Published in final edited form as:

J Hum Resour. 2008 ; 43(3): 630–659.

Gender Wage Disparities among the Highly Educated

Dan A. Black,

University of Chicago & NORC **Contact information:** Harris School University of Chicago 1155 East 60th Street Chicago, IL 60637

Amelia Haviland,

Rand **Contact information:** RAND Corporation Pittsburgh Office 201 N. Craig St. Pittsburgh, PA 15213

Seth G. Sanders, and

University of Maryland **Contact information:** Department of Economics 3105 Tydings Hall University of Maryland College Park, MD 20742 sanders@econ.umd.edu

Lowell J. Taylor

Carnegie Melon University **Contact information:** Heinz School Carnegie Mellon University Pittsburgh, PA 15213 (412) 268-3278 lt20@andrew.cmu.edu

Abstract

In the U.S. college-educated women earn approximately 30 percent less than their non-Hispanic white male counterparts. We conduct an empirical examination of this wage disparity for four groups of women—non-Hispanic white, black, Hispanic, and Asian—using the National Survey of College Graduates, a large data set that provides unusually detailed information on higher-level education. Nonparametric matching analysis indicates that among men and women who speak English at home, between 44 and 73 percent of the gender wage gaps are accounted for by such pre-market factors as highest degree and major. When we restrict attention further to women who have "high labor force attachment" (i.e., work experience that is similar to male comparables) we account for 54 to 99 percent of gender wage gaps. Our nonparametric approach differs from familiar regression-based decompositions, so for the sake of comparison we conduct parametric analyses as well. Inferences drawn from these latter decompositions can be quite misleading.

I. Introduction

In U.S. labor markets women earn substantially less than men. Hundreds of studies investigate this phenomenon, seeking to infer the extent to which the gender wage gap is the consequence of disparate treatment by employers. The statistical exercise is one of comparison; at issue is the difference between the wages women receive and those earned by individuals who are male but otherwise *comparable* in terms of relevant characteristics (e.g., men with similar levels of human capital). The standard means of drawing such comparisons, used in nearly every paper on the topic, is linear regression; the idea is to "control" for factors that reflect differences in preferences and human capital between men and women. Gender wage differentials that remain after such adjustments are often taken as evidence of disparate treatment in the labor market. Even this endeavor is not without controversy. If women anticipate discrimination in the labor market, they may alter their human capital investment. Similarly, women may be discouraged by their peers, parents, or schools from pursing lucrative fields of study. Thus, explaining the gender wage gap by "controlling" for such differences in human capital investment can be problematic. Such differences may, in fact, reflect anticipated or pre-labor market discrimination.

The degree to which discrimination impacts on human capital investment decisions is clearly an important question. The models which control for human capital investment can be more conservatively interpreted as isolating estimates of disparate treatment experienced *in* the labor market from differences *prior* to entering the labor market without assigning cause to the observed pre-market differences. Understanding whether employers pay comparable workers comparable wages, the isolated effect, is of critical importance in understanding the gender wage gap. Researchers using large representative data sets, such as the Current Population Survey (CPS) or the U.S. Census, generally have found that these distinctions have little practical relevance as the human capital model explains very little of the observed wage gaps between men and women. But these data sets often lack sufficient detail on relevant human capital variables; they typically have no data on years of work experience and have only rudimentary information on educational attainment. In the absence of adequate measures of pre-market human capital, researchers can use industry and occupation indicators as proxies for market skills, but this practice complicates interpretation of the estimated gender wage gap if industry and occupation assignments are themselves the consequence of disparate labor market treatment.

The alternative research approach is to rely on smaller specialized data sets that have greater labor market detail and carefully collected information on education. The relatively small size of these data sets can make inference about the gender wage gap problematic, particularly when the research focuses on a subset of the population, e.g., college-educated individuals. To draw inferences of reasonable precision researchers typically adopt parametric approaches—relying on assumptions that have been called into question in the recent literature.[1]

A prominent literature on the gender wage gap has emerged, with studies adopting different regression specifications, and also making use of different datasets covering different time periods. While there is, not surprisingly, considerable variability in inferences concerning gender wage gaps, there are also some broadly accepted generalizations. It appears that the wages of women were about 35 to 40 percent lower than the wages of men from the 1920s through the mid 1980s, and then started to converge (Smith and Ward, 1985); see Mulligan and Rubinstein, 2005, for more recent trends. Several studies find that the raw gender gap was between 25 and 30 percent by the mid 1990s. The portion of the gender wage gap explained by pre-labor market skills and occupational choice varies across studies. As one might expect, the more detailed the pre-market skills or occupational choices reported in the data, the larger the share of the gender wage gap that is "explained."[2] In most studies, at

[1]Heckman, Lochner and Todd (2006) express concerns about regression-based models of wage determination.

least one-third of the gender wage gap remains even after carefully conditioning on pre-labor market skill differences *and* on factors – such as occupation, labor market experience, and tenure with the employer – that could themselves be affected by discrimination experienced while in the labor market. Even if one accepts as a working assumption that occupational sorting is not the result of discrimination, there is evidence of gender wage disparities—disparities that occur within occupations and industries.

One widely held view is that the evidence of market discrimination against majority women is stronger than the evidence of market discrimination against minority men. The logic is compelling. When researchers compare economic outcomes of black or Hispanic men with their non-Hispanic white counterparts, non-Hispanic white men are seen to have considerable pre-labor market advantages. For instance, these men not only have more schooling than black and Hispanic men, on average, but also have access to better schools. There are, in short, substantial racial and ethnic differences in pre-market opportunities to build human capital. In contrast, non-Hispanic white men and women are born to the same parents, attend the same schools, and in recent years they have similar rates of high school and college completion. While there is mounting evidence that pre-labor market differences explain almost the entire black-white wage gap for men, these same factors explain very little of the white non-Hispanic gender wage gap.[3]

Against this backdrop, we conduct here an analysis that makes several contributions to the gender wage gap literature—contributions that ultimately derive from our use of a data source that has not previously been used in the analysis of the gender wage gap, the National Survey of College Graduates (NSCG).[4] In 1993, the NSCG resurveyed 214,643 individuals who indicated on their 1990 Census form that they had completed a bachelor's degree or an advanced degree. The size and detail of the NSCG allow us to address three issues for college-educated men and women.

First, the large sample size of the NSCG gives us license to explore an issue that is almost entirely neglected in the literature on the gender wage gap—the importance of restrictive parametric assumptions that underlie regression-based analyses.[5] Our use of nonparametric matching forces us to confront the "support" on which our inferences are drawn—an issue easily obscured in parametric work. As we note above, the central idea of all wage gap studies is to contrast the wages earned by women with those of *comparable* men. This issue of "support," in a nutshell, is that owing to gender-related pre-market sorting there are many women for whom there are no convincing male comparables. For example, there are many

[2]For example, Kidd and Shannon (1996) show that considering the sorting of men and women into 36 rather than 9 occupations increases the share of the wage gap explained by occupational sorting from 12 percent to 27 percent.

[3]Neal and Johnson (1996) report that black and white men in the National Longitudinal Survey of Youth, 1979 (NLSY79) with the same level of pre-labor market skills (as measured by the Armed Forces Qualifying Test score (AFQT)) have quite similar earnings. In contrast, Altonji and Blank (1999) find that in 1994 virtually the entire gender wage gap remains even after accounting for AFQT scores.

[4]In one exception, Graham and Smith (2005) report on gender differences in both employment and earnings in science and engineering occupations.

[5]Nonparametric methods have recently been used in some work on wage determination, though rarely in the study of gender wage gaps. Using a nonparametric kernel smoothing method applicable to mixed continuous and categorical data, Racine and Green (2004) test and reject the traditional parametric model. Similarly, Heckman, Lochner, and Todd (2006) test and reject the functional form of the Mincer earnings regression for the last 30 years of Census data. Nopo (forthcoming) uses nonparametric analysis in his study of gender wage gaps in Peru.

older women in the U.S. who earned a bachelor's degree in nursing, but few, if any, similarly aged men with this same education. When we conduct analyses that match on both pre-market characteristics (age and educational characteristics) *and* years of experience, the situation becomes even more difficult. Many college-educated women have sustained periods when they are not in the labor force, but few men do (and those men who do have limited labor market attachment may in any event be poor comparables). In our nonparametric analysis, we cannot sweep these issues under the rug by making functional form assumptions.[6]

Second, we are able to explore the role of the substantial existing gender differences in training at the bachelor's level and above. Male-dominated majors, such as chemical engineering, may generally have higher returns than such female-dominated majors as elementary education, and these differences in pre-labor market choices are a potentially crucial part of the story in understanding the gender wage gap among the well educated. The role of college major on earnings and the impact on gender wage gaps in the U.S. has been documented in several studies, including Altonji (1993), Brown and Corcoran (1997), Eide (1994), Graham and Smith (2005), Grogger and Eide (1995), Joy (2003), Loury (1997), McDonald and Thornton (2007), Paglin and Rufolo (1990), Turner and Bowen (1999), and Weinberger (1998, 1999). While all of these studies report that college major is associated with some portion of the wage gap, they differ in the size attributed to college major; in our reading, much of this difference is the result of the extent of aggregation of the college majors; the finer the detail in the measurement of college major, the greater the fraction of the wage gap that is explained by the major. Indeed, Machin and Puhani (2003) demonstrate similarly that college major is important to understanding wage gaps in the UK and Germany, and further indicate that use of more detailed major categories allows one to explain a higher portion of the gender wage gap. Our data have far greater detail on college major than previous research, and we are in addition able to explore the extent to which parametric methods influence inferences drawn about the role of major on wages.

Third, the large sample size of the NSCG allows us to conduct our analyses for four distinct racial and ethnic groups of women: non-Hispanic white, Hispanic, black, and Asian. There is, of course, inherent interest in the role of race and ethnicity in labor market outcomes for women, but there is an additional conceptual motivation for studying gender wage differences by ethnicity and race.[7] As we show below, among college-educated women there are substantial differences by race and ethnicity in the distributions of college major. For example, Asian women select college majors that are more similar to men's majors than do other women (e.g., in comparison to other female groups, a disproportionately high fraction of Asian women study engineering and computer science). An examination of wage patterns for Asian women is thus potentially helpful in drawing inferences about the likely effect on the gender wage gap of a more general shift by women toward male-dominated college majors.

[6]This theme is nicely developed in the analysis of black-white differences in asset ownership by Barsky, Bound, Charles, and Lupton (2002).

[7]In their examination of known work on gender and race in the labor market, Altonji and Blank (1999) suggest that the role of race and ethnicity among women in the labor market is an important understudied area.

Quite clearly, the primary focus of our paper is the vital role of early human capital investments for understanding subsequent earnings of men and women. Our paper has considerably less to say about two other issues that have received considerable attention: selection into the labor force and issues of household labor supply.[8] Based on the theory of comparative advantage for home production, we might expect women to invest in different forms of human capital and to have lower levels of labor market participation over their life cycle.[9] As Becker (1985) cautions, it is likely that if women make observably different investments in their careers than men—choosing less lucrative majors or withdrawing more frequently from the labor force—they may also make unobservable decisions that will lower their wages relative to men who are otherwise observational equivalent. Thus, gender wage differences that occur even among men and women with similar levels of observed human capital can reflect unobserved differences in underlying market productivity of men and women. In analyses presented near the end of the paper we do undertake some explorations of the role of labor market attachment for the gender wage gap, but as will be clear we have a limited contribution to make concerning this important issue.

Our paper proceeds as follows: In section II we discuss our data, the NSCG, and the unique advantages it has for studying the gender wage gap among the highly educated. In section III, we briefly outline the traditional regression-based approaches to estimating the gender wage gap and, as a means of establishing a baseline for comparison, conduct such an analysis using the NSCG. Section IV presents our nonparametric matching method and discusses subtle issues in constructing standard errors for these estimates. We present key findings in Section V and provide concluding remarks in Section VI.

We briefly preview our results. Using nonparametric matching, we compare the log wage of women—separately for non-Hispanic white, black, Hispanic, and Asian women—with non-Hispanic white men. Raw log wage gaps are substantial, between -0.26 and -0.34 across racial/ethnic groups. Our baseline comparison matches women to male counterparts on pre-market characteristics only: exact highest degree, major, and age. Consistent with previous literature, we find that very little of the gender earnings gap stems from gender differences in the highest degree attained. College major, in contrast, is important for subsequent earnings. Among women who speak English at home between 44 and 73 percent of the gender wage disparity is accounted for by highest degree, major, and age. By further restricting attention to women who have “high labor force attachment” (i.e., work experience that is similar to male comparables) we explain 54 to 99 percent of the gender wage disparity. Our nonparametric approach differs from the familiar Blinder-Oaxaca regression decompositions, so for the sake of comparison we conduct the parametric analyses as well. We find that in our context inferences drawn from these latter decompositions can be quite misleading.

[8]See Mulligan and Rubinstein (2005) for a nice statement of the issues concerning selection and human capital investment, and references to further literature.

[9]The home-production approach might help explain gender choices in completed education, including college major, and might also be relevant for subsequent human capital accumulation. For example, Light and Ureta (1995) find that differences in the quantity and timing of labor market experience explain about one half of the raw gender gap in wages, presumably because women accumulate less on-the-job training than men. Using direct measures of training, Altonji and Spletzer (1991), Barron, Black, and Loewenstein (1993), and Royalty (1996) all find that women receive less on-the-job training while employed.

II. Data and Distributions of Highest Degree and Major by Gender, Race, and Ethnicity

The data set used in this research is the 1993 National Survey of College Graduates (NSCG). The NSCG stems from an initiative of the National Science Foundation (NSF) to compile information on scientists and engineers. The NSF and the Census Bureau drew a stratified sample of 214,643 individuals based on the 1990 Decennial Census Long Form, with the sample limited to those reporting both at least a baccalaureate degree and who were 72 or younger as of April 1, 1990. The Census Bureau first contacted individuals by mail, then, if necessary, followed up with a telephone or in-person interview. In the collection of these data, a great deal of attention was paid to the accuracy of the education responses. Detailed information was gathered about the majors of the respondents for up to three degrees. In addition, the NSCG included better measures for labor market experience than is provided in the Census (e.g., the number of years of full-time work). An additional important feature of the NSCG is that a number of the respondents' 1990 Long Form responses were made available for analysis in the NSCG.

From those selected to be in the sample based on their 1990 Census data, it was found by 1993 that a few had emigrated from the United States (2,132), died (2,407), or were institutionalized (159) and were hence out of the survey's scope. Some were found to have misreported their age and were over 75 years old (211). Surprisingly, 14,319 respondents had no four-year college degree despite reporting, or being imputed to, a four-year degree on the 1990 Census. Another 46,487 declined to participate fully in the NSCG and information crucial to the analysis was missing (e.g., they failed to provide information about their last degree and field of study). Once the out-of-scope groups are excluded, there is a (weighted) response rate of 80 percent, or a sample of 148,928 respondents. In this paper we examine women and non-Hispanic white men only (which reduces the number of observations by 19,046) and because of the small sample size we choose to omit Native American women from the analysis (which reduces the sample by 630), giving 129,252 respondents who are non-Hispanic white men or women, or black, Hispanic, or Asian women.

Because the sampling frame of the NSCG is the 1990 Census Long Form, anyone not having a degree by 1990 would not be included in the sample. As a result, we restrict our sample to individuals who are at least 25 years of age (in 1990) to insure that most individuals would have had the opportunity to complete their undergraduate education. Similarly, to avoid complications that might arise with differential retirement ages, we restrict our sample to workers 60 years old and under. These age restrictions reduce the number of observations by 18,033. A small number of subjects are excluded due to item non-response (i.e., imputed answers) to gender, race, age, or ethnicity questions, reducing the number of observations by 3,032. A much larger proportion is excluded by item non-response related to the calculation of wages: we omit those who had imputed or zero wage incomes (16,286) and those who had imputed weeks worked or usual hours worked (9,079). Workers who reported self-employment income in addition to wage income were not included in our sample because there is no way of determining whether the hours and weeks worked refer only to the wage-earning job or to the self-employment job also, which would bias the calculated hourly wage (this restriction reduces the number of observations by 8,060). Another 149 respondents reported no major for their highest degree, and we dropped these respondents from most of our analyses. These exclusions leave us with a sample of 74,613 respondents. Because the data over sampled certain populations, in what follows we weight the data to reflect the sampling weights.

The NSCG provides detailed data on each respondent's education, including identification of more than 140 different majors. Table 1 provides evidence on the systematic heterogeneity in educational outcomes among individuals with at least a four-year college degree. In comparison to the benchmark majority group—non-Hispanic white men—women in each ethnic and racial group are less likely to pursue graduate education, especially the professional degree and Ph.D. There are also very large differences in the choice of college major at the undergraduate level.[10] Women are generally under-represented in the highest-paying majors, especially engineering, and over-represented in such low-paying majors as education, the humanities, and the fine arts; 26 percent of non-Hispanic white men major in the five lowest paying majors (education, humanities, professional degrees, fine arts, and agricultural sciences), as compared with approximately 50 percent of white, black, and Hispanic women and 22 percent of Asian women. Among these racial and ethnic groups of women, Asian women have a distribution of majors most like men. The index of dissimilarity, reported in the last line of Panel B, estimates the percentage of women in each group that would need to be strategically reallocated to another major for the distribution of majors to match that of white men.[11] For white, black, Hispanic and Asian women respectively, 45, 44, 42, and 36 percent would need to change major to match the major distribution for non-Hispanic white men. These patterns are seen again in Panel C, which shows the mean fraction female within undergraduate major for each group.

Panel A of Table 2 indicates that the distribution of undergraduate majors for women has changed markedly over recent cohorts. A particularly notable change is in the education major; 38 percent of the women in the 51-60 age cohort majored in education, compared with 15 percent for the 25-30 cohort. In contrast, there has been a large increase in business and economics majors, from 6 percent for the 51-60 cohort to 24 percent for the 25-30 cohort. Panel B provides corresponding statistics for men. Results in Tables 1 and 2 suggest that research using “years of education” as the lone human capital variable misses a major source of the gender-related differential in human capital, and indicate, furthermore, that the importance of this omission varies considerably by cohort.

III. Traditional Parametric Measures of Wage Gaps

The primary focus of our paper is a nonparametric investigation of wage differentials that exploits the detailed educational information we have just described. Before turning to that analysis, though, we take a brief digression to outline the more usual parametric approaches.

A very large number of papers use linear regression to study the wage gap between men and women, typically adopting one of two approaches—a “pooled regression” or “group-specific

[10] In Panel B of Table 1 we aggregate our major categories.

[11] For these calculations we used all 144 categories of major, not the broad categories shown in Panel B.

regression" model. In the first of these approaches, the logarithm of individual wage is regressed on control variables thought to reflect individual-level differences in productivity or preferences and an indicator variable equal to one if the respondent is a woman. The residual earnings differences between groups, as reflected in the coefficient on this dummy variable, can be taken as evidence of disparate labor market treatment. A typical exercise of this sort is reported by Altonji and Blank (1999) in their review piece on gender wage gaps. They specify

$$y_i=\alpha_m+\sum_{j\in\{f,b,h\}}\alpha_j b_i+X_j^{'}\beta+\varepsilon_i, \quad (1)$$

where m refers to men, and f, b, and h refer to female, black and Hispanic respectively, and y_i is the natural logarithm of wages.[12] This specification is referred to as the "pooled regression" model as the parameters on covariates, the βs in the model, are estimated from the pooled data for men and women.

As we note above, there is debate about what factors to include among covariates X. Pre-labor market skills are generally included (e.g., the level of schooling completed). Age or potential labor market experience (as measured by age – years of education – 6) is also usually included. There is less agreement on whether to include the respondent's occupation, industry, and sector of employment. The consensus opinion expressed by Blau and Ferber (1987) is that "specifications which exclude occupation (and other similar variables) yield upper-bound estimates of discrimination and those which include such variables yield a lower bound estimate."

In any event, results from Altonji and Blank (1999), reported in the first line of Panel A in our Table 3, are typical. Using data from the March 1996 Current Population Survey, Altonji and Blank estimate the wage gap between adult women and men using equation (1) The estimate of a_f in the first column, -0.279, is for a specification that has no covariates other than race and ethnicity. From the second column we notice that this estimate is little changed when the researchers also include education, potential experience (entered as a quadratic) and region controls. When occupation, industry, and job characteristics are included (in column 3), though, the estimated log wage gap falls to -0.221. Using Blau and Ferber's logic one might infer that gender discrimination accounts for wage losses of between approximately 22 and 28 percent (as, for small values, log points do not greatly differ from percentages) and that market as well as pre-market differences account for a relatively small portion of the unadjusted gap.

An assumption implicit in the "pooled regression" approach is that the returns to covariates are equal for men and women. The approach taken in the alternative "group-specific" model is to run separate wage regressions for women and men:

$$y_i=X_i^{'}\beta_j+\varepsilon_i, \quad (2)$$

[12]If gaps between non-Hispanic white men and specific race or ethnic groups of women are of interest, indicator variables for each group can be included. In equation (1), the difference between white women and white men is measured by a_f, between black women and white men by $a_f + a_b$, and between Hispanic women and white men by $a_f + a_h$.

where $j \in \{m, w\}$, and where covariates include race/ethnicity indicator variables as in (1). Having estimated (2), the tradition is to decompose wage differentials between men and women into "explained" and "unexplained" components. By differencing equation (2) across groups and taking the expected value, the Blinder-Oaxaca decomposition is:

$$E\left(y_m - y_f\right) = \overline{X}_f^{\prime}\left(\hat{\beta}_m - \hat{\beta}_f\right) + \left(\overline{X}_m^{\prime} - \overline{X}_f^{\prime}\right)\hat{\beta}_m, \quad (3)$$

where $\overline{X}_j^{\prime}$ is the mean level of earnings-related characteristics for group *j*.

The term $\left(\overline{X}_m^{\prime} - \overline{X}_f^{\prime}\right)\hat{\beta}_m$ is the portion of the log wage differential that is "explained" by the difference in the average level of earnings-related characteristics of men and women (evaluated at the βs of men). The remaining terms $\overline{X}_f^{\prime}\left(\hat{\beta}_m - \hat{\beta}_f\right)$ represent the portion of the difference in average wages due to differences in the estimated coefficients. This is labeled the "unexplained" portion of the wage gap, which can be taken in principle to be the "share due to discrimination."

The second row of Panel A in Table 3 reports the "unexplained" log wage gaps that Altonji and Blank (1999) find using the group-specific regression approach. In this example the inferences one draws are the same using either of these parametric approaches: the gender log wage gap among adults in the U.S. in 1995 is found to be approximately -0.28 when one compares men and women with the same education, potential experience, and region, and approximately -0.21 when one matches also on industry and occupation.

In Panel B of Table 3, we estimate the same specifications as Altonji and Blank but with the 1993 NSCG data.[13] The time frames are reasonably close (our wage data are taken from 1990 Census reports and are thus from 1989, while the CPS data used by Altonji and Blank are from 1995), but our analysis focuses exclusively on individuals who report having a college education. Results are strikingly similar for the two samples: among the well educated, the log wage disparity is approximately -0.28 in an exercise that controls for education, potential experience, and region, and approximately -0.21 when controls also include industry and occupation. Consistent with previous work, we would estimate that only a third of the unadjusted gap is associated with differences in pre-market and market covariates.

In sum, using traditional methods we would infer that the gender wage disparity is approximately the same for well-educated women as for the workforce generally, and that this disparity is quite large. With these findings in mind we now turn to the focus of our paper: understanding the extent to which these latter inferences depend on the strong assumptions made in regression-based approaches, and exploring the role of gender-specific variation in college majors.

[13]In particular, the specification we use is a quadratic in potential experience with dummy variables to account for: race/ethnicity (black, Hispanic, and Asian), highest degree (more than a bachelors degree), region (nine Census regions), occupation (13 Census codes), industry (14 Census codes), whether a job is in the public sector, and if the person is working part-time.

IV. Nonparametric Matching Measures of the Wage Gaps

In undertaking the empirical exercise of contrasting the wages of comparable men and women, nonparametric matching is an intuitive alternative to the use of linear regression. Let the raw gender wage gap be defined as

$$\Gamma(G_j) = E(y_j|G_j) - E(y_{WM}|WM), \quad (4)$$

where y_j is the natural logarithm of wages for the *j*th group, *WM* indicates that respondents are non-Hispanic white males, G_j indicates that respondents are members of the female demographic group *j* (non-Hispanic white, black, Hispanic, or Asian), and $\Gamma(G_j)$ is the wage gap. Let X be a vector of covariates (*not* including minority status) and $X = x$ be any specific value for these covariates. Then the wage gap that is "unexplained" for respondents with fixed values of the covariates $X = x$ is defined as

$$\Delta(G_j|X=x) = E(y_j|X=x, G_j) - E(y_{WM}|X=x, G_j) = E(y_j|X=x, G_j) - E(y_{WM}|X=x, WM), \quad (5)$$

which assumes that $E(y_{WM} \mid X = x, WM) = E(y_{WM} \mid X = x, G_j)$ for all groups of women, i.e., assumes that $E(y_{WM} \mid X = x, G_j)$ is the missing counterfactual—the expected log wage of a member of group G_j with characteristics x if she were treated in the labor market as a white male with characteristics x.

Given the detail of our data, in our analyses below we match on age, highest degree, *and* college major, and conduct analyses separately by race and ethnicity. Thus we might ask how much a 35-year-old Asian woman with a BS in biochemistry would earn if she were treated as a non-Hispanic white man in the labor market. Our answer comes from comparing her wage to the wages of non-Hispanic white men who are the same age, and have the same degree and major. Once these counterfactuals are estimated for each member of a demographic group, the mean gap (conditional on covariates) is estimated by averaging over the gaps for each individual in the group of interest. In the program evaluation literature this estimator is said to be the effect of "treatment on the treated." In this case "treatment" is demographic group membership. Restated, the estimator answers the question: What is the effect on log wage of being treated as a woman (of a particular race or ethnicity) in the labor market, relative to labor market treatment as a similarly-aged and similarly-educated member of the majority group (non-Hispanic white men)? The interpretation given here hinges on an assumption that, given the covariates used in the matching, the dependent variable y_{WM} has the same expectation regardless of group membership (Heckman, Ichimura, and Todd, 1998). Of course, if the assumption is violated, and there are other relevant unobservables that differ by demographic group (given the age and education distribution), our estimator will include the impact of those unobservables as well.

There is a simple, alternative interpretation of the matching approach that we use in this paper. Our matching estimators alter the distribution of the covariates so that the distributions of the covariates are identical between white males and our minority group members. This suggests that we may rewrite the matching estimator as a weighted least squares estimator, which in fact is easily done when the data are discrete. With some simple albeit tedious algebra, it can be shown that the matching estimator we use is mathematically equivalent to the weighted least squares estimates of the set of regressions of the form ln(y) = β_0 + $\beta_1 G_j$ +ε with separate regressions for each racial/ethnic group of women using the following weighting scheme: for all data that are not a match—both white males and members of the minority group—assigned weights are zero. For matched data, the minority group members are given a weight of one and white males are given a weight equal to $P(X/[1-P(X)]$, where $P(X)$ is the probability that the respondent is a member of the minority group, conditional on the covariates. This weight scheme ensures that the distribution of the covariates is the same between the treatment and control group in the matched data. Hence, our matching estimator uses none of the data for unmatched observations, but induces the covariates to be statistically independent of the minority group membership. As a result of this independence, there is no need for the researcher to specify (and risk misspecifying) the functional form of the conditional mean function. If we were using relatively small data sets, the loss of efficiency would of course be a matter of concern. Given the size of the NSCG, however, we are comfortable making the tradeoff between the potential loss of efficiency that would arise from not using a properly specified parametric model in return for avoiding the risk of misspecifying the parametric model.

A. Nonparametric Decompositions

We can easily construct wage gap decompositions that parallel the regression-based decompositions outlined above, i.e., find an average "explained" portion, $\Gamma(G_j)-\Delta(G_j)$, and average "unexplained" portion $\Delta(G_j)$. The raw gap can be written as a weighted average over X,

$$\Gamma(G_j)=\sum_X p_{G_j x} E(y|X=x, G_j) - p_{WMx} E(y|X=x, WM),$$

where $p_{G_j x}$ denotes the proportion of members of group G_j with characteristic $X = x$. Adding and subtracting $\sum_X p_{G_j x} E(y|X=x, WM)$ gives us

$$\Gamma(G_j)=\sum_X p_{G_j x}\{E(y|X=x, G_j) - E(y|X=x, WM)\} - \sum_X \left\{p_{WMx} - p_{G_j x}\right\} E(y|X=x, WM). \quad (6)$$

The first term in equation (6), $\Delta(G_j)$, is the portion of the gap specific to the distribution of covariates that is "unexplained" by the covariates. It is the sum of equation (5) over X for the probability distribution $p_{G_j x}$. The second term, the "explained" portion of the wage gap, is due to group differences in the proportions of individuals across cells. The "explained" part of the wage gap is

$$\Gamma(G_j) - \Delta(G_j)=\sum_X \left\{p_{G_j x} - p_{WMx}\right\} E(y|X=x, WM). \quad (7)$$

While these decompositions are clearly in the spirit of the usual regression-based decomposition, two distinctive features merit emphasis. First, our focus is on the impact of "treatment on the treated" obtained by averaging over the support of the characteristics of interest within the group of interest, not for the non-Hispanic white male distribution or a pooled distribution.[14] Second, our method is entirely nonparametric—based on matching each woman in a particular racial/ethnic group to corresponding non-Hispanic white males. As will be apparent shortly, in some of our analyses there are substantial proportions of women for whom we are unable to form matches with comparable men. Our approach is to draw inferences on the basis of cases for whom we can make direct comparisons, while remaining generally silent about wage disparities that might exist for women for whom we have no male comparables. Recent work by Barsky, Bound, Charles, and Lupton (2002) highlights the perils of the alternative approach—making parametric assumptions for the purpose of matching where there is no support. In reporting our estimated wage gaps we report matching rates, to give readers a sense of the severity of the support problem in our empirical work.

B. Standard Errors

To estimate standard errors for the results of the matching model we use a nonparametric bootstrap procedure. There are two advantages to using a nonparametric bootstrap in this setting. First, it allows us to incorporate the variability of the matching cell sizes due to random sampling and nonresponse. Second, it allows us to take advantage of the variance-reducing attributes of the stratified sampling design of the NSCG. In order to estimate the effect of "treatment on the treated" we average the differences in mean log wages over the distribution of age, highest degree, and field of study for each demographic group of interest. The weighted counts within each of the discrete cells of this distribution are themselves random variables, and the bootstrap incorporates the variance of these cell sizes into the overall variance estimate. In addition, the matching cell sizes are affected by unit and item nonresponse. These sources of variation are accounted for by resampling the original sample, before exclusions are made due to unit or item nonresponse, or being out of scope for the survey or this analysis. Then the exclusions are applied to each resampled data set, resulting in a random effective sample size and a random matching cell size. This procedure is an alternative to that presented by Canty and Davison (1999), who also recommend resampling the full original sample, but then re-estimate the adjusted sampling weights within each resampled data set (so that the final sampling weights are random variables).[15] As is common for large public-use data sets, we did not have the information necessary to recreate the adjustments. The alternative we use leaves the individual sampling weights fixed, but the sum varies over any unit of grouping and thus the relative weight of each person in the resampled data sets varies across bootstrap samples.

Stratified sample designs are variance reducing as long as the variance within sampling strata is smaller than the variance in the entire sample. The variance is reduced by calculating the overall variance as the (weighted) sum of the variance within each stratum so that the between-strata variance is omitted. This variance-reduction property is incorporated into the bootstrap by resampling independently within each stratum to create each resampled

[14]This distinction highlights that the difference in wage gap estimates obtained by averaging over the women's or men's distributions, referred to as the indeterminacy of the Blinder-Oaxacca decomposition, is simply the consequence of estimating different parameters —the effect of the "treatment on the treated" or the effect of "treatment on the untreated."

[15]Canty and Davison (1999) found that incorporating the variance of these random adjusted sampling weights substantially changed their variance estimates when estimating common labor force outcomes.

data set. Because Shao and Tu (1995) show that this simple within-strata procedure produces variance estimates that are too small when some of the strata are small, we use a modified bootstrap method referred to as the "with-replacement bootstrap" in Shao and Tu (1995, page 247). The modification consists of resampling $n_h - 1$ observations instead of n_h observations from each stratum, with replacement, where the stratum size is n_h for stratum h . The standard errors presented in this paper for the nonparametric matching estimates and Table 7 are based on 1,000 bootstrap iterations. See Haviland (2003) for a discussion with more details.

V. Empirical Findings

A. Nonparametric Matching on Pre-Market Factors

Our first nonparametric results, presented in Panel A of Table 4, are the unadjusted gender wage gaps as measured using wage and education data from the 1990 Census, which were provided by the women and non-Hispanic white men who were selected for the NSCG sample (i.e., who reported having a bachelor's degree or higher in the 1990 Census and who were selected to be in the NSCG). The unadjusted gap is calculated as the difference in the (weighted) mean log wage for the demographic group of interest and the (weighted) mean log wage for white men.[16] Using the matching method described above, matching on age and highest degree, the absolute value of log wage gaps decline by a modest amount for each demographic group of women.

Before turning to our general analysis, we dispense with a potentially troublesome issue of data quality—the poor measurement of educational level among the well educated. Related work (Black, Sanders, and Taylor, 2003) indicates that the misreport of higher education is substantial, and varies by gender and race in the U.S. Census. We argue in that paper that the education reports in the NSCG are likely to be much more accurate. Panel B reports the same estimation used in Panel A but with a sample that drops those selected to be in the NSCG who did not fully respond or who were out of scope (for reasons other than not having at least a four-year college degree). The unadjusted and adjusted wage gap estimates change only slightly. Results reported in Panel C are based on the NSCG measure of highest degree; changes between Panels B and C are due to differences in the reporting of highest degree between the Census and the NSCG.[17] Point estimates are slightly lower when the more accurate NSCG data are used, with the biggest changes recorded for Hispanic women, whose estimated log wage gaps drop by 0.02 to 0.03. We use NSCG education data in all subsequent analyses.

Table 5 presents our key analyses of the role of pre-market factors on the wage gap. Panel A shows that a relatively modest portion of the log wage gap, 0.04 to 0.09, is explained by highest degree and age. By comparing the unexplained gaps in Panels A and B, we note that

[16]At this stage, no balancing over the different age and educational characteristic distributions is done. The estimated raw wage gaps of -0.33, -0.28, -0.39, and -0.36 for non-Hispanic white, black, Hispanic, and Asian women respectively, compare with estimates of -0.36 to -0.37 found for women generally by Brown and Corcoran (1997) using 1984 data for college-educated individuals from the Survey of Income and Program Participation.

[17]The sample sizes decrease in moving from Panel B to Panel C because of those people who reported (or had imputed) having at least a four-year college degree on the Census but who reported they did not when they were responding to the NSCG.

including major for non-Hispanic white, black, and Hispanic women causes the log wage gaps decrease considerably—by approximately 0.10. For these three demographic groups, age, highest degree, and major account for between 45 percent and 53 percent of the gender wage gap. These same factors explain a smaller portion of the gender wage gap between Asian women and non-Hispanic white men, as Asian women's majors are more similar to white men's majors than are those of other women.[18]

Nearly all non-Hispanic white men in the U.S. are native English speakers, while a substantial number of the women in our comparison groups are not. (See Borjas, 1994, and Trejo, 1997, for the relative importance of language skills for the earnings of immigrants). In the final panel of Table 5, we conduct our same exercise but restrict attention to those individuals who report "speaking English at home."[19] Limiting the sample to those respondents who speak English at home makes little difference in the estimates of the wage gaps for non-Hispanic white and black women. For Hispanic women the adjusted log wage gap declines to approximately -0.08 and for Asian women the gap falls to -0.11. For Asian and Hispanic women who speak English at home, well over half of the observed wage gap is explained by pre-market factors age, highest degree, and major.

Our exact matching strategy is much more flexible than the usual parametric wage equations used for estimating gender wage gaps and is more parsimonious; we include only three pre-market covariates, and no market-related characteristics (industry, job characteristics, work attachment variables, etc.) that are themselves potentially endogenous labor market outcomes. Yet, thanks to the level of detail in our education variables, our relatively parsimonious specification explains more of the gender wage gap than many other studies using extensive, and controversial, industry and occupation control variables.

B. The Role of Experience

Even well-educated women have, on average, lower labor market attachment than men. Women are less likely than men to work full time on a roughly continuous basis over the course of their careers. To illustrate the differences, in Figure 1 we use a box-and-whiskers graph to plot the interquartile range (the box) and the 10^{th} to 90^{th} percentile range (the whiskers) of the experience measure for ages 25 to 29, 30 to 39, 40 to 49, and 50 to 60 for each of our five groups. The graph clearly shows that at the youngest ages there are few differences in experience by gender, but the differences grow monotonically with age. Not surprisingly, the wage gaps also grow monotonically with age. Using the same specification as in Table 5c, the wage gap is -0.09 for women of ages 25 to 29 years, -0.24 for women of ages 30 to 39 years, -0.39 for women of ages 40 to 49, and -0.43 for women of ages 50 to 60.[20]

[18]These inferences are drawn on the portion of the sample we were able to match, which is reasonable high here— nearly 87 percent in each demographic group.

[19]We do not match women who do not speak English at home with non-Hispanic white men who do not speak English at home for two reasons. First, because an overwhelming fraction of non-Hispanic white men speak English at home, we would only be able to match a small number of observations. More importantly, it is unclear whether language skills would be comparable for those we matched, particularly for Asian women. Most non-Hispanic white men who speak a language other than English at home speak another European language, which is probably closer linguistically to English than many Asian languages. Thus, we doubt whether such matches would represent workers of comparable English skills.

At older ages, the support problem is quite severe. For instance, for the 50 to 60 year old cohorts, the interquartile range of white men and white women no longer overlap and the median experience for women in this age group is below the 10th percentile of the white men's distribution. Asian women have generally lower experience levels than non-Hispanic white women, Hispanic women have similar experience levels to non-Hispanic white women, and black women have higher experience levels than white women.

Decisions to temporarily leave the labor market are themselves potentially influenced by labor market outcomes—for example, disparate treatment in the workplace might influence some women to take leave from the labor market—and it is thus difficult to know how to treat "experience" when estimating wage gaps. Here we focus on one approach that strikes us as sensible: we conduct an examination that is restricted to men and women who have "high labor market attachment." We note in advance, though, that care must be taken in interpreting findings from this exercise (and below we supplement our main results with three alternate specifications that provide us with some additional evidence about the role of experience).

There are at least two reasons to focus on those with high labor market attachment. First, the work of Light and Ureta (1995) indicates that it is not only the quantity of experience but the timing of experience that affects wages. Because our data only allow us to measure the quantity of experience, we necessarily can compare only those individuals without (substantial) labor market interruptions. Second, because women and men have different reasons for labor market interruptions, it is far from clear that we should compare, say, a 40 year old female accountant with a bachelor's degree who had a 10 year labor market interruption to rear her children with a 40 year old male accountant with a bachelor's degree who had a 10 year labor market interruption because of a disability or a felony conviction.

We implement our idea of "high labor market attachment" as follows: We form cells of men using age and highest degree, and then split these cells into smaller cells based on age, highest degree, *and experience*.[21] We retain for analysis only women and men with combinations of age, highest degree, and experience that contain more than 5 percent of the men from the corresponding cell formed on age and highest degree only. In short, we exclude a very small number of men who have *more* experience than most other men, a somewhat larger number of men who have abnormally low levels of experience given their age and highest degree, and a larger proportion yet of women with relatively low levels of experience. Thus in our matching exercise we are including only those women who have the roughly the same levels of experience as "typical" men.[22]

[20]Interestingly, using British data, Manning and Swaffield (forthcoming) document that there is no wage gap at the time of labor market entry but that the gap increases to about 25 log points after just ten years of experience. Using US data on initial offer, McDonald and Thornton (2007) find that among holders of bachelors degrees 95 percent of the wage gap is explained by majors selected at the time of entry into the labor market.

[21]The NSCG includes measures of full-time experience, gathered retrospectively as of April 1993 (rather than 1989, as are earnings). Of course this retrospective question may contain much measurement error, an issue we ignore here.

[22]Using this approach, however, we are unable to match a considerable number of women who have significant interruptions in their careers. This lack of a common support is a common problem with matching estimators; see Heckman, Ichimura, Smith, and Todd (1998) and Heckman, Ichimura, and Todd (1998) for a more detailed discussion. Our trimming, based on the conditional distribution of experience, is similar in spirit to trimming based on the propensity score used in Heckman, Ichimura, Smith, and Todd (1998).

Table 6 presents results of this exercise. Panel A shows that in this sample of individuals with high labor market attachment, there are still large raw wage gaps and substantial gaps not explained by highest degree and age. In Panel B we match workers on their age, highest degree, and major. In Panel C we repeat the exercise limiting our sample to those who speak English at home. For both Asian and Hispanic women the unexplained wage gap falls dramatically and is no longer statistically significant. Unexplained wage gaps are somewhat higher for non-Hispanic white and black women, but, at -0.09 and -0.13 respectively, are considerably smaller than raw gaps.

In forming the comparisons reported in Table 6, we are using data from only about half of the women in our sample (compare sample sizes in Tables 5 and 6). We are simply unable to draw inferences about wage gaps for a large group of women—primarily women with relatively lower labor market attachment. One alternative strategy is to match on experience, age, degree, and field of study for *all* women, including those with atypical work experience patterns. We do not report results from this exercise in the tables, but they are well within one standard error of the estimates in the last line in Panel C of Table 6. In forming these estimates, matching rates are quite low, between 0.35 and 0.40, so inferences are being drawn for a relatively small, not necessarily representative, sub-sample. A second alternative is to make a strong Mincerian assumption and match on experience (and education) but not age. This specification again gives similar estimates, -0.10 and -0.11 for non-Hispanic white and black women, and -0.08 and -0.04 for Hispanic and Asian women who speak English at home (with matching rates of between 83 and 85 percent).

A third alternative is to conduct a match in which we restrict attention to unmarried childless women. The idea behind this exercise is motivated by Becker (1985), who argues that even conditioning on labor market experience may not be sufficient to control for differences in labor force commitment. Becker argues that if women specialize in home production, men and women with identical abilities and years of full-time experience may have different labor market outcomes owing to differing choices of time and effort allocation. Restricting attention to unmarried women who do not have children—women who are less likely to specialize away from market production—may allow us to circumvent this issue. Once matches are made based on age, highest degree, and major and the sample is restricted to those who speak English at home, estimated wage gaps for Hispanic and Asian women relative to white men again do not differ significantly from zero, and the log wage gaps for white and black women are approximately -0.07 and -0.09 respectively.

C. Comparison of Nonparametric and Parametric Results

As discussed above, empirical studies of the gender wage gap generally use linear regression. Datasets with detailed data on education, labor market experience, and other human capital measures are often relatively small. Thus, researchers have found it useful to make parametric restrictions within a regression framework as a practical way to gain precision in making inferences about the gender wage gap. It is therefore of some interest to examine the extent to which the results we report in Table 6 differ from those one would find using the standard linear regression approach—making parametric restrictions that researchers typically use when working with smaller data sets.[23] This exercise helps us isolate the gains from the added flexibility of non-parametric estimation that our larger dataset affords.

We continue to use as our sample four racial/ethnic groups of women and non-Hispanic white men. We run the two most typical types of parametric models, as described in Section III—models in which coefficients are pooled across groups (but dummy variables capture an intercept shift), and models that are run separately for each demographic group. Our linear regression models include dummy variables for each of the 144 possible fields of study, dummy variables for degree, a quadratic in age, a quadratic in years of full-time experience, and an indicator for whether the respondent speaks English at home. By running separate regressions for each racial/ethnic group, and by including 144 possible fields of study, we allow for more flexibility than is common in the gender wage gap literature.

Table 7 presents the resulting estimated wage gaps—estimates that are directly comparable to those given in Panel C of Table 6. In the linear regression approaches, the unexplained log wage gap of -0.11 to -0.13 for black women is similar to the -0.13 gap we estimate using nonparametric methods. For white women, though, the parametric estimates of -0.11 to -0.14 are somewhat larger than the -0.09 estimate from the nonparametric approach. More strikingly, the regression-based estimates of the unexplained gap for Hispanic women (-0.05 to -0.09) and Asian women (-0.12 to -0.14) are quite different from the nonparametric estimates of -0.004 and -0.02 respectively.

D. An Additional Exploration of the Black-White Wage Gap

In our analyses that use exclusively pre-market factors we consistently estimate that the wage gap for non-Hispanic white women is larger than the gap for non-Hispanic black women. Once we condition on labor market experience by restricting the sample to men and women with high labor market attachment, however, the gap for white women drops below that of black women. This finding parallels analysis by Neal (2004), who demonstrates that estimates of the wage gap between black and white women are understated when one assumes that labor market participation rates are similar between the groups. Neal shows, in fact, that well-educated black women have higher labor market attachment than corresponding white women, whereas the reverse is true for black and white women with low educational levels.

In our empirical investigation of college-educated women, when we restrict attention to women with high labor market attachment, black women have the lowest wages of any demographic group, with a log wage gap of -0.13 relative to non-Hispanic white men. This finding motivates an additional examination of the wage disparities for black and white women. [Option to drop the next 4 sentences and insert instead: In particular, we conduct separate gender and racial wage gap analyses for men and women born in the South and born elsewhere in the country, which we loosely refer to as the "North". We speculate that there may be a larger gap for Black women born in the South stemming in part from a wide

[23]In principle regression models can be made parametrically flexible; for example, a fully saturated regression model (i.e., a model with all possible interactions of independent variables) would be equivalent to our non-parametric approach. Our purpose is to explore the sensitivity of results to common restrictions adopted in the literature.

racial disparity in educational opportunity. Perhaps with a footnote referencing our other work on this?] {In a related paper (Black, Haviland, Sanders, and Taylor, 2006), studying race and ethnic wage gaps among college-educated men, we similarly find that the gap (relative to non-Hispanic white men) is higher for black men than for Asian and Hispanic men. In that paper we conduct separate analyses for men born in the South and men born elsewhere, which we loosely refer to as the "North."[24] The race wage gap for men born in the South is substantially larger than for men born in the North. We speculate that the relatively large black-white wage gap we observe in the South stems in part from a wide racial disparity in educational opportunity.} Card and Krueger (1992) document that especially for school children born prior to 1940 (who would be among the older workers in our sample, or would be parents of the younger workers in our sample), the quality of the segregated public schools in much of the Southern U.S. was much worse for blacks than for whites.[25] At the college level, Daniel, Black and Smith (2001) note that many historically black institutions of higher education, particularly in the South, rank very low along a number of traditional measures of educational quality. Using evidence provided in Ehrenberg and Rothstein (1993, Table 2) from the NLS Class of 1972, we calculate that among blacks attending college, 66 percent of those born in the South attended a historically black institution, compared to 26 percent of those who were not born in the South.

In Table 8 we report our basic findings for the black-white wage gap among Northern- and Southern-born men, and present corresponding analyses for women. Our comparisons are for women and men who have high labor force attachment. In all cases we are looking at log wage gaps relative to non- Hispanic white men *born in the North.* Northern- and Southern-born black men alike earn less than the reference group, but this disparity is much higher for those born in the South. This same pattern holds for black women, and indeed is even more pronounced; the log wage gap is -0.05 for black women born in the North and -0.21 for those born in the South. These empirical results would seem to be consistent with our observations about the historical North-South differences in educational opportunities for blacks and whites: Black men and women generally attend the same schools, which may be of especially poor quality for many born in the South, and would therefore be subject to the same resulting disadvantage in the labor market. To our surprise, however, we find that *white* women born in the South, whose educational access is presumably similar to Southern-born white men, are also disadvantaged relative to the Northern-born white women and the magnitude of the effect is roughly comparable to the unexplained wage gap for white women in Table 6.

There are a number of possible explanations for these findings. Reasonable additional empirical work might focus on North-South differences in educational opportunities for women especially, or might ask if discrimination in labor markets is more pervasive in the South—for black individuals and women generally—than in the North.

[24]We define Southern states as Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Texas, and Virginia. We refer to individuals born elsewhere as being "not born in the South" or as "Northern-born."

[25]For example, blacks in the 1920-1929 birth cohort who attended public schools in Alabama, Georgia, Louisiana, Mississippi, or South Carolina typically were in classes that were 30 to 50 percent larger than those of white students and received instruction from teachers who earned less than half as much as teachers in white schools.

VI. Concluding Remarks

Well-educated women in the U.S. earn approximately 30 percent less than men, a gap that is similar to the gender gap for the workforce generally. In this paper we examine the gender wage gap using a matching estimation procedure and a data set that has considerable detail on education among individuals with higher education. A unique feature of our work is that we analyze wage gaps separately for four groups—non-Hispanic white, black, Hispanic, and Asian women.

When we focus analysis on men and women who speak English at home, we find that across racial/ethnic groups between 44 and 73 percent of the gender wage gaps are accounted for by such pre-market factors as age, highest degree, and major. When we restrict attention further to women who have "high labor force attachment" (i.e., work experience that is similar to male comparables) we account for between 54 and 99 percent of the gender wage gaps. In this latter analysis we find that estimated wage gaps are approximately zero for both Asian and Hispanic women. Thus, a relatively simple version of the basic human capital model seems to do remarkably well in explaining a substantial portion of the gender wage gaps for highly educated women.

One tempting interpretation for our findings is that gender discrimination is not a major factor in wage determination in labor markets for the college educated.[26] There are several important caveats to this interpretation, though. First, our estimates of relatively small wage gaps are based on a select group of women—those, for example, who have generally high levels of labor market experience. There are many women in our sample for whom we have no comparables; we can comfortably draw no inference about the potential role of discrimination for these women.[27] Second, young women who observe discriminatory practices in the labor market may shy away from occupations that are viewed as unfriendly to women, and may indeed make such choices when choosing college majors (i.e., market discrimination may be affecting our "pre-market" educational variables). Third, even though estimates of the unexplained gender gap are near zero for some demographic groups of women, there are other groups for whom the unexplained disparities are still quite substantial. Most notably, black and white women born in the South earn substantially less than comparable white men (both Northern- and Southern-born). Further investigation is merited into regional variation in race and gender wage disparities.

Our final observation concerns methodology. The inferences we draw in this paper are based on a simple and intuitively appealing matching model that has not heretofore been used in studying gender wage gaps. In some cases, our empirical findings using this methodology differ from those one would find using parametric models that are commonly used in labor economics. Our work thus reinforces concerns expressed in recent literature (e.g., Heckman,

[26]If such an interpretation is correct, then our work can be seen as reinforcing the idea that a primary key to reducing gender disparities lies in educational opportunities provided to girls and young women, and the gender norms that influence the choices these young women make.

[27]Moreover, it is possible that women who have high labor force attachment are disproportionately among the most talented women (along dimensions that are not measured in our data), and we may be therefore underestimating wage gaps for women generally when we focus on this group.

Lochner, and Todd, 2006) about the application of regression-based models in studying wage determination.

Acknowledgments

The authors gratefully acknowledge financial support from the NICHD, and thank seminar participants at the University of Chicago, University College London, London School of Economics, Florida Atlantic University, University of Michigan, Notre Dame, Yale University, Texas A&M University, and the annual meetings of the Population Association of America.

References

Altonji J. The Demand for and Return to Education when Education Outcomes are Uncertain. Journal of Labor Economics. 1993; 11(1):48–83.

Altonji, J.; Blank, R. Gender and Race in the Labor Market. In: Ashenfelter, O.; Card, D., editors. Handbook of Labor Economics. Vol. 3. Elsevier Science Press; New York: 1999. p. 3143-4259.

Altonji J, Spletzer J. Worker Characteristics, Job Characteristics, and the Receipt of On the-Job Training. Industrial and Labor Relations Review. 1991; 45(1):58–79.

Barsky R, Bound J, Charles K, Lupton J. Accounting for the Black-White Wealth Gap: A Nonparametric Approach. Journal of the American Statistical Association. 2002; 97:663–673.

Becker GS. Human Capital, Effort, and the Sexual Division of Labor. Journal of Labor Economics. 1985; 3(1):S33–S58.

Barron J, Black D, Loewenstein M. Gender Differences in Training, Capital, and Wages. Journal of Human Resources. 1993; 28(2):343–364.

Black D, Sanders S, Taylor L. Measurement of Higher Education in the Census and CPS. Journal of the American Statistical Association. 2003; 98(463):545–554.

Black D, Haviland A, Sanders S, Taylor L. Why Do Minority Men Earn Less? A Study of Wage Differentials among the Highly Educated. Review of Economics and Statistics. May; 2006 88(2): 300–13.

Blau F, Ferber M. Discrimination: Empirical Evidences from the United States. American Economic Review. 1987; 77(2):316–320.

Brown C, Corcoran M. Sex-Based Differences in School Content and the Male/Female Wage Gap. Journal of Labor Economics. 1997; 15:431–65.

Borjas GJ. The Economics of Immigration. Journal of Economic Literature. 1994; 32(4):1667–1717.

Canty A, Davison AC. Resampling-based Variance Estimation for Labour Force Surveys. The Statistician. 1999; 48(3):379–391.

Card D, Kruger A. School Quality and Black-White Relative Earnings: A Direct Assessment. Quarterly Journal of Economics. 1992; 107:151–200.

Daniel, K.; Black, D.; Smith, J. Does Affirmative Action Raise Wages? Racial Differences in the Effects of College Quality and Student Body Diversity on Wages. In: Orfield, Gary, editor. Diversity Challenged. Harvard Education Publishing Group; Cambridge: 2001.

Ehrenberg R, Rothstein D. Do Historically Black Institutions of Higher Education Confer Unique Advantages on Black Students: An Initial Analysis. 1993:4356. NBER Working Paper.

Edie E. College Major Choice and the Changes in the Gender Wage Gap. Contemporary Economic Policy. 1994; 12(2):55–64.

Graham J, Smith S. Gender Differences in Employment and Earnings in Science and Engineering in the US. Economics of Education Review. 2005; 24:341–354.

Grogger J, Eide E. Changes in College Skills and the Rise in the College Wage Premium. Journal of Human Relations. 1995; 30:280–310.

Haviland, A. Carnegie Mellon University, Department of Statistics and Heinz School of Public Policy; 2003. Understanding Wage Gaps among the Highly Educated. unpublished Ph. D. dissertation

Heckman J, Ichimura H, Smith J, Todd P. Characterizing Selection Bias Using Experimental Data. Econometrica. 1998; 66:1017–1098.

Heckman JJ, Ichimura H, Todd P. Matching As an Econometric Evaluation Estimator. Review of Economic Studies. 1998; 65:261–294.

Heckman, JJ.; Lochner, L.; Todd, P. Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond. In: Hanushek, Eric; Welch, Finis, editors. the Handbook of the Economics of Education v.1. Elvseier; Amsterdam: 2006.

Joy L. Salaries of Recent Male and Female College Graduates" Educational and Labor Market Effects. 2003; Industrial and Labor Relations Review; 54(4):606–21.

Kidd M, Shannon M. The Gender Wage Gap: A Comparison of Australia and Canada. Industrial and Labor Relations Review. 1996; 49(4):729–746.

Light A, Ureta M. Early-Career Work Experience and Gender Wage Differentials. Journal of Labor Economics. 1995; 13(1):121–154.

Loury LD. The Gender Earnings Gap among College-Educated Workers. Industrial and Labor Relations Review. 1997; 43:418–433.

Machin S, Puhani PA. Subject of Degree and the Gender Wage Differential: Evidence from the UK and Germany. Economic Letters. 2003; 79(3):393–400.

Manning, Alan; Swaffield, Judith. The Gender Gap in Early-Career Wage Growth. Economic Journal. forthcoming.

McDonald JA, Thornton RJ. Do Male and Female College Graduates Receive Unequal Pay? Journal of Human Resources. 2007; 42(1):32–48.

Mulligan C, Rubinstein Y. Selection, Investment, and Women's Relative Wages since 1975. 2005:11159. NBER Working Paper.

Neal D. The Measured Black-White Wage Gap among Women Is Too Small. Journal of Political Economy. 2004; 112:S1–S28.

Neal D, Johnson W. The Role of Premarket Factors in Black-White Wage Differences. Journal of Political Economy. 1996; 104:869–95.

Nopo H. Matching as a Tool to Decompose Wage Gaps. Review of Economics and Statistics. forthcoming.

Paglin M, Rufolo AM. Heterogeneous Human Capital, Occupations Choice, and Male- Female Earnings Differences. Journal of Labor Economics. 1990; 8:123–144.

Racine, JS.; Green, CA. Robust Estimation of Union and Gender Wage Gaps. McMaster University, Department of Economics; 2004. Unpublished paper

Royalty A. The Effects of Job Turnover on the Training of Men and Women. Industrial and Labor Relations Review. 1996; 49(3):506–521.

Shao, J.; Tu, D. The Jackknife and Bootstrap. Springer-Verlag; New York: 1995.

Smith JP, Ward MP. Time Series Growth in the Female Labor Force. Journal of Labor Economics. 1985; 3(1:S):S59–S90. [PubMed: 12267653]

Trejo S. Why Do Mexican Americans Earn Low Wages? Journal of Political Economy. 1997; 105(6): 1235–68.

Turner, Sarah; Bowen, William. Choice of Major" The Changing (Unchanging) Gender Gap. Industrial and Labor Relations Review. 1999; 52(2):289–313.

Weinberger C. Race and Gender Wage Gaps in the Market for Recent College Graduates. Industrial Relations. 1998; 37(1):67–84.

Weinberger C. Mathematical College Majors and Gender Gap in Wages. Industrial Relations. 1998; 38(3):407–13.

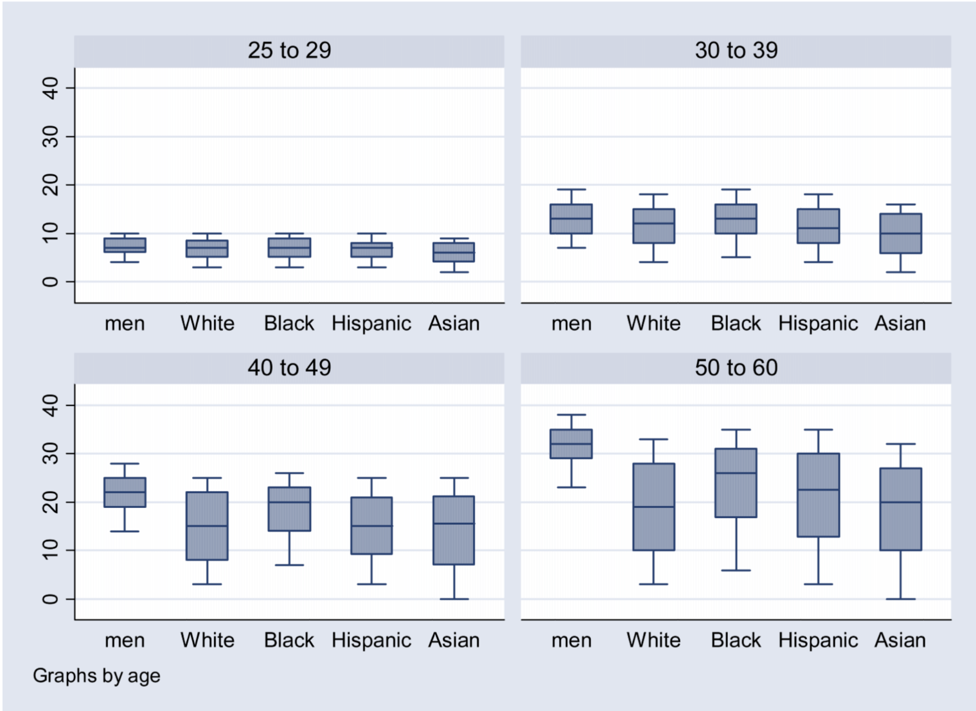

Figure 1.
Years of Work Experience for non-Hispanic White Men and Women (Non-Hispanic White, Black, Hispanic, and Asian) by Age

Table 1

Distributions of Highest Degrees and Bachelor's Major for Women and Men

Panel A: Highest degree	**White**		**Black**		**Hispanic**		**Asian**	
	F	**M**	**F**	**M**	**F**	**M**	**F**	**M**
Bachelor's	70.20	63.34	67.71	68.28	69.28	65.44	72.32	54.24
Master's	24.66	22.89	27.97	22.57	23.68	20.90	19.59	27.13
Professional degree	3.28	9.00	2.70	5.69	4.34	9.58	5.81	10.02
Ph.D.	1.87	4.76	1.62	3.46	2.70	4.08	2.29	8.62
N	36,256	56,524	6,514	4,887	3,250	4,103	5,422	7,633

Panel B: Bachelor's Major	**Mean Wages of Men with Bachelor's Degree in field**	**While Men**	**White Women**	**Black Women**	**Hispanic Women**	**Asian Women**
Engineering	$25.43	12.72%	1.04%	0.70%	1.85%	3.77%
Mathematical sciences	22.18	2.53	1.74	1.53	1.20	2.62
Business & economics	21.68	28.10	12.08	16.75	16.06	21.24
Physical sciences	19.96	4.57	1.25	0.91	1.36	4.08
Social sciences	19.69	13.91	13.90	16.56	15.45	9.96
Engineering technology	19.29	1.88	0.10	0.17	0.29	0.21
Health professions	19.24	2.61	10.47	8.92	9.00	16.64
Computer sciences	18.76	1.75	0.95	1.25	1.32	2.96
Life Sciences	17.58	4.94	3.93	3.85	4.19	6.76
Education	17.22	8.10	27.83	29.02	23.58	40.44
Professional degrees	17.16	5.33	9.01	11.15	8.52	4.86
Humanities	17.14	6.76	10.41	5.88	11.99	9.89
Agricultural sciences	16.46	2.58	0.83	0.39	1.06	1.29
Fine arts	16.22	3.30	6.02	2.46	3.79	4.54
Major not elsewhere classified	---	0.91	0.43	0.48	0.36	0.73
Dissimilarity Index		**0.00%**	**45.40%**	**43.55%**	**41.98%**	**35.93%**

Panel C: Mean Fraction Female Within Undergraduate Major	**White**	**Black**	**Hispanic**	**Asian**
Men	33.89%	39.15%	35.11%	26.45%
Women	61.44%	59.84%	57.60%	51.99%

Notes: Authors’ calculation, NSCG. The data are weighted to account for sample stratification. In Panel B, men's mean wage of bachelor's degree is estimated using only men whose highest degree completed is a BA, while the percentage of each group selecting each undergraduate college major includes those with higher degrees. The 144 majors in the NSCG are aggregated in Panel, B but the full set of majors is used to calculate the dissimilarity index in Panel B and all results in Panel C.

Table 2

Distribution of Undergraduate Majors for Four Cohorts of Women and White Men

Panel A: All Women		**Age Cohorts**			
Broad Major Categories	**Women's Mean Wage of Bachelor's Degree**	**25-30**	**31-40**	**41-50**	**51-60**
Health Professions	$16.84	10.55	11.92	9.25	9.88
Mathematical Sciences	16.30	1.37	1.75	2.18	1.58
Computer Sciences	15.83	2.66	0.85	0.36	0.08
Engineering technology	15.45	0.25	0.12	0.02	0.03
Physical Sciences	14.87	1.45	1.31	1.24	1.59
Engineering	14.47	2.81	0.91	0.39	0.28
Humanities	14.33	6.79	9.13	13.75	11.99
Business and Economics	13.91	23.93	11.57	7.56	6.27
Education	13.56	14.81	25.93	34.62	38.27
Social Sciences	13.42	12.50	14.70	14.93	12.39
Life Sciences	13.09	4.63	4.72	3.18	2.80
Fine Arts	12.67	5.07	6.23	5.47	5.66
Professional Degrees	12.48	11.10	9.49	6.44	8.42
Agricultural Sciences	11.08	1.51	0.98	0.22	0.29
Other Majors	***	0.58	0.40	0.38	0.48

Panel B: Non-Hispanic White Men		**Age Cohorts**			
Broad Major Categories	**Men's Mean Wage of Bachelor's Degree**	**25-30**	**31-40**	**41-50**	**51-60**
Health Professions	$19.24	1.74	2.95	2.37	3.42
Mathematical Sciences	22.18	1.76	2.06	3.56	2.50
Computer Sciences	18.76	4.48	1.85	0.67	0.20
Engineering Technology	19.29	2.75	1.82	1.58	1.51
Physical Sciences	19.96	3.92	4.23	4.70	5.82
Engineering	25.43	14.85	10.75	11.43	16.59
Humanities	17.14	4.80	6.50	7.75	7.85
Business and Economics	21.68	32.69	26.87	27.04	26.98
Education	17.22	3.90	7.77	9.89	10.60
Social Sciences	19.69	10.21	15.16	16.32	11.39
Life Sciences	17.58	4.39	6.12	4.77	3.50
Fine Arts	16.22	3.66	3.79	2.97	2.50
Professional Degrees	17.16	7.32	6.50	4.05	2.86
Agricultural Sciences	16.46	2.71	2.74	2.03	3.15
Other Majors	***	0.81	0.91	0.87	1.13

Notes: Authors' calculation, NSCG. The data are weighted to account for sample stratification. Mean wage of bachelor's degree is estimated using only women or men whose highest degree completed is a BA, while the percentage of each group selecting each college major includes those with higher degrees. The 144 majors in the NSCG are aggregated into the broad categories shown in these tables.

Table 3

Estimated Gender Wage Gaps using Regression-Based Specifications

Panel A			
Unexplained Wage Differences - from Altonji and Blank's (1999) Tables 4 and 5	**(1)**	**(2)**	**(3)**
Pooled regression model[a]	−0.279 (0.007)	−0.272 (0.006)	−0.221 (0.007)
Group-specific regression model[b]	−0.286	−0.279	−0.211
Panel B			
Unexplained Wage Differences, NSCG			
Pooled regression model[a]	−0.321 (0.004)	−0.293 (0.004)	−0.219 (0.004)
Group-specific regression model[b]	−0.316	−0.279	−0.208
Controls:			
Education and potential experience	No	Yes	Yes
Region controls	No	Yes	Yes
Occupation, industry, and job characteristics	No	No	Yes

Notes: For Panel B, the source is authors' calculation, NSCG. Standard errors for group specific regression models from Altonji and Blank (1999) were not provided nor do we present standard errors for the group specific estimates calculated here. The sample size for all pooled regressions in Panel B is 82,980. The sample does not include those with missing values on any controls or those whose industry was military. Sample sizes for the group specific regressions in Panel B are 49,661 for men and 33,319 for women. The data are weighted to account for sample stratification.

[a]The coefficient on the female dummy variable is reported, dummy variables for black, Asian and Hispanic are included in the model.

[b]The amount of the total wage gap due to differences in group specific coefficients is reported.

Table 4

Gender Wage Gaps – The Role of Census Measurement Error

	White	Black	Hispanic	Asian
Panel A: Census education measure				
Wage gap (relative to white men)	−0.329 (0.0050)	−0.279 (0.0076)	−0.387 (0.0123)	−0.356 (0.0101)
Gap not explained by differences in highest degree and age	−0.283 (0.0049)	−0.239 (0.0074)	−0.299 (0.0124)	−0.315 (0.0102)
N	30,494	7,127	3,455	5,157
Panel B: Census education measure, drop NSCG non-response and out of scope				
Wage gap (relative to white men)	−0.334 (0.0054)	−0.269 (0.0088)	−0.363 (0.0131)	−0.346 (0.0115)
Gap not explained by differences in highest degree and age	−0.293 (0.0054)	−0.239 (0.0085)	−0.281 (0.0132)	−0.312 (0.0116)
N	24,998	5,194	2,578	3,905
Panel C: NSCG education measure				
Wage gap (relative to white men)	−0.333 (0.0056)	−0.258 (0.0089)	−0.339 (0.0134)	−0.337 (0.0120)
Gap not explained by differences in highest degree and age	−0.282 (0.0055)	−0.221 (0.0087)	−0.251 (0.0130)	−0.299 (0.0121)
N	23,786	4,804	2,320	3,621

Notes: Authors' calculation, NSCG. The data are weighted to account for sample stratification. Estimates are from nonparametric regressions. All differentials are computed relative to white men. In Panels A and B, we match workers on their age and Census-reported highest degree. In Panel C, we match workers on their age and NSCG-reported highest degree. Bootstrapped standard errors are reported in parentheses based on 1,000 replications.

Table 5

Gender Wage Gaps Using Pre-Market Factors Only

	White	Black	Hispanic	Asian
Panel A: NSCG education measure				
Wage gap (relative to white men)	−0.333 (0.0056)	−0.258 (0.0089)	−0.339 (0.0134)	−0.337 (0.0120)
Gap not explained by differences in highest degree and age	−0.282 (0.0055)	−0.221 (0.0087)	−0.251 (0.0130)	−0.299 (0.0121)
N	23,786	4,804	2,320	3,621
Matching rates	1.00	1.00	1.00	1.00
Panel B: NSCG education measure and major				
Wage gap (relative to white men)	−0.339 (0.0062)	−0.268 (0.0104)	−0.345 (0.0149)	−0.340 (0.0133)
Gap not explained by differences in highest degree, majors, and age	−0.184 (0.0093)	−0.132 (0.0128)	−0.159 (0.0185)	−0.272 (0.0174)
N	20,622	4,188	2,024	3,106
Matching rates	0.867	0.872	0.872	0.858
Panel C: NSCG education measure and major, speak English at home				
Wage gap (relative to white men who speak English at home)	−0.342 (0.0065)	−0.265 (0.0108)	−0.299 (0.0258)	−0.260 (0.0203)
Gap not explained by differences in highest degree, majors, and age	−0.190 (0.0095)	−0.131 (0.0129)	−0.082 (0.0299)	−0.105 (0.0248)
N	19,095	3,917	645	950
Matching rates	0.860	0.866	0.888	0.859

Notes: Authors' calculation, NSCG. The data are weighted to account for sample stratification. Estimates are from nonparametric regressions. All differentials are computed relative to white men. In Panel A, workers are matched on their age and NSCG-reported highest degree. In Panel B, we match workers on their age, NSCG-reported highest degree, and their highest degree major field of study. In Panel C, we match workers as in Panel B, but only those workers who speak only English at home. Bootstrapped standard errors are reported in parentheses based on 1,000 replications.

Table 6

Gender Wage Gaps for Those with High Labor Market Attachment

	White	Black	Hispanic	Asian
Panel A: NSCG education measure				
Wage gap (relative to white men)	−0.293 (0.0065)	−0.273 (0.0107)	−0.330 (0.0160)	−0.249 (0.0153)
Gap not explained by differences in highest degree and age	−0.176 (0.0062)	−0.217 (0.0100)	−0.178 (0.0157)	−0.156 (0.0154)
N	12,509	2,950	1,251	1,660
Matching rates	1.00	1.00	1.00	1.00
Panel B: NSCG education measure and major				
Wage gap (relative to white men)	−0.297 (0.0075)	−0.281 (0.0122)	−0.340 (0.0174)	−0.253 (0.0181)
Gap not explained by differences in highest degree, majors, and age	−0.086 (0.0097)	−0.127 (0.0144)	−0.090 (0.0214)	−0.159 (0.0217)
N	10,426	2,494	1,056	1,376
Matching rates	0.833	0.845	0.844	0.829
Panel C: NSCG education measure and major, speak English at home				
Wage gap (relative to white men)	−0.302 (0.0077)	−0.279 (0.0123)	−0.268 (0.0279)	−0.213 (0.0255)
Gap not explained by differences in highest degree, majors, and age	−0.090 (0.0098)	−0.127 (0.0147)	−0.004 (0.0323)	−0.023 (0.0266)
N	9,724	2,368	360	522
Matching rate	0.828	0.843	0.876	0.846

Notes: Authors' calculation, NSCG. The data are weighted to account for sample stratification. Estimates are from nonparametric regressions. In Panel A, workers are matched on their age and NSCG-reported highest degree. In Panel B, we match workers on their age, NSCG-reported highest degree, and majors. In Panel C, we match workers as in Panel B, but only those workers who speak only English at home. Bootstrapped standard errors are reported in parentheses based on 1,000 replications. The sample is limited to women (and men) who are in an age-highest degree-full time experience category that holds more than 5 percent of the white males in that age-highest degree category.

Table 7

Parametric Gender Wage Gaps by Race and Ethnicity

	White	Black	Hispanic	Asian
Wage gap (relative to white men)	−0.334 (0.0060)	−0.259 (0.0092)	−0.339 (0.0133)	−0.340 (0.0123)
Panel A: Pooled Regression Model				
Gap not explained by controls	−0.142 (0.0060)	−0.132 (0.0085)	−0.091 (0.0146)	−0.136 (0.0132)
Panel B: Group-Specific Regression Model				
Gap not explained by controls	−0.113 (0.0089)	−0.105 (0.0104)	−0.052 (0.0170)	−0.115 (0.0168)
N	23,642	4,772	2,299	3,572

Notes: Authors' calculation, NSCG. The data are weighted to account for sample stratification. Covariates are age and age squared, degree, three-digit major, years of full time experience and experience squared, and an indicator for a language other than English spoken at home. There are 39,938 white men used in the regressions.

Table 8

North/South Gender Wage Gaps among Those with High Labor Market Attachment

Panel A: Southern Born	**White Women**	**Black Women**	**Black Men**	**White Men**
Gap not explained by differences in age, highest degree, and majors (relative to white men not born in the South)	−0.174 (0.0175)	−0.214 (0.0204)	−0.177 (0.0228)	−0.045 (0.0129)
N	1,972	1,325	930	4,802
Matching rate	0.813	0.818	0.877	0.887
Panel B: Not Southern Born				
Gap not explained by differences in age, highest degree, and majors (relative to white men not born in the South)	−0.082 (0.0115)	−0.048 (0.0212)	−0.074 (0.0227)	0
N	7,432	955	776	22,215
Matching rate	0.798	0.803	0.879	1.000

Notes: Authors' calculation, NSCG. The data are weighted to account for sample stratification. Estimates are from nonparametric regressions. In both panels we match workers to non-Hispanic white men who were not born in the South based on their age, NSCG-reported highest degree, and highest degree major field of study. Bootstrapped standard errors are reported in parentheses based on 1,000 replications. The sample is limited to women (and men) who are in an age-highest degree-full time experience category that holds more than 5 percent of the white males in that age-highest degree category.