The Relative Earnings of Young Mexican, Black, and White Women

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August, 2000

Abstract

Using the NLSY, we find that young Mexican women earn 9% less than young White women while young Black women earn 15% less than young White women. Although young Mexican women earn less than young White women, they do surprisingly well compared to young Black women. We show that it is crucially important to account for actual labor market experience. We further show that low labor force attachment is the most important determinant of the Black-White wage differential for young women while education is the most important explanation for the Mexican-White wage gap for young women.

We thank Eric Helland, Peter Kuhn, Lonnie Magee, Shelley Phipps, and Joanne Roberts for helpful comments. We gratefully acknowledge financial support from the Canadian International Labour Network (CILN) at McMaster University. The usual disclaimer applies.

Keywords: Wages, Discrimination, Women.
JEL Classifications: J1, J3, J7

Recent research (Trejo, 1997 and 1998; Reimers, 1994; Chavez, 1991; Smith, 1991; and Chapa, 1990) has renewed interest in the relatively poor labor market performance of Mexican men.[1] Trejo (1997) finds that lower levels of education, English deficiencies, and the relative youth of Mexican men can explain 75% of the gap between Mexican and White wages. In contrast, these factors explain less than 30% of the Black-White wage gap.[2] Despite the flurry of recent research exploring the poor performance of Mexican men, we are aware of only one study that includes women (Mora and Davila, 1998), and they focus on the differential return to English fluency across gender. We therefore seek to add to the current debate regarding Mexican labor market performance by comparing the 'plight' of young Mexican women with their Black and White counterparts.

Previous work focused on men because higher participation rates mean that Mincer experience measures more accurately reflect actual experience and selection issues are less important. While Mincer experience may be a relatively good approximation of true experience for men with high labor force attachment, it is a poor proxy for women and possibly some minority groups.[3] We are able to overcome this measurement problem using the National Longitudinal Survey of Youth (NLSY). In particular, the longitudinal nature of the NLSY allows us to construct true experience measures, as well as complete education, childbirth, and marital histories. Since these factors may play important roles in determining the labor market participation decisions and success of women, the NLSY is well suited to this study.

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[1] Earlier studies include DeFreitas (1986), Grenier (1984), Reimers (1983), McManus, Gould and Welch (1983), and Chiswick (1977).

[2] The differing Black and Mexican experiences suggest that comparing the labor market outcomes for two economically disadvantaged groups may also help uncover the factors that influence wages (Trejo, 1997; Cotton, 1985; and Reimers 1983).

[3] Mora and Davila (1998) use the 1980 and 1990 Public Use Micro Samples (PUMS) and are therefore forced to use Mincer experience. Tangentially, we also construct actual experience measures for men to investigate Trejo's (1997) suggestion that Mincer experience may be a poor proxy for Blacks because they are less attached to the labor market. We do indeed find that replacing Mincer experience with actual experience allows us to explain 46% of the Black-White wage gap in the NLSY compared to 27% when the Mincer approximation is used.

It is well established that women tend to move in and out of the labor market more frequently than men, and that job interruptions surrounding childbirth have long-term implications for women's wages (Jacobsen and Levin, 1995, and Waldfogel, 1997 and 1998). Waldfogel (1997, 1998) shows that children have a negative impact on earnings despite controls for actual labor market experience. In her 1997 paper Waldfogel finds that women who are covered by formal maternity leave programs, and return to their former employer after childbirth, earn higher wages than women who do not return to their former employer after childbirth and are not covered by formal maternity leave. Further, Waldfogel (1998) shows that the positive impact of maternity leave outweighs the negative effect of children by increasing the probability that women return to their former employer after childbirth.[4] Unfortunately, we are unable to determine whether or not a woman returns to her pre-birth employer or has access to maternity leave in the NLSY for the entire cohort.[5] We do, however, allow for the possibility that a woman's experience profile may change slope after successive childbirth experiences.

Accounting for the wage gap between race groups for women clearly requires a careful accounting of differences in labor market participation and family structure in addition to educational differences. In 1994, the average young Mexican woman earned 10% less than the average young White woman while the average young Black women earned 13% less than the average young White woman.[6] Education, fertility, and labor force attachment differences at various points in the lifecycle play a crucial role in determining differences across racial/ethnic groups. We show that low labor force attachment is a particularly important explanation for the

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[4] Phipps, Burton, and Lethbridge (1998) echo Waldfogel, they find that returning to the pre-birth employer has a positive impact on wages for Canadian women.
[5] Maternity leave information is only reported after 1983. Restricting our analysis to women who give birth after 1983 reduces the Mexican sample to an unmanageable size.
[6] These percentages are based on NLSY data from 1994 (and 1993 when 1994 data are unavailable).

Black-White wage differential, while education plays a more prominent role in explaining the Mexican-White wage gap.

The remainder of the paper is as follows. The next section briefly describes the data and variables used. Section 3 details the socioeconomic characteristics by race group. Section 4 presents the basic wage patterns for each race group and explores the factors that contribute to wage differentials across groups. Section 5 decomposes the race wage gaps to identify the driving factors. Section 6 discusses the possibility of ethnic-specific labor market participation. Section 7 summarizes and concludes.

2. Data

We use the National Longitudinal Survey of Youth (NLSY) which contains longitudinal data from 1979-1998 for a sample of men and women aged 14-22 in 1979. There are several features of this data that are crucial for our purposes. First, the NLSY contains information that allows us to construct actual (rather than potential) work experience. This is particularly important when studying women. Secondly, this data includes detailed information on marital and childbirth patterns. Finally, the NLSY allows us to identify non-immigrants and separate individuals into racial/ethnic origin groups.

The NLSY contains 2403 non-immigrant Mexican, Black, and White women who were employed and report an hourly wage between \$1 and \$100 per hour in 1993 or 1994 and are not self-employed.[7] 1993 data are only used if the respondent failed to report the information required

[7] An individual is considered self-employed if they reported being self-employed or working without pay in jobs 1 through 5. Alternatively we could have used information from the current/most recent job, however, this information was not available for 1994.

to construct an hourly wage measure in 1994, but did report this information in 1993.[8] Hourly wages for 1994 are calculated as annual wages and salaries in 1994 divided by the number of annual hours worked in 1994.[9] Hourly wages for 1993 are calculated analogously but are inflated into 1994 dollars. All variables are matched to the hourly wage data. For instance, marital status in 1994 is replaced with marital status in 1993 if hourly wage data is missing in 1994, but available in 1993.

Given our interest in the number of children present in 1993/94, we construct all child variables using the number of children ever born. The lone exception is children born during 1993. Since the number of children ever born was not reported in 1993, we use retrospective day, month, and year of birth reports from 1994-1998 and the day and month of the interview date in 1993 to calculate the number of children born in 1993. We than add the number of children born in 1993 to the number of children reported in 1992.

We use two measures of experience: Mincer experience and actual experience. Mincer experience is calculated as age minus years of education minus six. Actual experience is years of employment for individuals greater than 18 years of age reported between 1976 and 1994.[10]

Individuals are assigned to a racial/ethnic origin group by reports of first, or only, racial/ethnic origin. We focus on three racial/ethnic groups: Mexicans, Blacks and Whites. An individual is considered Mexican if she claims to be Mexican or Mexican American. Similarly, an individual is considered Black if she claims to be Black. A respondent is considered White if

[8] As in Waldfogel (1998), we use wage data for multiple years to maintain an adequate sample of young Mexican women and mitigate sample selection.
[9] Alternatively, we could have utilized the "key" variable hourly rate of pay in the current/most recent job created by the NLSY. However, this variable is problematic at extreme values (see Section 1.35 of the NLSY User's Guide). Furthermore, for the panel estimation discussed below, it seems more reasonable to have all information corresponding with the past calendar year rather than since last interview. For instance, some individuals have an hourly rate of pay but did not work during the past calendar year. Having said this, the cross section results are similar when hourly rate of pay is used.
[10] Actual experience is based on weeks worked since last interview in the NLSY. We convert the weekly experience into annual experience by dividing total weekly experience by 52.

she claims to be English, French, German, Greek, Irish, Italian, Polish, Portuguese, Russian, Scottish, Welsh, or American, and is not Black or Mexican.

Place of birth is used to define immigrant status. An individual is considered a non-immigrant if they were born in the United States. The results are not sensitive to this definition. All results are similar if we require that the respondent and both parents be U.S. born, or require that the respondent and at least one parent be U.S. born. Restricting our analysis to non-immigrants allows for easier comparison with previous work by Trejo (1997, 1998) and reduces the potential influence of English proficiency, for which we have no measure.

3. Socioeconomic Characteristics

Table 1 presents descriptive statistics for the main variables used in the cross-sectional analysis. Inspection of Table 1 reveals that the average young Mexican woman earns 10% less than the average young White woman, while the average young Black woman earns 13% less than the average young White woman. The obvious question is: Why do young Mexican women fare relatively better than their Black counterparts?

Part of the relative success enjoyed by young Mexican women may be due to differences in socioeconomic characteristics. For example, race-specific fertility differences may be an important determinant of wages. Waldfogel (1997, 1998) and Korenman and Neumark (1992) find that children have a negative effect on wages for women, all else being equal. Larger relative Black families might therefore help explain the relative success of young Mexican women. While young White women have significantly fewer children than their Mexican and Black counterparts, Table 1 reveals that the average Mexican woman has more rather than fewer children than her average Black counterpart. It is therefore unlikely that childbearing differences play a significant role in explaining differences in Mexican and Black labor market performance, unless it is through the timing of children. The average Black woman has her first child when she is 20 and her second when she is 24, while the average Mexican woman does not have her first child until she is 21 and has her second child when she is 24.[11]

The second obvious question is: Are young Mexican women more educated than young Black women? Table 1 clearly shows that the answer is again no. The average young Mexican woman has 12.7 years of education, while the Black women average 13.3 years of education and the average White women has 13.7 years of education.

The third obvious question is: Are young Mexican women more attached to the labor force than their Black counterparts? Both Mexicans and Blacks spend less time in the labor market than White women. For instance, the average 30-year-old Mexican woman has 9.2 years of post-schooling experience while her Black counterpart has only 7.9 years and her White counterpart has 9.8 years. However, factoring in educational differences, Mexicans and Blacks have similar amounts of experience.

Marriage patterns are the most pronounced difference across young female ethnic groups. In our sample, 61.9% of Mexican women and 66.6% of White women are married. In contrast, only 36.3% of Black women are married in 1994, or 1993 if missing information has forced the use of the previous year. While it is not entirely clear how marital status differences impact labor market participation, Moffitt (1992) finds that female heads with children under age eighteen work about the same amount as single women and more than married women most of whom also have children. Although the average wages of married and single Black women are almost identical, 87.2% of Black married women are employed while only 72.7% of unmarried Black women are

[11] A similar pattern is found if one looks only at women who are participating in the labor market.

employed.[12] We will return to the possibility of non-random employment participation in Section 6.

The similarities in average socioeconomic characteristics across young Mexican and Black women do not of course imply that the time patterns, variation within race groups, or the return to certain attributes are the same across all race groups. In fact, they clearly indicate that some, or all, of these factors must differ. We draw two main conclusions, or more accurately hypotheses, from this preliminary perusal of descriptive statistics. First, if fertility rate differences play a role in explaining the wage gap between Mexicans and Blacks it must be through timing and a differential impact on experience. Second, education and experience differences between Mexicans and Blacks must therefore play an important role in explaining their respective wages gaps compared to White women. The remainder of the paper more formally explores these possibilities.

4. Wages

Following standard practice, we compare the wages of ethnic-specific groups by running log hourly wage regressions of the following form:[13]

$$w_{ri} = \boldsymbol{a}_r + X_{ri}\boldsymbol{b}_r + \boldsymbol{e}_{ri} \qquad (1)$$

where w is the log hourly wage, r denotes race ($r = M, B,$ or W), i denotes individual, and X includes: experience, education, marital status, child variables, region of residence, SMSA, and a year dummy (set to 1 if the reporting year is 1994), and a constant.[14]

[12] Similarly, 86.0% of married Black women with children work while only 67.9% of single Black women with children are employed.

[13] All regressions and decompositions are estimated using STATA.

[14] We also ran regressions including parental education, number of siblings, and husband's employment status to check that we were not missing important variables. The results for these regressions are not reported since the additional variables were generally statistically insignificant and their inclusion does not change the results presented. We also ran all regressions using Hispanic in place of Mexican as the race definition, again the results did not differ in any substantive way.

There are several noteworthy results presented in the middle column of Panel A. First, education has a positive impact on the wages of young women in all racial/ethnic origin groups. Secondly, having a single child has a negative impact on wages for young White women, and having two or more children has a negative impact on wages for both young Black and White women. Thirdly, the relationship between potential experience and wages is statistically insignificant for all racial/ethnic groups.

There are, of course, many good reasons to be skeptical about estimates based on Mincer experience for women. The movement of women in and out of the labor market, especially surrounding childbirth, may render Mincer experience an extremely inaccurate proxy for actual experience for many women. The right-hand column of panel A of Table 2 replicates the *base* regressions replacing Mincer experience with actual experience and age. Comparing these results to the *base* estimates highlights the importance of measuring actual experience. The level experience term is positive and statistically significant at the 10% level or better for the Black and White samples. While the squared experience term is never individually statistically significant at the 10% level, experience and experience squared are jointly significant at better than the 1% level for all groups. The squared terms are negative for Blacks and positive for Mexicans and Whites.[15] Age is included to capture out of the labor force spells. Time out of the labor force has a negative affect on wages for White women at the 10% level or better. Each year of absence from the labor market reduces wages by 4.5% for White women.

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[15] In order allow for the possibility that experience profiles differ across birth patterns, we experimented with allowing the slope to change after childbirth experiences. To do this we constructed three experience measures. The first measure is years of actual experience until the year in which the first child is born, or until the cut-off (1993/94) if there is no first child. The second measure is years of actual experience between the years of the first and second births, or until the cut-off if there is no second child, and zero otherwise. The third measure is years of actual experience after the year of the second birth, and zero if there is no second child. However, we find little evidence that experience profiles change slope after childbirth experiences for any of the racial/ethnic groups and therefore do not report the results.

The pattern of socioeconomic influences change very little when Mincer experience is replaced by actual experience, although the magnitudes do change somewhat. Education continues to have a positive and statistically significant impact on wages, although smaller in magnitude for all racial/ethnic groups. Each additional year of education increases wages by 3.3%, 7.3%, and 7.2% for Mexican, Black, and White women respectively. In contrast, 2 or more children is no longer statistically significant for Black or White women.

Education enters all Panel A regressions as a continuous (linear) variable. Since it seems likely that the relationship between educational attainment and wages is non-linear, for at least some racial/ethnic groups, Panel B replicates Panel A with education entering as three dummy variables: high school graduate, some college, and college graduate, with high school drop-out being the excluded category. Focusing on the regression that includes actual labor market experience and age, it is clear that the impact of educational attainment differs substantially across racial/ethnic groups. Relative to Whites, Mexicans earn a lower return from college graduation, and Blacks earn a higher return from all levels of education. Of further interest, all child variables are now insignificant for all racial/ethnic groups, this result is in sharp contrast to that of Waldfogel (1997).

5. What Explains the Wage Gap?

Quantification of racial earnings gaps requires computing what minority workers would earn if they had the same characteristics as majority workers. Following Oaxaca (1973), there are two ways to decompose the White/Minority (w/m) earnings gap.

$$\overline{w_w} - \overline{w_m} = (\overline{X_w} - \overline{X_m})\hat{b}_w + \overline{X_m}(\hat{b}_w - \hat{b}_m) + (\hat{a}_w - \hat{a}_m) \quad \text{or,} \tag{2a}$$

$$\overline{w_w} - \overline{w_m} = (\overline{X_w} - \overline{X_m})\hat{b}_m + \overline{X_w}(\hat{b}_w - \hat{b}_m) + (\hat{a}_w - \hat{a}_m). \tag{2b}$$

Bars denote means and hats denote predicted values from equation (1).

The decomposition results using both the White weights (2a) and the minority weights (2b) are reported in Table 3. The first row reports the total log wage differential. The second and third blocks report the proportion of the total wage differential attributable to observable and unobservable socioeconomic characteristics, respectively.

Unlike Trejo (1997), we do not find that observable characteristics play a larger role in explaining the relative labor market performance of Mexicans than Blacks. We do, however, find that different factors are more important in explaining the Mexican/White gap and the Black/White gap. All else being equal, observable differences in education account for 32%-36% of the Black/White gap and 61%-64% of the Mexican/White gap. Ranges bound the White and minority weighted decompositions. In contrast, observable differences in experience account for 56%-65% of the Black/White gap but only 39%-43% of the Mexican/White gap. Finally, observable differences in childbearing account for 0%-3% of the Black/White gap and 1%-4% of the Mexican/White gap. Interestingly, when the Mexican weights are used, the other category, which includes region, smsa, and marker, can over-explain the entire Mexican/White gap. This is largely driven by the fact that the small number of Mexicans who live in the Northeast earn a relatively higher wage than Mexicans who live in the West. Overall, observable factors explain more than the entire Black/White gap and 99.5%-229% of the Mexican/White gap.

To check that our results are not driven by the omission of occupational differences across racial/ethnic groups, Table 4 replicates the right-hand side of Panel B of Table 2 and the decomposition in Table 3 with the addition of three occupational dummy variables: professional, blue collar (including the military and farm laborers), and services, with sales being the excluded category. The regression results are largely similar.[16] Interestingly, for Mexicans the inclusion of occupation does not appear to be important, while for Black and White women being in a professional occupation increases wages and being in a service occupation decreases wages. Turning to the decomposition results, occupation explains 4%-13% of the Mexican/White gap and 23%-32% of the Black/White gap, however, it does not cause the magnitude of the other explanatory factors, in particular education and experience, to change very much. Given the similarity of results in Tables 3 and 4 and the possible endogeneity of occupation, for the remainder of the analysis we exclude occupation.

6. Selection

Cross-sectional estimates of discrimination may be biased by selection effects that differ across racial lines. Preferences for work, or motivation may differ across races in ways that are difficult to measure directly. Stated somewhat differently, the decision to participate in the labor market is not random and may differ systematically across ethnic groups. Wage gap measures that fail to account for such differences may be inaccurate because they include unmeasured preference and motivational differences.

The Heckman selection model is one way to account for non-random labor market participation. However, in our sample very few women are not working: the 1994 employment rates are 81.4%, 76.9%, and 83.8% for Mexicans, Blacks, and Whites, respectively. Furthermore, we lack suitable controls for the participation equation. Although we have information on the education level of each individual's mother and father, the presence of a library card, newspaper subscription, and magazine subscription in the household at age 14, and non-labor income, many of these variables are not well reported. For example, 5% of the sample does not report mother's education, 15% of the sample does not report father's education, and 16% of the sample does not

[16] The sample sizes are slightly smaller due to the non-reporting of occupation for some individuals.

report non-labor income.[17] This non-reporting reduces the Mexican sample size to an unacceptable level.

We instead address selection using panel data and fixed effect estimation. This approach has the advantage of separating individual-specific characteristics that are constant over time from other factors effecting earnings by including individual-specific intercepts. Following a given individual purges the estimates of idiosyncratic person-specific and time-invariant factors, rendering unbiased estimates of labor market factors. More concretely, Equation (1) is re-written in a form appropriate for panel data,

$$w_{rit} = X_{rit}\beta_r + Z_{ri}\gamma_r + \alpha_{ri} + \varepsilon_{rit} \tag{3}$$

where X_{rit} denotes time-varying characteristics, Z_{ri} denotes time-invariant characteristics, α_{ri} are unobservable individual fixed effects, and ε_{rit} represents unobservable effects varying both across individuals and over time. As is standard, we assume that α and ε are independent, that ε is serially uncorrelated, and that ε has a zero mean.

Following Polachek and Kim (1994), we transform equation (3) into its mean deviation form[18] which eliminates the person specific effects. However, this transformation also eliminates all time-invariant factors making a second-stage analysis of residuals necessary to obtain the time invariant coefficients.

In the first stage we obtain consistent estimates of β using OLS from,

$$(w_{rit} - \tilde{w}_{ri}) = (X_{rit} - \tilde{X}_{ri})\beta_r + (\varepsilon_{rit} - \tilde{\varepsilon}_{ri})$$

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[17] Non-labor income is defined as total family income in the past calendar year minus the respondent's wages and salaries in the past calendar year.

[18] We use mean differences rather than first differences to mitigate missing observations.

where $\tilde{w}_{ri} = (1/T)\sum_t w_{rit}$ and X contains all Table 2 variables with the exception of education. To identify γ we substitute $\hat{\boldsymbol{b}}_r$ from the first stage into the individual-specific averaged version of (3), to obtain

$$w_{ri} - X_{ri}\hat{\boldsymbol{b}}_r = Z_{ri}\boldsymbol{g}_{ri} + X_{ri}(\boldsymbol{b}_r - \hat{\boldsymbol{b}}_r) + \boldsymbol{a}_{ri} + \boldsymbol{e}_{ri} = Z_{ri}\boldsymbol{g}_r + \boldsymbol{n}_{ri} \tag{4}$$

where, $\boldsymbol{n}_{ri} = X_{ri}(\boldsymbol{b}_r - \hat{\boldsymbol{b}}_r) + \boldsymbol{a}_{ri} + \boldsymbol{e}_{ri}$. Making the usual assumption that $\boldsymbol{n}_{ri}$ is uncorrelated with Z_{ri}, equation (4) can be estimated using OLS. Z includes education and a constant.

The panel estimates for each racial/ethnic group are reported in the top panel of Table 5. These regressions include all previously included variables and cover the period 1982-1994.[19] An individual does not enter the panel until they are 19 years of age or older and have completely finished their education. For example, if an individual was 19 in 1982 and had 12 years of education in 1982 and 1983, but in 1984 they had 13 years of education, and in 1985 onward they had 14 years of education, the individual would not enter the panel until 1986. As in the cross section, we only include women who are employed and earning between \$1 per hour and \$100 per hour and are not self-employed.[20] All remaining variables are as defined in the cross section (see Section 2).

While the magnitude of some results differ across the panel and cross-sectional estimates, the pattern of results are remarkably similar. The most notable difference is the re-appearance of a negative and statistically significant relationship children and wages for White women. These coefficients continue to be insignificantly different from zero for both Mexican and Black women. The estimated returns to experience are also interesting. First, both experience and experience squared are significant at the 10% level or better for all racial/ethnic groups. Secondly, the

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[19] Data from 1979-1981 are not utilized in the analysis because the number of children born was reported in a different manner than the time period 1982-1994.

returns to experience are now larger for Mexican women relative to Black women. Finally, marriage now has a negative and significant effect on the wages of Mexican women.

Two-stage estimation makes decomposing the wage-gap between races somewhat more complicated. The race specific mean wage is $\overline{w_r} = (1/n_r)\sum_{i=1}^{n_r} \hat{a}_{ri} + \overline{X_r}\hat{b}_r$, where bars denote the mean of person-specific averages, so that each person enters the average once. Removing education from the fixed-effects, $\hat{\hat{a}}_r = (1/n_r)\sum_{i=1}^{n_r} \hat{a}_{ri} - \overline{Z}_r\hat{g}_r$ and average wages are given by $\overline{w_r} = \hat{\hat{a}}_r + \overline{X_r}\hat{b}_r + \overline{Z}_r\hat{g}_r$, allowing us to use Oaxaca (1973) decomposition:

$$\overline{w_w} - \overline{w_m} = (\overline{X_w} - \overline{X_m})\hat{b}_w + \overline{X_m}(\hat{b}_w - \hat{b}_m) + (\hat{\hat{a}}_w - \hat{\hat{a}}_m) \qquad \text{or,} \tag{5a}$$

$$\overline{w_w} - \overline{w_m} = (\overline{X_w} - \overline{X_m})\hat{b}_m + \overline{X_w}(\hat{b}_w - \hat{b}_m) + (\hat{\hat{a}}_w - \hat{\hat{a}}_m). \tag{5b}$$

The bottom panel of Table 5 reports the decomposition results for the panel estimates. The biggest difference between the panel and cross-section results lies in the raw wage gap; the Mexican/White gap is 1.3 percentage points smaller while the Black/White gap is 2.2 percentage points larger. Thus, raising the estimated advantage that Mexican women enjoy relative to Black women. However, education and experience continue to be the driving explanatory factors. Experience explains approximately 25%-54% of the Mexican/White gap and 21%-44% of the Black/White gap. Education accounts for 72%-75% of the Mexican/White gap but only 27%-32% of the Black/White gap.

Using the White weights we are able to explain more than the Mexican/White gap and 94% of the Black/White gap. In contrast, using minority weights we explain only 13% and 52% of the Mexican/White gap and the Black/White gap, respectively. For the Black/White gap this is largely due to the decline in the relative importance of experience and age while for the Mexican/White

[20] All hourly wages are inflated into 1994 dollars.

gap this is almost entirely due to the large negative effect of the “other” category. In contrast to the cross-sectional analysis, the coefficient on Northeast is large and negative in the Mexican regression. Once fixed effects are accounted for, the small number of Mexican women who move in and/or out of the Northeast do relatively poorly while in the Northeast. As a result, Northeast enters the observable component as a large negative in the Mexican-weighted decomposition. This results because the negative coefficient is weighted by the average percentage of the white sample living in the Northeast, which is large, minus the average percentage of the Mexican sample living in the Northeast, which is small.

7. Conclusion

There has been increasing interest in the relatively poor labor market outcomes of economically disadvantaged groups in the United States. However, with the exception of one study, all existing research focuses on the labor market outcomes of economically disadvantaged men. This paper has attempts to fill this void by examining the relative labor market outcomes of two economically disadvantaged groups of young women, Mexicans and Blacks. We find that young Mexican and Black women earn 9 and 15 percent less than young White women, respectively, but that the factors driving the relative wage gaps differ. The most important determinant of the Mexican/White wage gap is low levels of education, while low levels of labor force attachment is the most important determinant of the Black/White wage gap.

The results presented in this paper are encouraging for Mexican women because it seems more likely that we can develop programs to encourage young Mexican women to stay in school than that we will be successful in encouraging Black women to participate in the labor market. Numerous studies, see Moffit (1991) for a survey, have shown that female labor supply is highly inelastic and that welfare reforms, negative income tax schemes, and the like therefore have little impact on labor supply behavior. On the other, hand head-start programs have proven somewhat successful with Hispanic children (Currie and Thomas, 1997). The combination of childhood intervention and financial aid for post-secondary education might therefore significantly change educational attainment levels for Mexican women, and hence their wages and poverty status.

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Table 1. Descriptive Statistics

	Mexican		Black		White	
	Mean	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
Log Hourly Wages	2.1310	0.5700	2.1054	0.6192	2.2312	0.6436
Age	32.5283	2.4047	32.6571	2.3390	32.6769	2.3480
Experience*						
Mincer	13.7814	3.4837	13.3933	3.2943	12.9867	3.5240
Actual	10.9001	3.8067	10.3132	3.8727	11.5508	3.6019
Education						
Years of Education	12.7469	2.6442	13.2638	2.2762	13.6902	2.6313
Less than High School	0.2251	0.4185	0.1227	0.3282	0.1072	0.3094
High School Graduate	0.3259	0.4696	0.3525	0.4780	0.3500	0.4772
Some College	0.2982	0.4584	0.3410	0.4743	0.2362	0.4249
College Graduate	0.1508	0.3585	0.1838	0.3876	0.3067	0.4613
Marital Status						
Married	0.6193	0.4865	0.3633	0.4812	0.6661	0.4718
Fertility						
1 Child	0.1570	0.3646	0.2133	0.4099	0.2174	0.4127
2+ Children	0.6425	0.4802	0.5529	0.4975	0.4729	0.4995
Sample Size	249		859		1295	

All estimates based on 1994 weights.

Table 2. OLS Regressions

	Mincer Experience			Actual Experience		
	Mexican	**Black**	**White**	**Mexican**	**Black**	**White**
Panel A						
Experience	-0.0696	-0.0041	-0.0154	0.0439	**0.0723**	**0.0419**
	(0.0927)	(0.0331)	(0.0348)	(0.0419)	(0.0228)	(0.0244)
Experience^2	0.0033	0.0010	0.0009	0.0006	-0.0006	0.0010
	(0.0034)	(0.0012)	(0.0013)	(0.0022)	(0.0011)	(0.0011)
Age				-0.0191	-0.0162	**-0.0447**
				0.0247	0.0102	0.0095
Education	**0.0701**	**0.1158**	**0.0841**	**0.0325**	**0.0729**	**0.0715**
	(0.0275)	(0.0134)	(0.0105)	(0.0184)	(0.0087)	(0.0076)
Married	-0.0155	0.0575	**0.0845**	-0.0822	0.0195	0.0262
	(0.0992)	(0.0404)	(0.0358)	(0.0942)	(0.0377)	(0.0346)
1 Child	0.0562	-0.0304	**-0.1097**	0.0955	-0.0386	**-0.0758**
	(0.1334)	(0.0609)	(0.0444)	(0.1350)	(0.0559)	(0.0428)
2+ Children	-0.1239	**-0.0928**	**-0.1945**	-0.0105	0.0004	-0.0570
	(0.0970)	(0.0547)	(0.0419)	(0.0867)	(0.0506)	(0.0409)
Sample Size	249	859	1295	249	859	1295
R^2	0.1541	0.2179	0.2083	0.2331	0.3138	0.2857
P-Value: Joint Significance of Experience	0.3373	0.0253	0.4969	0.0002	0.0000	0.0000
Panel B						
Experience	0.0075	0.0295	0.0082	0.0483	**0.0751**	**0.0521**
	(0.0837)	(0.0264)	(0.0302)	(0.0418)	(0.0232)	(0.0249)
Experience^2	0.0007	-0.0005	-0.0003	0.0006	-0.0009	0.0007
	(0.0031)	(0.0008)	(0.0012)	(0.0021)	(0.0011)	(0.0011)
Age				-0.0297	-0.0140	**-0.0464**
				0.0229	0.0105	0.0095
High School Grad	0.0802	**0.3536**	**0.1481**	-0.1239	**0.1969**	0.0016
	(0.1153)	(0.0801)	(0.0607)	(0.1141)	(0.0712)	(0.0575)
Some College	**0.2573**	**0.5064**	**0.2703**	0.0133	**0.2811**	**0.0977**
	(0.1313)	(0.0856)	(0.0668)	(0.1041)	(0.0728)	(0.0593)
College Grad	**0.7395**	**0.8816**	**0.5815**	**0.4184**	**0.5734**	**0.4516**
	(0.1750)	(0.1015)	(0.0762)	(0.1309)	(0.0787)	(0.0605)
Married	-0.0346	0.0356	**0.0741**	-0.1026	0.0111	0.0144
	(0.0944)	(0.0410)	(0.0358)	(0.0926)	(0.0383)	(0.0342)
1 Child	0.0698	-0.0206	**-0.1114**	0.1225	-0.0262	-0.0646
	(0.1231)	(0.0622)	(0.0446)	(0.1188)	(0.0572)	(0.0429)
2+ Children	-0.1165	-0.0864	**-0.1880**	0.0364	0.0030	-0.0491
	(0.0932)	(0.0554)	(0.0426)	(0.0856)	(0.0523)	(0.0416)
Sample Size	249	859	1295	249	859	1295
R^2	0.2078	0.2247	0.2093	0.3006	0.3132	0.2940
P-Value: Joint Significance of Experience	0.2666	0.1417	0.9625	0.0001	0.0000	0.0000

Absolute value of heterscedastic consistent standard errors are in parentheses. All regressions also include region of residence, SMSA, a dummy variable if 1993 data is used, and a constant. 1994 weights are used in all cases. The dependent variable is the log hourly wage. Bold coefficients are statistically significant at the 10% level or bette

Table 3. Decomposition of Log Hourly Wage Differences

	Whites & Mexicans		Whites & Blacks	
	White Weight	Mexican Weight	White Weight	Black Weight
Total Log Wage Differential	0.1002	0.1002	0.1258	0.1258
Attributable to Differences in Observable Characteristics				
Experience	0.0433	0.0394	0.0823	0.0702
Age	-0.0069	-0.0044	-0.0009	-0.0003
Education	0.0644	0.0614	0.0452	0.0405
Marriage	0.0007	-0.0048	0.0044	0.0034
Children	0.0044	0.0012	0.0037	-0.0004
Other	-0.0062	0.1369	0.0147	0.0361
Total	0.0997	0.2297	0.1493	0.1495
Attributable to Differences in Unobservable Characteristics				
Intercept	0.2633	0.2633	1.0065	1.0065
Experience	0.0551	0.0590	-0.0405	-0.0283
Age	-0.5422	-0.5447	-1.0588	-1.0594
Education	0.0711	0.0741	-0.1538	-0.1490
Marriage	0.0725	0.0779	0.0012	0.0022
Children	-0.0844	-0.0811	-0.0370	-0.0330
Other	0.1651	0.0220	0.2588	0.2373
Total	0.0005	-0.1296	-0.0235	-0.0237

Based on regression results presented in Table 2, Panel B for actual experience. 1994 weights are used in all cases.

Table 4. OLS Regressions Including Occupation Categories

Regression Results	Mexican	Black	White
Experience	0.0424	**0.0697**	**0.0509**
	(0.0437)	(0.0232)	(0.0249)
Experience^2	0.0007	-0.0009	0.0005
	(0.0021)	(0.0011)	(0.0011)
Age	-0.0298	-0.0079	**-0.0413**
	(0.0230)	(0.0107)	(0.0094)
High School Grad	-0.1451	**0.1864**	-0.0133
	(0.1047)	(0.0709)	(0.0575)
Some College	-0.0276	**0.2460**	0.0370
	(0.0931)	(0.0724)	(0.0586)
College Grad	**0.3389**	**0.4759**	**0.2856**
	(0.1268)	(0.0796)	(0.0653)
Married	-0.0961	-0.0016	0.0156
	(0.0903)	(0.0369)	(0.0343)
1 Child	0.1076	-0.0169	-0.0631
	(0.1185)	(0.0559)	(0.0422)
2+ Children	0.0307	0.0093	-0.0490
	(0.0852)	(0.0504)	(0.0404)
Professional	0.0972	**0.1714**	**0.1853**
	(0.0868)	(0.0466)	(0.0390)
Blue Collar	-0.0190	0.0164	-0.0834
	(0.1273)	(0.0562)	(0.0616)
Service	-0.1397	**-0.1096**	**-0.1833**
	(0.1272)	(0.0572)	(0.0489)
Sample Size	246	858	1292
R^2	0.3142	0.3341	0.3262
P-Value: Joint Significance of Experience	0.0003	0.0000	0.0000

Decomposition Results	Whites & Mexicans		Whites & Blacks	
Based on Actual Experience	White Weight	Mexican Weight	White Weight	Black Weight
Total Log Wage Differential	0.0951	0.0951	0.1253	0.1253
Attributable to Differences in Observables				
Experience	0.0379	0.0355	0.0752	0.0638
Age	-0.0058	-0.0042	-0.0009	-0.0002
Education	0.0414	0.0505	0.0311	0.0320
Marriage	0.0008	-0.0047	0.0047	-0.0005
Children	0.0045	0.0013	0.0037	-0.0008
Occupation	0.0123	0.0042	0.0402	0.0284
Other	-0.0005	0.1352	0.0193	0.0383
Total	0.0906	0.2177	0.1733	0.1610
Attributable to Differences in Unobservables				
Intercept	0.1070	0.1070	1.0603	1.0603
Experience	0.0622	0.0646	-0.0262	-0.0147
Age	-0.3753	-0.3770	-1.0907	-1.0914
Education	0.0542	0.0451	-0.1766	-0.1776
Marriage	0.0688	0.0743	0.0062	0.0114
Children	-0.0780	-0.0748	-0.0420	-0.0375
Occupation	0.0105	0.0186	-0.0304	-0.0185
Other	0.1552	0.0194	0.2514	0.2323
Total	0.0045	-0.1227	-0.0479	-0.0357

Heteroscedastic consistent standard errors are in parentheses. Bold coefficients are statistically significant at the 10% level or better. All regressions also include region of residence, SMSA, a data year dummy, and a constant. The dependent variable is the log hourly wage.

Table 5. Panel Estimates and Decompositions

Regression Results	Mexican	Black	White
Experience	**0.0949**	**0.0792**	**0.1313**
	(0.0230)	(0.0115)	(0.0087)
Experience^2	**-0.0042**	**-0.0028**	**-0.0032**
	(0.0007)	(0.0003)	(0.0002)
Age	0.0129	0.0073	**-0.0328**
	(0.0147)	(0.0080)	(0.0066)
High School Grad	0.0386	**0.1794**	0.0308
	(0.0714)	(0.0359)	(0.0313)
Some College	0.1248	**0.3186**	**0.1516**
	(0.0808)	(0.0377)	(0.0346)
College Grad	**0.4325**	**0.6100**	**0.4567**
	(0.1108)	(0.0414)	(0.0339)
Married	**-0.0781**	0.0201	-0.0148
	(0.0349)	(0.0171)	(0.0115)
1 Child	-0.0438	0.0331	**-0.0669**
	(0.0459)	(0.0260)	(0.0147)
2+ Children	-0.0670	0.0088	**-0.0822**
	(0.0556)	(0.0345)	(0.0210)
Sample Size	2333	8395	16364
P-Value: Joint Significance of Experience	0.0000	0.0000	0.0000

Decomposition Results	Whites & Mexicans		Whites & Blacks	
Based on Actual Experience	White Weight	Mexican Weight	White Weight	Black Weight
Total Log Wage Differential	0.0876	0.0876	0.1477	0.1477
Attributable to Differences in Observables				
Experience	0.0475	0.0223	0.0643	0.0304
Age	0.0024	-0.0009	0.0131	-0.0029
Education	0.0653	0.0631	0.0410	0.0479
Marriage	-0.0002	-0.0009	-0.0038	0.0051
Children	0.0156	0.0125	0.0139	-0.0028
Other	0.0280	-0.0850	0.0107	-0.0006
Total	0.1587	0.0110	0.1393	0.0771
Attributable to Differences in Unobservables				
Experience	0.3097	0.3350	0.3197	0.3537
Age	-1.2507	-1.2474	-1.1087	-1.0927
Education	0.0073	0.0094	-0.1295	-0.1364
Marriage	0.0362	0.0370	-0.0115	-0.0204
Children	-0.0122	-0.0091	-0.0627	-0.0460
Fixed Effects	0.7611	0.7611	0.8596	0.8596
Other	0.0774	0.1905	0.1415	0.1528
Total	-0.0711	0.0766	0.0084	0.0705

Bold coefficients are statistically significant at the 10% level or better. All regressions also include region of residence, SMSA, and fixed effects. The dependent variable is the log hourly wage.