent, residual category).

The education variable is the highest grade completed (up to 18 years). Workers in the sample averaged slightly over 13 years of formal schooling. Unfortunately, the sample contains no information on apprenticeships, trade school training, or on-the-job training. As a result, the education of some individuals may be understated. Moreover, the data set does not contain measures of differences in the quality of education. Thus if a group has an inferior education, the (quality-adjusted) education for that group may be overstated.

The mean number of years of experience is 18.4 years, where a worker's labor force experience is defined as age - education - 6. Anyone who temporarily dropped out of the labor force for any reason except to continue their education (such as a women who stayed home to raise children) has an overstated number of years of experience.

Our five occupational categories are:

- Service (13 percent): Private household, protective service, food, health, cleaning and personal service [residual category].
- Blue Collar (29 percent): Precision production, craft and repair, operators, fabricators, and laborers.

- Clerical (19 percent): Administrative support including clerical, computer equipment operators, secretaries, mail and message distributors, and financial records processing.
- Technical and Sales (14 percent): Health technologists, engineering and science technicians, sales representatives, sales workers, and sales related.
- Administrative and Professional (25 percent): Administrative and managerial, engineers, scientists, teachers, health workers, and lawyers.

Dummy variables for region were included to reflect the concentration of occupations in certain areas of the country and geographic wage and hours differentials. Of our sample respondents, 25 percent are in the northeast, 31 percent in the south, 25 percent in the midwest, and 19 percent in the west (residual category).

Also included in the occupation and earnings equations is the size of one's community. The residual category is rural or small city. Medium-size cities are defined as having a population of 1,000,000-2,499,999. Large cities have a population of 2,500,000 or more.

IV. Estimation

We use maximum likelihood techniques to estimate a reduced-form, multinomial logit equation for our five occupation categories. Next, we estimate a wage equation and an hours equation for each of the five occupations using a consistent technique that avoid sample selection bias.

Gender, race, and ethnicity, as expected, lower a worker's expected wage, hours, and earnings and affect the probability of being in each occupation. We find evidence that ordinary least squares occupational wage and hours estimates would have a selectivity bias for service wages and hours, blue collar wages, clerical wages and hours, technical and sales hours, and administration and professional wages.

A. Occupation Equation

Occupational distributions differ by gender, race, and ethnicity, as shown in the multinomial logit estimate of the occupation equation (Table 2). Based on asymptotic t-tests and Wald tests using a 0.05 criterion, the occupational distributions of females, blacks, other nonwhites, and Hispanics are statistically significantly different from those of white males.

The predicted probabilities of being in a given occupation vary across major demographic groups. In Table 3, we evaluate these probabilities for a member of various demographic groups who have the sample average characteristics of 13.1 years of education, 18.4 years of experience, and who are nonunion members, nonveterans, and live in a small city in the west. As shown in Table 3, blacks and Hispanics are more likely to be in services than whites. Blacks and Hispanic males are much less likely to be in administration or professional occupations than comparable whites or Hispanic females. White women are more likely to be in services or clerical jobs than white men, and very much less likely to be in blue-collar jobs. Black women are even more likely to be in service or blue collar jobs than white women, and they are less likely to be in other occupations.

Both experience and education have a nonlinear (quadratic) effect. Workers with greater experience are more likely to be in a blue collar occupation (up to 22 years), or professional (up to 30 years) than in service. At the sample means, one percent more education lowers one's probability of being in service, blue collar, or administration and professional occupations.

B. Wage Equations

We estimate a separate wage equations for each of the five occupational groups adjusting for possible sample selection by including an inverse Mills' ratio, λ (Table 4). The estimated λ is asymptotically statistically significantly different from zero at .05 level based on a t-test using the corrected standard errors in the service, blue collar, clerical, and administration and professional equations.[4]

A white male earns a wage that is 23 percent higher than does a Hispanic male with the same characteristics in blue collar occupations. This differential is 20 percent in clerical and 3 percent in administration and professional occupations. In the other occupations, this differential is not asymptotically statistically significantly different from zero at the .05 level.

In all of the wage equations except for clerical (where the coefficient is a large positive number), the coefficient on the female dummy was not statistically significantly different from zero. To calculate the effect of gender, race, or ethnicity on wages, however, one must also consider the interaction terms. Most of these, however, are also statistically insignificant except for the education and experience interactions with gender.[5]

At the average level of education, a white, non-Hispanic woman with the sample average education (13.1 years) and experience (18.4 years) earns a wage that is 42 percent lower than that of a comparable male. For low or moderate levels of education and experience, females' wages respond less to experience and education than do males'. For example, in the administration and professional equation, the more education or experience a women has, the lower her wage relative to males up until 13 years of education or 25 years of experience. Thereafter, more education or experience lowers the differential.

The effect of education and experience on the wage differential varies by occupation. In administration and professional occupations, a woman with this education and experience level earns 22 percent more than a male; whereas, such a woman earns a wage that is 25 percent less than that of a male in service.

The wage of nonwhite females is higher than that of their male counterparts in service and technical and sales but lower in clerical occupations. Female Hispanics earn significantly less in service and blue collar occupations than male Hispanics.

In all occupations except clerical, blacks earn statistically significantly lower wage and whites. A black female's wage is slightly higher than her black male counterpart in all but the service and the administration and professional occupations. In service, blue collar, and technical and sales occupations, other nonwhite workers have significantly lower wages than their white counterparts. Conversely, other nonwhites earn significantly more in clerical and administration and professional.

Experience has a greater positive impact on one's wages than education. Union members have significantly higher wages in all occupations.[6] Being a veteran increases one's wage in blue collar and administration and professional occupations but decreases it in clerical and technical and sales occupations. Similarly, individuals who live in medium and large cities have significantly greater hourly wages than their rural-small city counterparts.

C. Hours Equations

There is statistical evidence of sample selection bias in the service, clerical, and technical and sales hours equations based on the asymptotic adjusted standard errors (Table 5).[7] Gender, race, and ethnicity matter in all of the hours equations.

Hispanic males and blacks work statistically significantly fewer hours than do whites in all occupations except clerical. For example, in service, blacks worked 5.2 fewer hours per week and Hispanics work .3 hours fewer per week than do whites.

The coefficient on the female dummy variable is statistically significantly negative in the service equation and statistically significantly positive in the clerical, technical and sales, and administration and professional equations. To calculate the gender differential, we also need to consider the interaction effects with education and experience. A white female with average education and experience works 8.1 fewer hours in the service industry than a comparable male. In technical and sales, she works 10.4 fewer hours (despite the positive coefficient on the female dummy in this equation).

Black females work significantly more hours than black males in all occupations. Other nonwhite females work more hours than other nonwhite males in service, clerical, and administration and professional occupations. Hispanic females work more than Hispanic males in blue collar, clerical, and technical and sales occupations.

Union members worked significantly more hours than nonunion members in service, blue collar, and clerical occupations and significantly fewer hours in technical and sales occupations. The hours worked varied substantially with education and experience. More education has first a negative and then a positive effect in all occupations except technical and sales, where the pattern is reversed. More years of experience first raises then lowers hours in all occupations.

V. Simulations

Based on these estimated equations, we can calculate sample selection-adjusted earnings, wages, and hours for various demographic groups.[8] First, we compare the total earnings differences between white males and other demographic groups for people with identical characteristics. Second, we decompose these total earnings differences into occupational, wage, and hours differences. Third, we compare the earnings of women and men taking into account the actual difference in characteristics between these two groups.

A. Earnings Differential For a Typical Worker

Table 6 shows the expected earnings for white males, white females, black males and females, and Hispanic males and females with sample-average characteristics.[9] Across all occupations, an individual with these typical characteristics earned a maximum of $506 per week if he was white, or a low of $255 per week is she were Hispanic. The percentage earnings differential between white males and the other groups ranged from 19 percent for Hispanic males to 49 percent for Hispanic females. As shown in the table, the earnings differentials vary substantially by occupation.

B. Decomposition of the Earnings Differential

The earnings differential is the sum of the wage, hours, and occupational distribution differentials. Let the expected earnings (where the expectation is taken over occupations) of a white male be E and the expected earnings of a member of another group (such as white females) be E^*. The difference in expected earnings between white males and the other group is

$$\Delta E^* = E - E^* = \sum_i p_i E_i - \sum_i p_i^* E_i^*, \tag{4}$$

where E_i is the earnings of a white male in occupation i, E_i^* is the earnings of a member of another group (such as white females) in occupation i, p_i is the probability that a white male is in occupation i, and p_i^* is the probability that the member of the other group is in occupation i (Kossoudji, 1988). In other words, the difference in expected earnings equals the expected earnings of a white male minus the expected earnings of someone in another group, where the expectation is taken over occupations.

Equation (4) can be rewritten as approximately

$$\Delta E^* = \sum_i E_i^*(p_i - p_i^*) + \sum_i p_i(E_i - E_i^*). \tag{5}$$

That is, the difference in earnings equals other group's earnings times the difference in the probabilities of a white male and that of the other group plus the white male's occupational probability times the earnings differential between the two groups summed over the occupations.

Earnings in occupation i are a product of the wage in that occupation times the hours worked: $E_i = w_i H_i$. Thus, we can rewrite our approximation Equation (5) as

$$\Delta E^* \approx \sum_i E_i^*(p_i - p_i^*) + \sum_i p_i\,[w_i - w_i^*]\bar{H}_i + \sum_i p_i\,(H_i - H_i^*)\bar{w}_i. \tag{6}$$

The first term on the right hand side of Equation (6), $\Sigma_i\, E_i^*(p_i - p_i^*)$, which we call the "occupation difference," is the differential in earnings due to a difference in probabilities of being in a given occupation. The second term, $\Sigma_i\, p_i(w_i - w_i^*)\bar{H}_i$, is the "wage difference." The final term, $\Sigma_i\, p_i(H_i - H_i^*)\bar{w}_i$, is the "hours difference." Thus, the total earnings difference is approximately equal to the probability differential plus the wage differential plus the hours differential.

In Table 7, the total differences in earnings is decomposed into the share due to the occupation, wage, and hours effects. That is the columns of Table 7 are the percentage differences (the differences divided by ΔE^*) due to the occupation, wage, and hours effects.

For each of our demographic groups, between half and three-quarters of the total earning difference between them and white men is due to the wage differences. The largest share (74 percent) of the total earnings difference due to the wage effect is for Hispanic women; the smallest share (51 percent) is for Hispanic men.

For white women and Hispanic women, virtually none of the total earnings difference is due to different occupational distributions. In contrast, for black women and men and Hispanic men, occupational segregation may play an important role. For Hispanic men, the occupational differences explain nearly a quarter of the total earnings difference, whereas for black women, they are responsible for about one ninth of the difference, and for black men, occupational differences cause nearly one fifth of the total difference in earnings.

Hours differentials explain between 17 and 32 percent of the total earnings differential across our demographic groups. The largest contribution, 32 percent is for white women, and the smallest, 17 percent, is for black men.

C. Sample Earnings Differentials

An alternative way of expressing the earnings differences is to determine how much more each demographic group would have earned if, given their characteristic, their hours and wages were determined in the same way as, say, white men. To illustrate this technique, we calculate how much higher the earnings of women would have been had they been men.

Women have a different distributions of characteristics such as education and experience than males, even though the two groups have similar means, which we take into account in our simulations. For example, the earning difference between men and women has a non-linear shape with respect to experience. At both low levels of experience (say, 2 years) and at high levels (say, 25 years), the earning differential is smaller than at the mean experience level of 18.4 years.

Taking account of the distribution of characteristics, women earned $132.65 less per week than if they had been men on average.[10] That is, for each women in our sample, we calculated how much she would have earned, given her actual characteristics, if we calculated her earnings as if she was a male (that is, we set the "female" coefficients to zero).

The advantage of calculating the earnings difference in this manner is that we can then "blow up" the difference to determine a national differential. To calculate the national effect, we multiply the average difference between women and men by the number of employed, civilian, noninstitutional, nonagricultural women (at least 16 years old) in 1988, 51.0 million, and multiply by 50 weeks in the year (the government's definition of a year-round worker).[11] Based on this calculation, we conclude that if women were treated like men in the work place in 1988, they would have earned $338 billion more.

Males would have earned \$198.61 less per week on average, given their actual distribution of characteristics, if they were females (the estimated coefficients on the female dummy terms are used to calculate their earnings). That is, the earnings of the 60.7 million males in the United States would have been \$603 billion lower if they were treated like females.

VI. Summary and Conclusions

Using a model that takes into account possible sample selection, we estimated the earnings differentials by gender, race, and ethnicity. We decomposed the difference in total earnings into wage differences, hours differences, and differences due to different occupational distributions.

Between half and three-quarters of the earnings differences between white men and other demographic groups is due to wage differences. Treiman and Hartmann (1981), Miller (1987), Polachek (1987), Goldin (1990), and Reilly (1991) also find that wage discrimination is more important than occupation discrimination.

Which type of discrimination is most important differs by demographic group. For example, three-quarters of Hispanic women's earnings gap is due to wage discrimination and none due to occupational segregation. In contrast, occupational segregation explains nearly a quarter of Hispanic males' earning differential. Similarly, hours effects are responsible for a third of the difference in earnings for white women but only a quarter for black women.

Given our results, a comparable-worth approach may have relatively little effect in equalizing earnings, even given substantial occupational segregation. Our results show that, contrary to the occupational-crowding hypothesis, women's lower earnings are due primarily to wage differentials and, to a lesser degree hours differentials, within an occupation rather than to occupational segregation.

It is possible that our results, at least in part, are due to our use of only five occupational groups. By using broad aggregate occupations, we may be missing some occupational discrimination. Unfortunately, with existing sample sizes and computer techniques, we do not believe it is feasible to estimate our model with a substantially larger set of occupations. Moreover, Treiman and Hartmann (1981) and Polachek (1987), using many more occupational groups than we do, but simpler statistical techniques, find that only about 20 percent of the wage differential is due to occupational differences — a result comparable to ours.

Given better data sets, our analysis could be strengthened in two important ways. First, more accurate gender discrimination estimates could be obtained using better measures of experience that take explicit account of life-time labor-force participation decisions. Because some women temporarily drop out of the labor market to bear children and run households, our measures of these women's experience are likely to be overstated relative to those for men.

Second, this type of analysis would be more useful if we could determine whether the observed differentials in earnings reflect only discrimination or if they also reflect taste differences. To distinguish between these two effects, we believe researchers would need, at a minimum, cross-sectional, time-series.

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Footnotes

1. Given our data, we cannot distinguish between discrimination and taste differences. Presumably tastes cannot explain lower wages, but they may explain why certain demographic groups work fewer hours or are over-represented in certain occupational groups (e. g., women are more likely to work in nursing than are men). They may work in these occupations due to their own choice (taste differences) or because they are barred from entering other more lucrative occupations. In this paper, we loosely use the word "discrimination" to cover both actual discrimination and taste differences. Thus, our calculations of hours and occupation discrimination differentials may be viewed as upper bounds.

2. The following presentation of the method to handle sample selection follows Lee (1983) and Greene (1991). We use occupational categories similar to those in Schmidt and Strauss (1975) and Reilly (1991).

3. Individuals were dropped from the sample if their hourly wage (calculated as their weekly earnings divided by usual weekly hours) was implausible, which we define as less than two or greater than $85.00. Individuals were also dropped if they reported working more than 85 hours a week. We dropped workers with fewer than 10 hours because, for most of them, the associated reported earnings were implausible.

4. We cannot reject that these coefficients are zero at the 0.05 level for any of the equation when using the uncorrected standard error.

5. This result with respect to experience may be due in part to how we measure experience (= age - education - 6). Our experience measure is too high for individuals who temporarily dropped out of the labor force to have children or for any other reason.

6. Union membership was treated, perhaps inappropriately, as exogenous. It was not included in the occupational equations to avoid circularity.

7. Based on the assumption that there is no sample selection (unadjusted asymptotic standard errors), we can reject that $\lambda = 0$ at the 0.05 level for clerical only.

8. Because we estimated a log-linear wage equation, our adjusted wage in occupation *j* is calculated as $\exp\{X\beta_j - \lambda_j + \frac{1}{2}\sigma_j^2\}$, where σ_j^2 is the element of the covariance matrix corresponding to β_j. Similarly, based on the wage and hours equations, we calculate workers' weekly earnings adjusting for sample selection and for the loglinearity of the wage equation (Perloff & Sickles, 1987).

9. Our "typical" individual is 37.5 years old, has the sample average education (13.1 years) and experience (18.4 years), nonunion member, nonveteran who lives in the west outside of a major metropolitan area.

10. This difference, because it takes into account differences in the actual characteristics of the sample, is lower than the difference reported in Table 6, where we compare the earnings of a female and a male with identical, average characteristics.

11. That is, we ignore the general equilibrium effects on equilibrium wages, hours, and occupational distributions that would result if discrimination were suddenly ended (the earnings of women were determined by the same equations as the earnings of men).

Table 1
Means

Variable	Mean
Qualitative Variables: percentage	
Female	47.6
Hispanic	4.8
Black	9.5
Other Nonwhite	3.3
Northeast	24.6
South	31.1
Midwest	25.1
Veteran	16.0
Medium Size City	16.3
Large Size City	29.7
Union	18.0
Continuous Variables: Years (Standard Deviation)	
Education	13.1 (2.7)
Experience	18.4 (12.5)

Sample Sample = 7460.

Table 2
Multinomial Logit Occupation Equations

	Blue Collar		Clerical		Technical Sales		Administration Professional	
	Coeff	ASE	Coeff	ASE	Coeff	ASE	Coeff	ASE
Constant	.704	.578	-6.651	2.050	-7.107	1.918	-2.537	1.131
Female	-1.563	.876	-4.428	2.651	4.280	2.260	-6.453	2.754
Hispanic	-.462	.223	-.596	.351	-.985	.325	-1.273	.327
Black	-1.017	.164	-.983	.255	-1.857	.264	-1.500	.225
Other Nonwhite	-.565	.285	-.903	.440	-.836	.341	-1.476	.350
Female × Hispanic	.469	.344	.104	.429	.388	.445	.853	.450
Female × Black	.650	.237	-.141	.296	.680	.326	-.059	.303
Female × Nonwhite	.477	.437	.160	.523	.332	.464	.415	.482
Veteran Status	-.259	.139	-.053	.185	-.320	.169	-.269	.160
Medium City	.021	.119	.211	.126	.132	.132	.028	.131
Large City	-.213	.104	.553	.108	.300	.115	.327	.112
Northeast	.313	.134	-.023	.139	-.244	.147	-.135	.143
South	.599	.128	.181	.134	.324	.138	.308	.137
Midwest	.366	.131	-.059	.136	-.150	.143	-.115	.139
Education	.223	.091	.736	.302	.783	.277	-.222	.165
Education^2	-.015	.004	-.020	.011	-.016	.010	.029	.006
Female × Education	-.096	.152	.838	.398	-.655	.335	.725	.399
Female × Education^2	.003	.007	-.031	.015	.023	.013	-.018	.015
Experience	.053	.014	.021	.021	.020	.018	.102	.018
Experience^2	-.001	.0003	-.0003	.0004	-.0003	.0004	-.002	.0004
Female × Experience	.015	.022	.004	.025	-.0008	.024	-.008	.025
Female × Experience^2	-.0002	.0004	-.0002	.0005	-.0002	.0005	-.0001	.0005

(continued)

(Table 2 continued)

	Predicted				
Actual	Service	Blue Collar	Clerical	Techical Sales	Administration Professional
Service	127	366	364	3	98
Blue Collar	66	1697	279	6	138
Clerical	53	220	897	6	210
Technical Sales	32	322	351	8	328
Administration Professional	9	302	297	0	1281

Table 3
Predicted Probabilities*

	Service	Blue Collar	Clerical	Technical Sales	Administration Professional
White Male	8.8	45.2	7.5	17.5	21.0
White Female	13.0	7.7	39.2	17.1	23.0
Black Male	24.9	46.2	8.0	7.7	13.2
Black Female	31.5	13.0	31.0	12.8	11.7
Hispanic Male	16.4	52.9	7.7	12.1	10.9
Hispanic Female	18.8	11.2	34.7	13.6	21.8

* Evaluated for an individual with the "basic" characteristics: 13.1 years of education, 18.4 years of experience, nonunion members, nonveterans, and live in a small city in the west.

Table 4
Occupational Wage Equations

	Service		*Blue Collar*		*Clerical*		*Technical/Sales*		*Administration/ Professional*	
	Coeff	ASE	Coeff	ASE	Coeff	ASE	Coeff	ASE	Coeff	ASE
Constant	1.341	.117	1.816	.094	1.777	.291	2.009	.516	2.189	.283
Female	.147	.103	-.155	.113	1.008	.187	-.513	.399	.730	.380
Hispanic	.021	.032	-.203	.023	-.182	.034	.047	.040	-.034	.045
Black	-.150	.040	-.195	.018	-.029	.025	-.288	.042	-.114	.031
Other Nonwhite	-.379	.041	-.181	.031	.100	.040	-.204	.037	.104	.044
Female × Hispanic	-.083	.037	-.115	.044	.049	.042	.059	.055	-.071	.059
Female × Black	.039	.026	.121	.036	.073	.030	.241	.045	.195	.040
Female × Nonwhite	.340	.044	.025	.059	-.106	.048	.248	.052	.0004	.054
Union Member	.359	.013	.250	.010	.187	.011	.061	.019	.031	.014
Veteran Status	-.005	.018	.027	.013	-.065	.016	-.063	.018	.051	.016
Medium City	.102	.014	.081	.013	.073	.012	.125	.014	.122	.013
Large City	.125	.012	.201	.019	.146	.013	.229	.012	.189	.012
Northeast	.026	.015	-.118	.020	-.022	.012	.050	.018	.020	.015
South	-.050	.018	-.161	.019	-.036	.012	.002	.014	-.046	.014
Midwest	-.075	.014	-.129	.020	-.068	.012	-.039	.016	-.041	.015
Education	.014	.011	-.038	.018	.0004	.032	-.076	.060	.038	.023
Education^2	.002	.0005	.005	.001	.002	.001	.005	.002	-.001	.001
Female × Education	-.060	.016	.024	.022	-.146	.032	.028	.054	-.132	.053

Female × $Education^2$	.002	.0008	-.0007	.001	.005	.001	-.0001	.002	.005	.002
Experience	.029	.002	.030	.002	.051	.002	.047	.002	.0240	.003
$Experience^2$	-.0005	.0000	-.0005	.000	-.0008	.000	-.0008	.0001	-.0004	.000
Female × Experience	-.006	.002	-.018	.003	-.040	.002	-.017	.003	-.020	.003
Female × $Experience^2$	.0001	.000	.0003	.0001	.0007	.000	.0002	.0001	.0004	.0001
λ	-.163	.060	-.206	.083	-.235	.050	-.119	.066	-.209	.072
R^2	.335		.364		.267		.364		.304	
N	958		2186		1386		1041		1889	

Table 5
Occupational Hours Equations

	Service		*Blue Collar*		*Clerical**		*Technical/Sales*		*Administration/ Professional*	
	Coeff	ASE	Coeff	ASE	Coeff	ASE	Coeff	ASE	Coeff	ASE
Constant	50.230	3.29	44.701	1.90	87.481	21.90	16.460	10.48	47.214	7.14
Female	-7.423	3.05	-3.995	2.31	14.192	15.73	23.192	8.10	26.964	9.38
Hispanic	-.289	.88	-1.918	.46	-4.608	2.45	-4.566	.83	-2.839	1.09
Black	-5.190	1.10	-1.755	.36	.210	1.77	-6.513	.86	-1.744	.73
Other Nonwhite	-5.733	1.12	-2.054	.63	-3.361	2.98	1.254	.77	-3.820	1.02
Female × Hispanic	-.776	1.04	2.377	.91	7.528	2.83	4.837	1.13	.485	1.40
Female × Black	4.541	.73	2.251	.74	2.336	2.06	8.137	.92	2.732	.95
Female × Nonwhite	4.054	1.22	1.106	1.23	6.898	3.36	.872	1.07	3.323	1.24
Union Member	4.149	.34	.100	.21	1.763	.69	-2.306	.40	-.394	.31
Veteran Status	1.460	.48	-.311	.25	-.950	1.13	-1.667	.37	-1.026	.36
Medium City	1.302	.37	-.721	.26	-.345	.68	1.301	.29	.052	.30
Large City	1.675	.34	.555	.39	-1.262	.86	-.775	.26	.165	.26
Northeast	-.955	.40	-.730	.41	-.820	.69	-.299	.36	-.813	.33
South	1.874	.49	-.486	.39	1.427	.69	1.080	.30	.351	.31
Midwest	.240	.38	-.669	.41	.690	.69	-.610	.33	.236	.33
Education	-.872	.31	-1.039	.37	-4.603	2.50	2.607	1.23	-.786	.58
Education^2	.045	.02	.069	.03	.164	.09	-.088	.04	.029	.02
Female × Education	-.721	.47	1.172	.44	-4.214	2.66	-4.292	1.11	-4.419	1.28

Female × Education^2	.064	.02	-.066	.02	.186	.10	.169	.04	.161	.04
Experience	.593	.06	.369	.03	.694	.14	.559	.05	.392	.06
Experience^2	-.014	.001	-.009	.001	-.017	.003	-.013	.001	-.010	.001
Female × Experience	-.195	.06	-.262	.064	-.590	.15	-.528	.06	-.473	.06
Female × Experience^2	.004	.001	.006	.001	.013	.003	.010	.001	.010	.002
λ	-7.685	1.80	-3.125	1.71	-10.892	3.57	3.393	1.36	.179	1.69
R^2	.167		.089		.086		.206		.117	
N	958		2186		1386		1041		1889	

* The ASE for the clerical equation are uncorrected. We were unable to calculate the corrected ASE.

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Table 6
Expected Weekly Earnings for a Typical Worker*

	All	Service	Blue Collar	Clerical	Technical Sales	Administration Professional
White Male	506	293	492	470	547	606
White Female	286	186	294	285	287	341
Black Male	376	269	390	464	348	495
Black Female	269	198	297	293	284	353
Hispanic Male	410	331	398	351	514	513
Hispanic Female	255	182	228	258	320	286

* Our typical worker has 13.1 years of education and 18.4 years of experience, is 37.5 years old, is not a union member or a veteran, and lives in the west in a small city or rural area.

Table 7
Percentage Share of the Earnings Difference Due to Occupation, Wage, and Hours Discrimination for a Typical Worker*

	Occupation	*Wage*	*Hours*
White women	3.0	65.0	32.0
Black men	18.0	65.4	16.6
Black women	11.8	64.5	23.7
Hispanic men	23.8	50.7	25.5
Hispanic women	-.1	73.8	26.4

* Our typical worker has 13.1 years of education and 18.4 years of experience, is 37.5 years old, is not a union member or a veteran, and lives in the west in a small city or rural area.