AN ALTERNATIVE EXPLANATION FOR THE EQUALITY OF MALE AND FEMALE UNEMPLOYMENT RATES IN THE U.S. LABOR MARKET IN THE LATE 1980s

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In the early 1970s, the gap between male and female unemployment rates in the U.S. labor market was significantly large. Several studies raised concerns about this disparity and there was a cry for gender egalitarianism [Barrett and Morgenstern, 1974; Lingle and Jones, 1978; Niemi, 1974]. Using the data from the same period, a number of other studies estimating male-female wage differentials demonstrated that women, in general, also received lower wages than otherwise identical male workers [Oaxaca, 1973; Blau and Beller, 1988; Gill, 1989; Hersch, 1991]. Thus, the 1970s, like the 1960s, experienced both employment and wage trends that in general were unfavorable to women.

Several authors attributed the large gender gaps in wages and employment in the U.S. labor market during the 1960s and 1970s partly to the presence of employers' discrimination against females [Niemi, 1974; Oaxaca, 1973]. Their conclusion is supported in Becker's [1971] famous theory of taste discrimination, which suggests that in a labor market infused with gender discrimination, a female job applicant would be hired only if the employer's disutility of having such an employee is fully neutralized by lower costs of hiring her. Thus, gender discrimination, according to Becker's theory, leads to both lower wages and higher unemployment rates for women. In the presence of widespread labor market discrimination in the 1970s, the conclusion drawn by several authors that the adverse wage-employment scenario facing women during this period may partly be due to employers' discriminatory attitudes towards female employees seems reasonable.

Interestingly, the employment scenario started to change dramatically in favor of women in the early 1980s. The gender gap in female and male unemployment rates started to show a declining trend and during the late 1980s it converged almost to zero [*Economic Report of the President*, 2001; DeBoer and Seeborg, 1989]. In the 1990s, this gender gap remained close to zero for most part of the decade, and at times, the female unemployment rate even fell below the male unemployment rate. During the same period, however, the male-female wage differential presented a different scenario. Although the differential narrowed throughout the 1980s, it remained well above zero. In fact, the female-male wage ratio, after remaining around 0.6 between 1930 and 1980, increased to .72 by 1990 [O'Neill and Polachek, 1993].

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The evidence of zero or even negative gaps between female and male unemployment rates along with large gender wage gaps raises the following questions: (1) Why were the unemployment rates of males and females equal when their wages were far apart? and (2) Does the zero unemployment rate gap during the late 1980s signal the absence of employers' hiring discrimination against females during that period?

To answer these questions, it is necessary to examine whether a zero unemployment rate gap can coexist with a substantially large wage gap, and how labor market discrimination affects such a wage-employment scenario. Several studies in different contexts have provided different explanations for why a zero unemployment rate gap may exist simultaneously with a sizeable wage gap. First, inaccurate measurement may lead to an incorrect conclusion regarding the equality of male and female unemployment rates [Johnson, 1983]. In fact, prior to the 1994 revisions of the Current Population Survey (CPS) data collection, unemployment rates for women were slightly underestimated because interviewers often assumed out-of-labor force status, instead of unemployed status, for women who appeared as housewives. [*Monthly Labor Review*, 1993] Under the revised procedure, female unemployment rates in the late 1980s and the early 1990s exceed the reported rates by approximately 0.8 percentage point. The male-female unemployment rate equality in the late 1980s may not therefore be considered as a true equality in a mathematical sense.[1]

Second, the female-dominated service sector remained more or less unaffected by the fluctuations in business cycles during the 1980s, whereas the male-dominated manufacturing sector experienced a secular decline in employment [Bluestone and Harrison, 1988]. These changes in the *demand* for male and female workers were partly responsible for closing the gap in male and female unemployment rates. No such trend, however, was found for wages, and consequently the wage gap continued to persist during the 1980s.

Several authors have demonstrated that due to traditional family obligations, women, especially those who are married and have children, may prefer to work part time. They may also prefer to work in low-skill jobs that do not require further investments in education and training. [Blau, Ferber, and Winkler, 1998] All these jobs, however, are low-paying in nature, and consequently female wages, in general, are lower than wages of male workers with otherwise identical characteristics. Thus, considering the nature of women's jobs, it is not surprising to find that the unemployment rates of men and women converge while their wages remain far apart.

An alternative demand-side explanation of the conflicting evidence just mentioned follows from the possibility that labor market discrimination may lead indirectly to occupational segregation. Discriminatory attitudes of employers, co-workers and customers towards women adversely affect women's incentives to invest in education, and consequently, they acquire fewer skills and end up in low-paying jobs [Blau, ibid., Ch. 6]. The presence of statistical discrimination, resulting from incorrect perception of employers regarding low productivity and job instability of women, also plays a crucial role in forcing women to be placed in low-paying occupations [Aigner and Cain, 1978; Phelps, 1972; Arrow, 1972]. Discrimination of any type (statistical or otherwise), through its feedback effects, may lead to occupational segregation that results in overcrowding of women in a few low-paying, so-called female occupations [Bergmann, 1974]. This overcrowding lowers their wages still further. Thus, while the unemployment rate of women declines and converges to that of men, their wages lag due to the type of jobs they have.

Another explanation of the problem under consideration follows from the quality-sorting hypothesis. Recently, Holzer [1998] has demonstrated that the rising employer skill demand contributes substantially to changes in relative employment outcomes across different demographic groups. He finds the evidence that employer skill demand has a positive effect on the employment of white women. Since white women constitute a significantly large percentage of the total employed female population, the narrowing of the gender unemployment rate gap in the 1980s may have resulted from an increase in the skill demands by the employers during that period.[2] The gender wage gap, on the other hand, is known to be affected adversely by the same quality sorting behavior of the employer because it leads to further segregation. In a recent study, Carrington and Troske [1998] have shown that the extent of gender segregation between firms in the U.S. labor market is substantial and that it results partly from employers' quality sorting (or skill demand). They find the evidence that wages are generally lower in plants that are predominantly staffed by women. Thus, irrespective of the source of segregation, the evidence suggests that women are systematically selected into occupations or plants where they earn less, and consequently the gender wage gap persists even if the unemployment rates have converged.

Several other theories explain why a substantial positive wage gap may coexist with a near-zero gap in male and female unemployment rates. All these theories agree that discrepancies in wages of identical male and female workers do not contradict the possibility of an equality of male and female unemployment rates. None of these theories, however, examines the possible causal connection between these two differentials. In his seminal article on the theory of discrimination, Arrow [1972] demonstrates that although the hiring decision of a discriminating employer is governed to a large extent by the prejudice against women, it is not completely independent of the profit motive. One of the variables that significantly influences the profits and hence the hiring policy of an employer is the wage that would be paid if the worker were hired. Under the assumption that a discriminating employer also maximizes profits, the employer will hire a lower wage worker with other characteristics including productivity, held constant. Since in the presence of wage discrimination, women in general are paid lower wages than otherwise identical men, a profit-maximizing employer may hire more females than would be hired otherwise. This leads to a decline in the female unemployment rate which, of course, cannot be attributed to employers' favoritism towards female workers. Thus, the equality of male and female unemployment rates in the United States during the late 1980s does not necessarily indicate the absence of gender discrimination. This equality may, in fact, be attributed *partly* to the employer's ability to pay lower discriminatory wages to otherwise identical female employees.

Using the U.S. data from the 1980s, the current study tests the above implication of Arrow's argument, thus providing another alternative explanation of why male and female unemployment rates were equal in the late 1980s even as large discrepancies between average male and female wages remained. The study claims that the convergence of male and female unemployment rates in the U.S. labor market, although real, was not truly complete in the late 1980s. It was the very presence of wage discrimination against females during this period that, by increasing female employment, still further closed the remaining gap, leading to the observed equality of male and female unemployment rates.

It is important to note that the study of the relationship between wage discrimination and employment just mentioned is not new in the literature. In a remarkable study, Baldwin and Johnson [1992] have demonstrated that wage discrimination against women by creating disincentive effects causes significant job losses. Their study focuses primarily on the effect of wage discrimination on the supply of female labor. The current study, on the other hand, focuses only on the demand side. This is the first study in the literature that, by following a demand-side approach, demonstrates that the increase in female employment results partly from a rise in the employer's demand for female workers whose wages, due to the presence of gender discrimination, are generally lower than the wages of otherwise identical males.

ESTIMATION ISSUES AND SAMPLE RESTRICTIONS

This section examines different estimation and sampling issues for testing the hypothesis that the presence of wage discrimination against females leads to a decline in the female unemployment rate. The test of such a hypothesis requires developing a framework that models the relationship between workers' individual discriminatory wages and the aggregate unemployment rate. Both of these rates, however, are related to workers' employment probabilities.[3] Estimation of these probabilities from male and female samples therefore is crucial to test the hypothesis proposed in this study. The following subsection presents a standard employment model, outlines the relationship between these three important variables (employment probability, wage rate and unemployment rate), and suggests an appropriate testing procedure.

Estimating Equations

The employment probability of the i^{th} worker, at a given point in time, depends on the employer's preference function for that worker (y_i), which is defined as the utility derived from the worker's expected contribution minus the utility sacrificed on account of the payment of wages. The variable y_i therefore depends on the worker's personal and human capital characteristics (Z_i) and the log wage rate ($\ln w_i$) that the employer will have to pay if the worker is hired. The employer hires the i^{th} worker only if $y_i > 0$. Thus,

$$EMP_i = 1, \text{ if } y_i > 0 \qquad (1)$$
$$= 0, \text{ otherwise, where}$$

$$y_i = Z_i\,\alpha + \gamma \ln w_i + \epsilon_i. \qquad (2)$$

The structural employment probability of the i^{th} worker therefore reduces to

$$P\,(EMP_i = 1) = P\,(y_i > 0) = P\,(\epsilon_i > -\,Z_i\,\alpha - \gamma \ln w_i). \tag{3}$$

The wage rate depends on a vector of personal, human capital, and job-related characteristics (V_i). In its semi-log form, the wage equation can be written as

$$\ln w_i = V_i\,\delta + u_i. \tag{4}$$

Note that wages are observed only for those who are employed. Estimation of structural employment probabilities for all workers therefore requires prior prediction of log wages based on estimates obtained from the observed wage sample. With the predicted wage as an explanatory variable,[4] the employment probability of the i^{th} worker can be written as

$$P\,(EMP_i = 1) = P\,(\epsilon_i > -Z_i\,\alpha - \gamma \ln \hat{w}_i). \tag{5}$$

Assuming normality of error terms, equations (4) and (5) can be estimated simultaneously by a two-stage probit [Lee, 1979] which, in fact, involves a three-step estimation procedure. In the first step, the reduced-form hiring equation is estimated by probit, which generates the selectivity variable for Heckman's [1979] two-step estimation of the wage equation. In the second step, the wage equation, corrected for the selectivity bias, is estimated by ordinary least squares. These wage estimates are used to generate the predicted wage variable which then is controlled in the structural hiring equation estimated in step 3 by probit. The structural employment probability generated from the last stage probit is as follows:

$$P\,(EMP_i = 1) = \Phi(Z_i\,\alpha + \gamma(V_i\,\hat{\delta})) \tag{6}$$

Using the average Φ as an estimate of the population mean employment probability, the relationship between workers' predicted wages ($V_i\,\hat{\delta}$) and the aggregate unemployment rate (UR) can be expressed as

$$UR = 1 - \bar{\Phi}(Z_i\,\alpha + \gamma(V_i\,\hat{\delta})). \tag{7}$$

Note that in the presence of wage discrimination, actual wages of employed workers are biased against females. Consequently, predicted wages obtained from such gender-specific wage samples are likely to be discriminatory. Equation (7) therefore establishes a straightforward relationship between workers' discriminatory wages and the unemployment rate, and thus it provides a convenient tool to examine the effect of wage discrimination on the equality of male and female unemployment rates.

To test the hypothesis that the unemployment rate equality results partly from the presence of wage discrimination, it is necessary first to examine whether employers, in fact, discriminate against women in the payment of wages. Following the literature, several alternative indicators of wage discrimination are examined in the remainder of this subsection. All these indicators focus on differences between male and female wages that remain unexplained by workers' observed productivity characteristics [Oaxaca, 1973; Neumark, 1988; Oaxaca and Ransom, 1994].

Estimation of these unexplained wage differentials requires prior estimation of wage equations (equation 4) from labor markets with and without discrimination. Using coefficients of the female wage equation ($\hat{\delta}^F$), male wage equation ($\hat{\delta}^M$) and the pooled wage equation ($\hat{\delta}^A$) as no-discrimination coefficients,[5] three different measures of unexplained differentials are computed respectively as follows:

$$D_1 = \overline{V^M}\,\hat{\delta}^M - \overline{V^M}\,\hat{\delta}^F \tag{8}$$

$$D_2 = \overline{V^M}\,\hat{\delta}^M - \overline{V^M}\,\hat{\delta}^F \tag{9}$$

$$D_3 = D_{31} + D_{32} = (\overline{V^M}\,\hat{\delta}^M - \overline{V^M}\,\hat{\delta}^A) + (\overline{V^F}\,\hat{\delta}^A - \overline{V^F}\,\hat{\delta}^F). \tag{10}$$

Superscripts M, F and A are used to denote males, females and all workers, respectively; $\overline{V}$s denote vectors of average worker characteristics in different samples. Note that in all the Ds defined above, the variable vectors are for the workers of the same gender group, whereas the coefficient vectors are for different groups. Thus, these Ds measure wage differentials that arise due to differences in treatments and not due to differences in observed characteristics. For example, D_1 in equation (8) measures the premium that a male worker with sample average characteristics receives over the wage he would have received, had he been treated as a female employee. These Ds therefore act as good indicators of the presence of discrimination in the labor market [Oaxaca, 1973].

Viewed from an appropriate nondiscriminatory situation, D_1 and D_{31} represent males' gains from discrimination and therefore are interpreted as the employers' favoritism towards males. D_2 and D_{32}, on the other hand, measure females' losses due to discrimination and consequently are considered as the employers' prejudice against females [Neumark, 1988]. Although they are interpreted differently, both male favoritism and prejudice against females refer to the same phenomenon: the presence of discrimination against females.

It is important to note that the unexplained differential is not an exact measure of discrimination, because in the absence of detailed controls for all possible relevant job characteristics and person-specific skills [Macpherson and Hirsch, 1995], this differential is likely to overestimate the magnitude of discrimination [Blau and Beller, 1988]. However, when the unexplained differential constitutes a large percentage of the total differential, the possibility of gender discrimination cannot be completely ruled out [Blau, Ferber, and Winkler, 1998]. In fact, Blau, Ferber, and Winkler conclude that even after controlling for a large set of relevant characteristics, more than 50 percent of the male-female wage differential in the U.S. labor market remains unexplained, and consequently this differential acts as a good indicator (not measure) of gender discrimination.

In the presence of positive unexplained wage differentials, the hypothesis that wage discrimination lowers the true female unemployment rate can be tested directly by estimating the female structural employment probability as a probit (equation 6) with the estimated discriminatory wage as an explanatory variable,[6] and then comparing the average female employment probability evaluated at discriminatory female wages with that evaluated at wages of comparable male workers, with other characteristics held constant. If workers' employment probabilities, as hypothesized earlier, are negatively related to their predicted wages, and if women, in fact, receive lower discriminatory wages than identical males, the female employment probabilities evaluated at female wages would invariably be higher than the same probabilities evaluated at higher male wages. Thus, a decline in female employment probabilities, when they are evaluated at wages of otherwise identical males, would confirm that lower female wages result in higher female employment probabilities which, in turn, lead to lower female unemployment rates.

Sampling Issues and the Sign of the Wage Coefficient

Estimation of relevant employment probabilities and the resulting unemployment rates raise several sampling issues. It is important to note that the unemployment rate is traditionally estimated as a ratio of the number of unemployed workers looking for jobs to total number of workers in the labor force. Consequently, it is necessary to estimate workers' employment probabilities and hence the aggregate unemployment rate from a sample of labor market participants only. This sample restriction should not, however, be confused with ignoring the role of supply forces in the determination of workers' employment probabilities because the supply forces, in fact, enter the hiring equation indirectly through the predicted wage variable controlled in the second-stage probit.

As pointed out earlier, predicted wages obtained from gender-specific samples do, in fact, represent workers' discriminatory wages, and consequently inclusion of this variable as a regressor in the employer's hiring equation is crucial to testing the hypothesis proposed in this study. There are also other justifications for including this variable in the employer's hiring decision. First, this wage acts as one of the best available *proxies* for the wage that the employer would pay if the worker is hired. Second, the predicted wage estimated traditionally from a supply driven model acts as an aspiration or target wage for an unemployed worker, and consequently, from the point of view of the employer, it serves as an ideal *measurable* indicator of the wage expected by the worker. Note that the reservation wage, which influences the worker's labor supply decision, depends to a large extent on the market wage, and moreover, it is hardly observed by the employer. The predicted wage, on the other hand, provides a close estimatable approximation of not only what the employer would actually pay, but also to what the worker would actually aspire. These arguments suggest that the predicted wage is an ideal proxy for the price of labor that the employer is likely to pay, and consequently its omission from the hiring (labor demand) equation may result in biased estimates.

It is important to understand the sign of the predicted wage variable in the employer's hiring equation because, as pointed out earlier, the test of the proposed hypothesis relies exclusively on the coefficient of this variable assuming a negative sign. Note, however, that since the wage rate depends primarily on the worker's human capital characteristics, a worker with a higher predicted wage is expected to be more productive, and therefore is more likely to be hired than someone with a lower predicted wage. This seemingly contradicts the inverse relationship between the wage rate (the price of labor) and the employment probability mentioned earlier. A close scrutiny of the employer's hiring behavior, however, suggests that this is not necessarily true in all situations. For example, an engineer, despite his/her higher education, is less likely to be employed in an administrative support position than someone who has hardly any college education. This results because a higher wage predicted for the engineer would make him/her more costly to the employer than a less-skilled worker who is suitable for the job and would be paid a lower wage.[7] The predicted wage in this example affects the employment probability negatively as hypothesized earlier.

As pointed out earlier, the predicted wage, which represents the worker's human capital endowments, also represents the worker's aspiration wage, the asking price for labor. Consequently, like any other price, this wage, with other characteristics held constant, is likely to influence the employer's hiring decision negatively. It may influence the employment probability positively *only if* the selection is made for a specific job. For example, if the employer is looking for an electrical engineer, a more experienced engineer (with higher predicted wage) is more likely to be selected than an engineer who is relatively less experienced (with lower predicted wage). If, on the other hand, a single hiring equation that does not distinguish between different kinds of jobs is estimated from a sample of all workers, the predicted wage, with other characteristics held constant, is likely to have a negative coefficient, because the predicted wage in that case is more likely to act as a price of labor than as an instrument for the productivity of labor. Since this study examines the *aggregate* unemployment rate of the economy, the hiring equation has to be estimated from the whole sample, and consequently the sign of the predicted wage variable in the hiring equation is expected to be negative. In fact, the empirical estimates of this study reported below suggest that, other factors remaining constant, higher predicted wages reduce workers' chances of being hired.[8]

Note that like wages, employment probabilities of males and females may also differ between occupations [Gill, 1989, 1994] and between industries [Blau, Ferber, and Winkler, 1998, 125]. This calls for separate estimation of relevant equations by occupation [Mohanty, 1998] and by industry. Such a strategy, however, is not followed because, as pointed out earlier, the objective of this study is to examine the relationship between wage discrimination and the *general* unemployment rate, and consequently, it is irrelevant to estimate workers' employment probabilities separately by occupation.

DATA

A sample of 67,822 observations was drawn from the 1987 Current Population Survey Annual Demographic File. The 1987 data were chosen because the official male and female unemployment rates during this year were exactly identical [*Economic Report of the President*, 2001].[9] Of course, with the pre-1994 measurement error in data collection mentioned earlier, this equality cannot be considered exact. However, the gap between male and female unemployment rates in 1987 is certainly one of the smallest ever. This sample consists of those employed and actively searching unemployed workers in the labor force for whom the data on all relevant variables were available. The sample contains 36,314 males and 31,508 females. The employed work force in this sample consists of 33,410 males and 29,353 females.

The employer's hiring decision depends primarily on the worker's human capital characteristics, such as completed years of schooling , educational degree, potential experience, age, and the number of weeks worked during the previous year. Other variables that may influence the employer's hiring decision are region of residence, whether residence is located in an urban area, race, marital status, and income of other family members. Note that family income represents the economic and social status of the job applicant's family, and thus it provides easier access to the job market which, in turn, leads to greater likelihood of finding a job.

It is important to note that employment probabilities of men and women may differ significantly between industries [Bluestone and Harrison, 1988]. For example, the likelihood of employment in the manufacturing sector is higher for a man than for a woman. In the service sector, on the other hand, the scenario is just the opposite. The presence of discrimination may also force women to bid for jobs in the less favored industries [Bergmann, 1974]. To control for these industry-specific characteristics, the demand-side variables, such as percentages of workers employed in service and manufacturing industries of the local labor market, are controlled in the hiring equation.

Another demand side variable that affects the employer's hiring decision is the state unemployment rate.[10] This variable, to a large extent, represents the local economic condition. Since the hiring decision is derived essentially from a labor demand function, it cannot be independent of the conditions of the local economy. The state-level data on all these aggregate variables were obtained from *Geographic Profile of Employment and Unemployment, 1987* [April 1988] and were matched with the CPS.

As mentioned earlier, one of the important determinants of employment probability that has been ignored in the literature is the predicted wage that the employer would pay if the worker were hired. To estimate this wage, hourly wages of all employed workers in the sample were obtained by dividing their annual *labor* earnings by the number of hours worked during that year. Hourly wages of those who did not report their annual earnings were obtained from their weekly or hourly earnings. Employed workers with no data on any one of the three earning variables just mentioned were excluded from the sample.

The regressors in the wage equation include essentially the same set of worker characteristics that are included in the hiring equation. In addition, the wage rate also depends on the worker's occupation and industry affiliation. As pointed out earlier, separate estimation by occupation and industry is not pursued in this study because it is not necessary for testing the proposed hypothesis. However, to control for their effects on wages, a number of dummy variables representing the worker's industry-affiliation and occupation are included as explanatory variables in wage equations.

It is important to note that the occupational and industry dummy variables included in the wage equation appear as explanatory variables in the first-stage reduced–form probit. Moreover, these variables are also used to predict wages for all workers, employed and unemployed, which enter the second stage structural probit as an explanatory variable. This raises a serious data problem because unemployed workers do not have occupations or industry affiliations. One way to solve this problem is to exclude all industry and occupation dummies from the wage regression. This approach, although a possibility, is not without limitation because the worker's occupation and industry affiliation are known in the literature as significant determinants of the wage rate, and consequently, their exclusion leads to serious omitted variable misspecification. A more desirable alternative therefore is to use some suitable instruments for these omitted variables. The data on the worker's longest occupation and industry affiliation available in the CPS provide the desired proxies because, first, they are available for both employed and unemployed workers, and second, they represent industries and occupations that the unemployed workers would most likely have chosen, had they been employed [Mohanty, 1998].

Combining the information on the longest industry affiliation and the longest occupation of the unemployed workers with the current occupation and industry affiliation of employed workers, several industry and occupational dummy variables were generated for all workers in the labor force. These variables are used to predict wages of all workers which enter the second stage structural probit as an explanatory variable. These variables also enter the first stage probit through the reduced form. Thus, the problem of unnecessarily omitting the relevant occupational and industry dummy variables from the wage regression is resolved. All these variables are defined in Appendix A.[11]

To identify both wage and hiring equations, it is necessary to exclude some variables from one equation while including them in the other. Variables excluded from the hiring equation but included in the wage equation are the dummy variables that represent the worker's occupation and industry affiliation. The only variable that has been excluded from the wage equation but included in the hiring equation is the income of the worker's other family members. Higher family income, through better preparation and networking, may improve the worker's chances of being selected, but the employer would find it difficult to pay this worker a wage higher than wages of similar employees with identical characteristics. Consequently this variable acts as an ideal source of identification in a typical wage-hiring model [Mohanty, 1998].[12]

It is important to note that the worker's family income is most unlikely to influence the employer's hiring decision *directly* because it is almost impossible for an employer to observe the applicant's family income directly, and moreover, the employers have no reason to consider one's family income while making a selection. This variable, however, does influence the employer's hiring decision *indirectly* through its effects on several other characteristics, such as an impressive job application package, a more organized presentation technique, effective job contacts and so forth, which the employers may consider important. Thus, the family income, by being an ideal proxy for a host of other factors that affect the employer's hiring decision positively, acts as an indirect but significant determinant of hiring, and consequently it is used as an identifying variable in this model. The significance of this variable in the hiring equation, as reported in the next section, justifies its inclusion as an identifying restriction. With all these restrictions, both hiring and wage equations are identified.

RESULTS

The first stage probit generates the selectivity variable that enters the wage equation as a regressor. Wage equations from different samples are then estimated by Heckman's two-step method.[13] Predicted log wages corrected for the selectivity bias are presented in Table 1. This table also reports unexplained male-female wage differentials computed from different equations with different no-discrimination coefficient vectors. (See Ds in equations 8, 9 and 10). With the female coefficient vector δ^F as the no-discrimination coefficient vector, D_1 represents the males' gain from discrimination, and in Table 1, it is positive. With the male coefficient vector δ^M as the discrimination-free coefficient vector, D_2 denotes the females' loss from discrimination which also assumes a positive value. As pointed out earlier, both these Ds, although interpreted differently, refer to the presence of discrimination against females.

Following Neumark [1988], a third set of discrimination-free coefficients δ^A are obtained from the pooled sample. These coefficients have the advantage of separating the unexplained differential into male favoritism (D_{31}) and bias against females (D_{32}). Although both D_{31} and D_{32} indicate discrimination against women, they may be interpreted as males' gain and females' loss respectively in a discriminatory labor market relative to an unbiased market. Table 1 shows that both these components are positive. Thus, irrespective of the type of no-discrimination coefficients used, the evidence suggests that more than 50 percent of the male-female log wage differential remains unexplained, indicating the presence of wage discrimination against females in the U.S. labor market.

As discussed earlier, the presence of wage discrimination increases the importance of the discriminatory wage as a determinant of the worker's employment probability. The hiring equations that include the predicted wage as an explanatory variable are estimated in step 3 by probit and are presented in Table 2. For comparison purposes, hiring equations that completely ignore the role of the wage rate are also estimated and their log likelihoods are reported in the last row of Table 2. Likelihood ratio tests between models with and without wage controls (Table 2) reject at all conventional significance levels the specification that ignores the role of wage rate as a determinant of the employment probability.[14] Note that the coefficient of the predicted wage variable in all samples assumes a negative sign and is statistically significant. Thus, it confirms the presumed inverse relationship between the wage the employer will have to pay and the worker's employment probability, with other variables held constant. Including predicted log wages in the structural hiring equation improves the sign and significance of several variable coefficients, indicating possible misspecification when it is omitted.

It is interesting to note that the size of the predicted wage coefficient differs considerably between male and female employment equations. Since these coefficients, due to inherent nonlinearities, do not measure the actual impact of the wage

TABLE 1
Estimated Average Log Wage Rates and Unexplained Male-Female Wage Differentials

Estimated Average Log Wage Rates			**Unexplained Log Wage Differential**
	Males	**Females**	**D**
No-discrimination Coefficients	**(1)**	**(2)**	**(3)**
With Male	2.3674	2.2750	$D_1 = \overline{V^M}\,\overline{\delta^M} - \overline{V^M}\,\overline{\delta^F} = .4130$
Coefficient (δ^M)	(0.3611)	(0.3649)	
With Female	1.9544	1.9021	$D_2 = \overline{V^F}\,\overline{\delta^M} - \overline{V^F}\,\overline{\delta^F} = .3729$
Coefficient (δ^F)	(0.3216)	(0.3098)	
With Coefficients	2.2060	2.0557	$D_{31} = \overline{V^M}\,\overline{\delta^M} - \overline{V^M}\,\overline{\delta^A} = .1614$
from the Combined	(0.3418)	(0.3342)	
Sample (δ^A)			$D_{32} = \overline{V^F}\,\overline{\delta^A} - \overline{V^F}\,\overline{\delta^F} = .1536$
Sample Size	33,410	29,353	

Quantities in parentheses are standard deviations of predicted wages. They should not be confused with standard deviations of mean predicted wages which can be obtained by dividing the standard deviations reported in this table by the square root of their respective sample sizes.

change on the employment probability directly, relevant partial derivatives (that is $\partial\Phi[X\beta]/\partial[PREDWAGE] = \Phi[X\beta]\times\beta_{PREDWAGE}$) are computed from both male and female samples. They are reported in the last row of Table 2. In absolute value, the partial derivative in the male sample is approximately four times as large as that in the female sample, indicating greater sensitiveness of employment probabilities of males than those of females to changes in wages. On the surface, the smaller partial derivative associated with the female wage coefficient may appear to be a contradiction to the proposed hypothesis that employers hire more females because their wages are lower.[15] Close scrutiny of this problem, however, reveals that it is the difference in the male and female demand curves, and not their slopes, that determines the size of their employment probabilities. Note that, regardless of whether the male demand curve is flatter or steeper than the female demand curve, a profit-maximizing employer is most likely to hire female employees as long as their wages are lower than the wages paid to otherwise identical males, (that is, the demand curve for females remains below the demand curve for males at every employment level).[16] Since this is guaranteed in a typical labor market characterized by gender discrimination, the estimated partial derivatives as shown in Table 2 are consistent with, and do not contradict, the hypothesis that employers hire more females because their wages are lower.

To test the hypothesis that lower discriminatory wages paid to female workers result in lower female unemployment rates, female employment probabilities evaluated at discriminatory female wages are compared with those evaluated at wages paid to otherwise identical males, holding all other characteristics constant.[17] The first row of Table 3 reports these probabilities. They suggest that, all else held constant, the average female employment probability declines (that is, the female unem-

TABLE 2
Second Stage Structural Probit Estimates with Discriminatory Predicted Wage as an Explanatory Variable (Absolute *t*-ratio in Parentheses)

Variables	Males	Females	All
Constant	.0747	−1.0436[a]	−.5015[a]
	(0.415)	(5.464)	(4.061)
Years of Schooling	.0911[a]	.0851[a]	.0987[a]
	(11.673)	(8.929)	(17.843)
High School	.0080	−.0737[a]	−.0431[a]
	(0.300)	(2.445)	(2.182)
2-year Degree	.0191	−.0040	.0071
	(0.365)	(0.066)	(0.183)
4-year Degree	.1396[a]	.0734	.1175[a]
	(2.640)	(1.154)	(2.929)
Graduate School	.2914[a]	−.1731[b]	.1521[a]
	(3.574)	(1.860)	(2.492)
Years of Experience	.0050	.0071	.0059
	(0.738)	(0.955)	(1.226)
Years of Experience^2	.0002[b]	.0001	.0002
	(1.714)	(0.444)	(1.516)
Number of Weeks Worked	.0270[a]	.0380[a]	.0353[a]
	(18.736)	(50.920)	(66.297)
Income of Other Family Members	.0059[a]	.0060[a]	.0061[a]
	(9.389)	(7.989)	(12.687)
Age 20 to 25	.0883[b]	−.0614	.0390
	(1.711)	(1.071)	(1.039)
Age 26 to 40	.2420[a]	−.0158	.1788[a]
	(3.118)	(0.178)	(3.136)
Age 41 to 50	.2225[a]	−.0606	.1455[b]
	(1.993)	(0.474)	(1.744)
Age 51 to 60	.0014	−.0730	.0120
	(0.010)	(0.433)	(0.112)
Age 61 or above	−.1002	−.1785	−.0670
	(0.546)	(0.804)	(0.477)
Resides in the South	.0632[b]	.0578	.0488[a]
	(1.836)	(1.498)	(1.935)
Resides in the Northeast	−.0232	.0369	.0105
	(0.538)	(0.746)	(0.326)
Resides in the Midwest	−.0965[a]	.1006[a]	−.0371
	(2.639)	(2.325)	(1.345)
Resides in an Urban Area	−.0184	−.0790[a]	−.0249
	(0.667)	(2.483)	(1.205)
Married	.2309[a]	.1116[a]	.1739[a]
	(7.866)	(3.635)	(8.581)
White	.2497[a]	.2951[a]	.2630[a]
	(6.432)	(7.686)	(9.703)
Non- White	.1265[b]	.3078[a]	.1892[a]
	(1.755)	(3.817)	(3.554)
State Unemployment Rate	−.0384[a]	−.0483[a]	−.0413[a]
	(4.406)	(4.991)	(6.463)
Percent Workers in Manufacturing	.0090[a]	−.0007	.0057[a]
	(3.814)	(0.243)	(3.257)

TABLE 2 (cont.)
Second Stage Structural Probit Estimates with Discriminatory Predicted Wage as an Explanatory Variable
(Absolute t-ratio in parentheses)

Variables	Males	Females	All
Percent Workers in Services	.0161[a]	.0154[a]	.0186[a]
	(3.593)	(3.008)	(5.592)
Predicted Log Wages	−.8460[a]	−.2824[a]	−.7853[a]
	(10.929)	(3.520)	(18.448)
Sample Size	36,314	31,508	67,822
Log Likelihood	−7222.69	−5491.69	−12771.55
Log Likelihood without any wage control	−7284.03	−5497.88	−12945.64
$(\partial\Phi(X\beta)/\partial(PREDWAGE)$	−.1258	−.0374	—

a. Significant at the 5 percent level.
b. Significant at the 10 percent level.

ployment rate rises) by more than two percentage points when female wages are raised to the same level as wages of *identical* male workers. This indicates that if females were paid the same wages as identical males, the female unemployment rate would have been approximately two percentage points higher than what it actually was. But since the female workers in the late 1980s were paid lower wages than identical males, their employment probabilities were higher, and consequently their unemployment rates were lower. Thus, the equality of male and female unemployment rates in the late 1980s resulted partly from the employers' ability to pay lower discriminatory wages to females, and not necessarily from their preference for female employees.

To see if the conclusion drawn above from the 1987 data applies to other years, two separate samples were drawn from the Current Population Surveys of 1977 and 1996. The procedure used to draw the 1987 sample was also used to draw these two samples. The year 1977 was chosen because like 1987 it belonged to the prosperity phase of the business cycle, but unlike 1987 there was a large gap between male and female unemployment rates. The reason for choosing 1996 is to see whether the results obtained from the 1970s and the 1980s are still valid in the 1990s. Moreover, like 1987, this was one of the years in the 1990s when the male and female unemployment rates were equal.[18]

Following the procedure discussed above, two-stage probit estimates of hiring equations were obtained from male and female samples of both 1977 and 1996 data.[19] These estimates were used to compute female employment probabilities reported in the second and third rows of Table 3. The female employment probabilities in the first column are evaluated at the discriminatory female wages, whereas those in the second column are evaluated at wages paid to otherwise identical males. These estimates suggest that had women employees been paid the wages paid to identical males, their average employment probabilities would have been approximately two percent-

TABLE 3
Average Female Employment Probabilities Evaluated at Female and Male Wages

Year	Sample Size	Average Female P (EMP=1) With Female Wages	Average Female P (EMP=1) With Male Wages
1987	31,508	.9311	.9136
		(.0007)	(.0009)
1977	26,258	.9032	.8747
		(.0062)	(.0011)
1996	26,828	.9457	.9270
		(.0007)	(.0009)

Quantities in parentheses are standard deviations of the mean probabilities which are obtained by dividing the standard deviations of predicted probabilities by the square root of their respective sample sizes.

age points lower in both 1977 and 1996, and consequently their unemployment rates would have been two percentage points higher. But since they were paid lower discriminatory wages, it was profitable for employers to hire female workers, and consequently their unemployment rates were lower. These lower unemployment rates therefore do not necessarily indicate the absence of discrimination against female employees.

The results obtained from the 1977 and 1996 data add significantly to the robustness of the finding that lower female wages lead to higher female employment probabilities. Thus, regardless of the time period considered, the study confirms that the presence of wage discrimination against women invariably lowers the female unemployment rate, and as a result, helps to narrow the observed gap between male and female unemployment rates. This is *one* of the reasons why the male and female unemployment rates were equal in the late 1980s and 1990s.

The question then arises, If the presence of wage discrimination against females leads to a zero unemployment rate gap, as was the case during the 1980s and 1990s, why did male and female unemployment rates remain far apart in the 1970s when the extent of wage discrimination against females was even more severe than what was experienced in the 1980s?[20] In fact, compared to the female-male wage ratio of .65 in the year 1987, the female-male wage ratio in 1977 was .589 [O'Neill and Polachek, 1993, 206]. Despite this wider discrepancy between male and female wages in 1977, the female unemployment rate in this year, as reported in the footnote 18, was approximately two percentage points higher than the male unemployment rate. This clearly suggests that the presence of wage discrimination is not necessarily the only factor that reduces the unemployment rate disparity to zero. The convergence in unemployment rates results primarily from changes in a host of other factors over time, and the presence of wage discrimination simply adds to that process.

It has already been demonstrated by several authors that an increase in women's schooling, a rise in their work experience, a change in their preference for different occupations etc. have contributed significantly to the narrowing of the gender gaps in the 1980s.[21] This convergence is also attributed partly to a decline in employers' discriminatory treatments towards female employees in the 1980s and 1990s. The current study does not address this issue nor does it examine the factors that led to this convergence. It simply suggests that regardless of the causes of convergence, the presence of wage discrimination in the labor market against females, by lowering female unemployment rates, helps to narrow the gap between male and female unemployment rates still further.

As pointed out above, the extent of gender discrimination, which according to Becker's theory invariably lowers both employment and wages of females, was more severe in the 1970s than in the 1980s and 1990s. Consequently, the positive impact of lower discriminatory female wages on female employment probabilities was not strong enough to completely eliminate the large gaps between male and female unemployment rates, and thus the unemployment rate gap continued to persist during the 1970s. However, with a significant decline in the extent of labor market discrimination in the 1980s and 1990s, and a rise in women's human capital endowments, both gender gaps in wages and employment started to show declining trends, and consequently the impact of lower discriminatory female wages on female employment was good enough to completely eliminate the already narrow unemployment rate gap during this period. The study thus confirms that the convergence of male and female unemployment rates in the U.S. labor market, although real, was not truly complete in the 1980s and 1990s. It was the presence of wage discrimination, which by lowering the female unemployment rate still further bridged the remaining gap, leading to an equality of observed male and female unemployment rates. This equality should not therefore be confused with the *true* absence of gender discrimination in the 1980s and 1990s.

DISCRIMINATORY WAGE AND UNEXPLAINED UNEMPLOYMENT RATE DIFFERENTIAL

The conclusion drawn in the last section follows directly from the specification of the hiring equation that recognizes the importance of workers' predicted wages as a determinant of the employers' hiring decision. The coefficient of this wage variable is not only significantly different from zero, but also is large enough in absolute value to reveal the true differential, which otherwise remains disguised. To show the importance of this variable from another perspective, this section estimates the *unexplained* unemployment rate differential under different specifications, and finds the evidence that exclusion of the discriminatory wage rate from the hiring equation may, in fact, change the sign and the size of this differential.

Following Johnson [1983] and using the coefficients obtained separately from male sample, female sample and the sample of all workers as the no-discrimination coefficients, three alternative measures of unexplained employment probability differentials (or unemployment rate differentials) are obtained respectively as follows:

$$D_1^* = \bar{\Phi}(X^M\hat{\beta}^M) - \bar{\Phi}(X^M\hat{\beta}^F) \tag{11}$$

$$D_2^* = \bar{\Phi}(X^F\hat{\beta}^M) - \bar{\Phi}(X^F\hat{\beta}^F) \tag{12}$$

(13) $$D_3^* = D_{31}^* + D_{32}^* = [\bar{\Phi}(X^M\hat{\beta}^M) - \bar{\Phi}(X^M\hat{\beta}^A)] + [(X^F\hat{\beta}^A) - \bar{\Phi}(X^F\hat{\beta}^F),$$

where superscripts M, F and A denote males, females and all workers respectively. $\bar{\Phi}$ denotes the sample average of $\Phi(X_i\hat{\beta})$, $X_i = [Z_i, (V_i\hat{\delta})]$, and $\hat{\beta}' = [\hat{\alpha}', \hat{\gamma}]$.

To examine the effects of discriminatory wages on unexplained unemployment rate differentials, D^*s defined in equations (11)-(13) are obtained from hiring equations *with* and *without* discriminatory wage controls. The unexplained differentials estimated from equations with non-discriminatory wage controls are also computed to compare them with those obtained from equations with discriminatory wage controls. To compute these unexplained differentials, average employment probabilities of males and females from equations *with* and *without* wage controls are estimated for all three years and are reported in Table 4 (1977A, 1987A, 1996A).[22] Column 1 presents the probabilities estimated from the hiring equations that do not control for any wage rate. The probabilities in column 3, on the other hand, are based on discriminatory wage controls.[23] To facilitate comparison, hiring equations are also estimated with Neumark-type discrimination-free wage controls.[24] These coefficients are used to estimate average employment probabilities which are presented in column 2 of Table 4 (1977A, 1987A, and 1996A).

Employment probabilities in Table 4 are used to compute unexplained employment probability differentials defined in this section. They are presented in Table 4 (1977B, 1987B, 1996B). Note that in the 1977 sample, the unexplained differential D_1^*, which assumes $\hat{\beta}^F$ as the no-discrimination coefficient vector, is negative when the role of the wage rate is completely ignored or a discrimination-free wage is controlled in the hiring equation (see columns 1 and 2, 1977B). However, it becomes positive when the discriminatory wage is included as an explanatory variable (see column 3, 1977B). A similar situation emerges when the male coefficient vector $\hat{\beta}^M$ is considered discrimination-free. In this case, the unexplained differential D_2^* is found to be negative in columns 1 and 2, but positive in column 3. The Neumark measures of unexplained differentials, D_{31}^* and D_{32}^*, also follow exactly the same pattern. The results in Table 4 (1977B) have interesting implications. A positive unexplained employment probability differential results only when the predicted discriminatory wage rate, which the employer would most likely pay if the worker is hired, is controlled in the hiring equation, and it vanishes when this wage is omitted or a nondiscriminatory wage is included.

The results for the 1987 data are very similar to those for 1977. In column 3 of 1987B, all unexplained differentials except the first one are positive, whereas they are all negative in columns 1 and 2. Interestingly, the unexplained differentials in both 1977 and 1987 data decline significantly in absolute value when discriminatory wages are controlled in the hiring equations. The 1996 data present very similar results. Although only one out of four D^*s assumes a positive value (column 3, 1996B), a comparison between column 1 and column 3 suggests that the inclusion of discriminatory wage control in the hiring equation invariably lowers the size of the unexplained unemployment rate differential.

The residual difference exercise in this section provides further support to the hypothesis that the ability of the employer to pay discriminatory wages hides not

TABLE 4
Average Hiring Probabilities and Differentials With and Without Wage Controls

	No Wage (1)	Discrimination-free Wage (full sample) (2)	Discriminatory Wage (gender-specific sample) (3)
1977 Sample			
A. Estimated Average Hiring Probabilities			
$\Phi(X^M\beta^M)$	.9165	.9164	.9164
	(.1422)	(.1427)	(.1425)
$\Phi(X^M\beta^F)$	.9314	.9174	.9099
	(.1237)	(.1357)	(.1522)
$\Phi(X^M\beta^M)$	.8809	.8877	.9151
	(.1687)	(.1655)	(.1282)
$\Phi(X^F\beta^F)$	.9033	.9029	.9032
	(.1454)	(.1511)	(.1461)
$\Phi(X^M\beta^A)$	.9239	.9191	.8965
	(.1313)	(.1374)	(.1752)
$\Phi(X^F\beta^A)$	.8928	.8992	.9106
	(.1545)	(.1551)	(.1418)
B. Unexplained Differentials			
D_1^*	−.0149	−.0010	.0065
D_2^*	−.0224	−.0152	.0119
D_{31}^*	−.0074	−.0027	.0199
D_{32}^*	−.0105	−.0037	.0074
1987 Sample			
A. Estimated Average Hiring Probabilities			
$\Phi(X^M\beta^M)$	.9201	.9201	.9200
	(.1366)	(.1378)	(.1383)
$\Phi(X^M\beta^F)$	.9442	.9362	.9280
	(.1104)	(.1205)	(.1380)
$\Phi(X^F\beta^M)$	.9013	.9111	.9584
	(.1535)	(.1465)	(.0683)
$\Phi(X^F\beta^F)$	.9311	.9310	.9311
	(.1234)	(.1260)	(.1234)
$\Phi(X^M\beta^A)$	.9322	.9271	.9032
	(.1216)	(.1292)	(.1702)
$\Phi(X^F\beta^A)$	.9169	.9227	.9396
	(.1354)	(.1337)	(.1065)
B. Unexplained Differentials			
D_1^*	−.0241	−.0161	−.0080
D_2^*	−.0298	−.0199	.0273
D_{31}^*	−.0121	−.0070	.0168
D_{32}^*	−.0142	−.0083	.0085

TABLE 4 (cont.)
Average Hiring Probabilities and Differentials With and Without Wage Controls

	No Wage (1)	Discrimination-free Wage (full sample) (2)	Discriminatory Wage (gender-specific sample) (3)
<u>1996 Sample</u>			
A. Estimated Average Hiring Probabilities			
$\Phi(X^M\beta^M)$	.9304	.9304	.9304
	(.1286)	(.1290)	(.1287)
$\Phi(X^M\beta^F)$	.9510	.9478	.9380
	(.1036)	(.1078)	(.1253)
$\Phi(X^F\beta^M)$	.9147	.9172	.9206
	(.1450)	(.1435)	(.1383)
$\Phi(X^F\beta^F)$	.9410	.9409	.9457
	(.1153)	(.1166)	(.1124)
$\Phi(X^M\beta^A)$	.9411	.9394	.9295
	(.1140)	(.1166)	(.1331)
$\Phi(X^F\beta^A)$	.9289	.9307	.9359
	(.1273)	(.1271)	(.1232)
B. Unexplained Differentials			
D_1^*	−.0206	−.0174	−.0076
D_2^*	−.0263	−.0237	−.0251
D_{31}^*	−.0107	−.0090	.0009
D_{32}^*	−.0121	−.0102	−.0098

Quantities in the parentheses are standard deviations of predicted probabilities (and not of mean predicted probabilities).

only the actual unemployment rate differential, but also the unexplained part of this differential. The true differentials are revealed only when discriminatory wages are controlled in the hiring decision. This reinforces the importance of this wage variable as a determinant of the employer's hiring decision. Its omission therefore is likely to result in misspecification leading to biased conclusions.[25]

SUMMARY AND CONCLUSION

Using data from the Current Population Surveys of 1977, 1987 and 1996, this study demonstrates that in the presence of wage discrimination against females, the ability of the employer to pay lower discriminatory wages to female workers raises average female employment probabilities which, in turn, yields lower female unemployment rates. This is one of the several other reasons why male and female unemployment rates were equal in the late 1980s. The study finds the evidence that if female wages were raised to the level of wages paid to identical male workers, female unemployment rates in the 1980s would have been approximately 2 percentage points higher than male unemployment rates. The equality of male and female unemployment rates in the 1980s and 1990s should not therefore be confused with the absence of hiring discrimination against females. The current study further demonstrates that the predicted wage rate is, in fact, a significant determinant of the hiring decision. Its inclusion in the wage equation as an explanatory variable improves the model specification and thus yields more reliable estimates.

I conclude with a few notes of caution. First, like other discrimination studies, the estimates in this study may suffer from omitted variable bias. Consequently, the Ds and D^*s should be treated only as indicators of discrimination and *not* as measures of discrimination. Second, the reliability of the results from a simultaneous equations model depends primarily on the identification of the model. Due to the problem of finding suitable identifying restrictions, both wage and hiring equations in this model are identified by "income of other family members" only. Imposing other identifying restrictions may improve the results, and therefore the findings of this study should be carefully interpreted.

Third, preference for different occupations differs between men and women. Moreover, occupational segregation may force women to choose low-paying jobs. Estimation of employment probabilities separately by occupation therefore may yield interesting results. Although it is not difficult to reestimate this model separately for different occupational groups [Mohanty, 1998], such a strategy has not been followed here because the study focuses primarily on the aggregate unemployment rate which ought to be estimated from the whole sample only. The findings of this study should not therefore be generalized to particular occupations.

The current study focuses exclusively on the effects of wage discrimination on the employer's demand for female workers and does not address its effects on labor supply. If the disincentive effects of wage discrimination, as demonstrated by Baldwin and Johnson [1992], are introduced into this model, the female employment probabilities would rise still further and the unemployment rate gap would be still smaller. The equality of unemployment rates in the late 1980s and 1990s in the United States therefore results *partly* from both supply and demand effects of gender wage discrimination. It should not exclusively be attributed to a greater demand for low-paid female workers. Lower supply of female labor resulting from wage discrimination plays an important role as well. Irrespective of whether wage discrimination affects supply forces more than the demand forces or demand forces more than the supply forces, the fact remains that in the presence of discrimination, they both contribute to an increase in the average female employment probability, leading to a decline in the female unemployment rate. Since several empirical studies find the evidence of significant wage discrimination against females in the U.S. labor market, equality of male and female unemployment rates in the 1980s may be attributed *partly* to the presence of this discrimination.

Finally, the conclusion of this study that the presence of wage discrimination against females lowers the female unemployment rate remains valid regardless of the time period considered. However, this does not necessarily suggest that wage discrimination by lowering the female unemployment rate would invariably lead to a zero unemployment rate gap. The true convergence of unemployment rates, in fact, depends on a host of other factors, such as changes in women's education, experience, job attachment and so forth. The current study does not address that issue. While recognizing and not contradicting the roles of other factors that contributed to the narrowing of female-male unemployment rate gaps, it simply suggests that this convergence, although real, was not truly complete during the late 1980s and 1990s. It was the presence of wage discrimination against females which by further lowering the female unemployment rate led to the observed equality of male and female unemployment rates during this period. Interestingly, this conclusion does not dispute the widely known fact that the extent of gender discrimination in the U.S. labor market declined considerably during the 1980s and 1990s. It simply suggests that, in spite of this decline, the era of gender discrimination was not truly over during this period and that the equality of unemployment rates was partly due to the presence of wage discrimination against females in the U.S. labor market.

The conclusion drawn in the above paragraph has important policy implications. It suggests that just by observing the equality of male and female unemployment rates, policymakers should not blindly conclude that the era of gender discrimination in the labor market has ended because the very presence of this discrimination in the payment of wages may have contributed to the equality of observed unemployment rates. A comprehensive study of gender discrimination therefore should consider both wage discrimination and hiring discrimination simultaneously. In addition, the study also suggests that any policy having an impact on employment must include wages, (the price of labor), as a determinant. Failure to do so may result in biased estimates, leading to unrealistic and misleading conclusions (see footnote 25).

NOTES

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1. Note that the convergence of male and female unemployment rates during the 1980s, despite the measurement error in the CPS data, was real. In other words, there is no denying the fact that the gap between observed unemployment rates converged nearly to zero, if not exactly to zero, in the late 1980s and the 1990s.
2. In 1987, white women constituted 85.7 percent of the total employed female population [*Economic Report of the President,* 2001].
3. The employment probability of a worker is defined as the likelihood of being hired by the employer given his/her presence in the labor force.
4. The predicted wage rate of an unemployed worker is the amount that he/she would receive if treated the same as an employed worker with identical characteristics.
5. No-discrimination coefficients or discrimination-free coefficients are assumed to prevail in a labor market that is free from employers' discriminatory practices. See Oaxaca [1973], and Oaxaca and Ransom [1994] for a detailed discussion of different types of no-discrimination coefficients used in the literature.
6. In examining the employment effects of wage discrimination against females from a labor supply perspective, Baldwin and Johnson [1992] estimated non-discriminatory employment probabilities by including the worker's discriminatory offer wage differential as an explanatory variable in the employment equation.
7. Another reason why the engineer will not be hired as an administrative support worker is that he/she may have applied for this job due to some personal reasons and is very likely to quit as soon as better opportunities are available.

8. The conclusion on the negative sign of the wage variable remains unchanged irrespective of the specification of the hiring equation and samples used.
9. Both male and female unemployment rates during 1987 were 6.2 percent.
10. Many studies use Metropolitan Statistical Area (MSA) level data on aggregate variables because the state level data may be too global to capture the variations in economic activities within the state. There are two reasons for using the state level aggregate variables in this study. First, the use of the MSA level data reduces the sample size drastically (by more than 50 percent) because workers living outside MSAs and those living in the MSAs, listed in the Geographic Profile and not in the CPS, are unnecessarily excluded from the sample. Such a sample cannot be a representative of the national population. Second, my unreported results indicate that sign and statistical significance of almost all the variables remain unchanged when state level aggregate variables are replaced by their MSA level counterparts. In other words, no generality is lost when state level aggregate variables are used in appropriate estimating equations.
11. Means and standard deviations of the variables are not reported to save space but can be obtained from the author on request.
12. It is important to note that, with a few exceptions, the variables that affect the employer's hiring decision are also the variables that determine the worker's wage. Consequently, the scope for choosing appropriate identifying variables is extremely limited.
13. These estimates may be obtained from the author on request.
14. For example, in the male equation, the estimated chi-square is $2(7{,}284.03 - 7{,}222.69) = 122.68$, whereas the critical value of the chi-square at one percent level of significance and with one degree of freedom is 6.535.
15. I thank a reviewer for raising the issue of this apparent contradiction.
16. A graphical solution of this proposition can be obtained from the author on request.
17. These wages are obtained by computing the vector product of female characteristics and male wage coefficients.
18. Male and female unemployment rates in 1977 were 6.3 and 8.2 respectively, whereas they were both 5.4 percent in the year 1996 [*Economic Report of the President*, 2001].
19. These estimates may be obtained from the author on request.
20. I thank a reviewer for raising and providing insights to this important issue.
21. In a different context, O'Neill and Polachek [1993] have demonstrated that one-third of the convergence in male-female wage differentials during the 1980s was due to increase in women's schooling and experience.
22. The probabilities in Table 4 are, in fact, the averages of individual employment probabilities which are different from employment probabilities of workers with sample average characteristics [Johnson, 1983].
23. The predicted wage rates controlled in the second stage male hiring equations are obtained from male samples. Similarly, wage rates controlled in structural female hiring equations are obtained form female samples.
24. Following Neumark's [1988] approach, a set of discrimination-free coefficients are obtained from the pooled sample of both male and female workers.
25. Earlier studies considered a positive unexplained employment probability differential as an indicator of the presence of hiring discrimination [Johnson, 1983; Mohanty, 1998]. Based on that criterion, the findings of this study suggest that in the absence of a control for the discriminatory wage rate in the employment equation, there is no evidence of hiring discrimination against females in the U.S. labor market. This conclusion, however, is reversed or weakened when the predicted wage is controlled as an explanatory variable in the hiring equation.

APPENDIX A
Definition of Variables Used in Wage and Hiring Equations

Variable		Definition	Used in Wage Equation[a]	Used in Hiring Equation[a]
GRADE	=	Years of schooling completed	Y	Y
HIGHSCHL	=	1, if the worker has a highschool diploma	Y	Y
COLLEGE1	=	1, if the worker has a 2-years college degree	Y	Y
COLLEGE2	=	1, if the worker has a 4-years college degree	Y	Y
GRADUATE	=	1, if the worker has Masters or Ph. D. degree	Y	Y
EXP	=	*AGE* − *GRADE* − 5	Y	Y
EXP2	=	EXP squared	Y	Y
YOUTH	=	1, if aged between 20 and 25 years	Y	Y
ADULT1	=	1, if aged between 26 and 40 years	Y	Y
ADULT2	=	1, if aged between 41 and 50 years	Y	Y
ADULT3	=	1, if aged between 51 and 60 years	Y	Y
ADULT4	=	1, if the worker's age is 61 or above	Y	Y
WKWKLSYR	=	Number of weeks worked during the previous year	Y	Y
FAMINC	=	Income of other family members (in ,000 of $)	N	Y
SOUTH	=	1, if the worker belongs to the South	Y	Y
MIDWEST	=	1, if the worker belongs to the Midwest	Y	Y
NORTHEAST	=	1, if the worker belongs to the Northeast	Y	Y
WHITE	=	1, if the worker is white	Y	Y
OTHRRACE	=	1, if the worker is nonwhite and nonblack	Y	Y
CENTCITY	=	1, if the worker lives in a inner cities	Y	Y
MARRIED	=	1, if the worker is married and the spouse is present	Y	Y
URATE	=	The unemployment rate of the state in which the worker lives	Y	Y
MNFPCT	=	The state employment percentage in the manufacturing sector	Y	Y
SERVPCT	=	The state employment percentage in the service sector	Y	Y
LONGMANF	=	1, if has worked longest in manufacturing	Y	N
LONGTRNS	=	1, if has worked longest in transportation	Y	N
LONGTRAD	=	1, if has worked the longest in trading (retail and whole-sale), banking, communication and utility industries	Y	N
LONGSERV	=	1, if has worked longest in service sector	Y	N
LONGPBAD	=	1, if has worked longest in public administration industry	Y	N
LONGMNGR	=	1, if the longest job of the worker is in managerial position	Y	N
LONGPROF	=	1, if longest prefessional job	Y	N
LONGTECH	=	1, if longest technician job	Y	N
LONGSALE	=	1, if longest sales occupation	Y	N
LONGADMN	=	1, if longest administrative support occ	Y	N
LONGSROP	=	1, if longest service occupation	Y	N
PREDWAGE	=	OLS estimate of ln w	N	Y
<u>Dependent Variable in the Wage Equation</u>				
ln *w*	=	natural log of the wage rate per hour		
<u>Dependent Variable in the Hiring Equation</u>				
EMP	=	1, if the worker is currently employed and 0 otherwise		

a. Y = Yes (i.e., the variable is included among regressors); N = No; (that is, the variable is not included).

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