Brains over brawn: Are there lower levels of wage discrimination between the sexes in industries that require less physical strength and more cognitive skill?

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With the advent of technological innovations, cognitive abilities have become increasingly valued in the workplace, while physical strength, an important requirement for manual labor, has become less important. One might expect, therefore, the gender wage gap to be lower in occupations that require more cognitive skills, as men's comparative advantage should be lower in those industries. Using 2010 individual data from the PUMS, I test whether the gender wage gap varies by industry or occupation, grouped according to skill level. I decompose the gaps using the Oaxaca decomposition, and find that, while there is not a clear pattern of wage discrimination between the industry or occupation groups that were deemed as high-skill, the largest wage gap, and resultant level of discrimination, exists in the lowest skill group.

I. Introduction

The wage gap between men and women in the U.S. has narrowed over the last 30 years. According to the Bureau of Labor Statistics, women's earnings as a percentage of men's earnings has increased from 62% in 1979 to a peak of 81% in 2006, as shown in Figure 1 (BLS, 2009). This increased earnings power of women could be attributed to many things: more women in higher levels of education could even the playing field in terms of the returns to human capital investment; a decrease in the number of children each woman has could lead to a decrease in the time a woman spends at home before re-entering the workforce, exhibiting perhaps a change in preferences in women's market-home production; or a change in the market itself, and the skill types required by different occupations. This final reason, that wage discrimination between the sexes is a function of the physical and cognitive skill requirements of a given industry, is the focus of this analysis.

With the advent of increased technological innovations, the importance of physical strength in manual labor jobs has decreased, while the importance of more technical, cognitive, and communication skills have increased. This shift from "brawns" to "brains" should have reduced the comparative advantage of men over women in the labor force, decreasing the wage gap overall. The industries that still require more physical strength should have a larger gender wage gap than those industries that favor cognitive skills (Altonji, 1999). This paper measures and compares the wage gap between men and women by industry in the United States to test this hypothesis.

This analysis is on individual data on wages and human capital characteristics is from the PUMS dataset in the most recent year available, 2010. Industries are categorized into four groups, with a high- and low-skill group for each sector. Using the Oaxaca decomposition, I measure the wage gap in each industry group, to show to what degree there are explained and unexplained levels of wage discrimination between men and women by skill (physical or cognitive) required. Because the results of the analysis are contingent on the industry group division, I also perform a robustness analysis, breaking down the groups by occupation level rather than industry. The results of both analyses on industry and occupation show that, while there is not a clear pattern of wage discrimination between the industry or occupation groups that were deemed as high-skill, the largest wage gap, and resultant level of discrimination, exists in the lowest skill group.

The subsequent sections of this paper are divided as follows: Section II provides a description of the literature on gender wage; Section III derives the theory of discrimination and describes the estimation techniques used in the analysis; Section IV includes summary statistics and the regression results; Section V summarizes and concludes; Section VI is a list of references; and Section VII is an appendix of all tables, figures, and additional data explanations.

II. Literature Review

The difficulty of measuring the wage gap between genders lies in controlling for human capital. Wood, Corcoran, and Courant (1995) attempt to circumvent this problem in their study of pay differences between graduates of Michigan Law School. The advantage of such a case study is that human capital controls are systematically built in, as the subjects have the same education, and assumedly the same skill set when entering the job market. Additionally, the fact that the students attained such a degree is an indication of their preferences and occupation aspirations. The results showed that, over time, the determining factor in wage differentiation was women leaving the workforce to care for children. According to their results, one year removed from full-time work penalized a woman's earnings by 5.6%. Because the point of my study is to vary by industry, I will not have the luxury of such a built-in control for human capital. However, this study is important in its demonstration of the use of occupation as a control variable. It also provides a list of human capital variables for my analysis, such as education, age, experience, marital status, the presence of children, race, and area of work.

Another major consideration when studying industry differentiation by skill is how to rank industries by skill. Zveglich and Rodgers (1997) examine how the shift of the Taiwanese industries from lower-skill to higher-skill occupations affected gender earnings inequality. Zveglich and Rodgers ranked industry by mean education attainment, and broke down the three main sectors of agriculture, manufacturing, and services into smaller, more specified industries, and then did a separate breakdown by occupation, as some occupations span across industries. The results of the study were that even with such a shift to less labor-intensive industries, the gender earnings gap did not shrink. When I run my robustness analysis, I use Zveglich & Rodgers' (1997) guidelines for dividing workers into occupations.

The subsequent study of inter-industry wage differentials in Korea by Ural, Horrace, and Jung (2009) suggest another method of industry differentiation. Ural, et al., define knowledge-intensity as the extent to which industries produce or employ high-technology products. They separate industries into manufacturing or service, and then break each into subsequent categories as either knowledge-based or non-knowledge-based. Knowledge-based manufacturing industries are classified based on R&D intensity, whereas knowledge-based service industries are determined by the ratio of college graduates. The results suggest that gender wage discrimination is in fact smaller in knowledge-based industries than non-knowledge-based industries (Ural, 2009). My division of industry categories is based upon this method used by Ural, et al. (2009).

There appears to be a gap in the literature in the measure of inter-industry gender wage discrimination in the U.S. Blau and Kahn (2000) compare wage ratios of male and female age cohorts, using data from the 1979, 1989, and 1999 Annual Demographic Files from the CPS. Though they do find that gender differences in qualifications and labor market structure in particular sectors influence the wage gap, they provide no measure of it. Fields and Wolff (1995) attempt to provide a measure of inter-industry wage differentials and gender wage gaps using the March 1988 CPS. However, their study's goal is to measure inter-industry wage differentials using gender as a control variable, by comparing women in one industry to women in the other, which is essentially the reverse of what this study's goal is. There also is a distinctive discrepancy in previous literature with how best to define the difference between high- and low-skill, labor-intensive and non-labor intensive, industries.

This study will contribute to the literature by combining the methods of industry and occupation division by Zveglich & Rodgers (1997) and Ural, et al. (2009). The analysis examines cross-sectional data from one year in order to determine an absolute measure of gender discrimination within each industry and occupation in the United States for 2010. A comparison of these measures by industry reveals a pattern between gender wage differentials and the level of skill and labor-intensiveness among these respective industries.

III. Theory

Wage & Human Capital

This paper investigates the notion that there is a smaller wage gap between men and women in one industry versus another. Firstly, how is a worker's wage determined? The law of diminishing productivity to labor states that, holding all other inputs constant, the marginal product of labor (MP_L) eventually declines, meaning that for each additional worker the firm hires, the firm will eventually get less additional output (Borjas, 2009). With perfect information, the firm can determine the each worker's additional output by viewing the marginal product curve (the derivative of the firm's total product curve). The firm can also determine the value of the marginal product of labor, which is the dollar value of the marginal revenue (*MR*) that is the result of the addition of one worker to the firm. The value of the marginal product of labor can be written as:

$$VMP_L=MR*MP_L,$$

where the value of the marginal product of labor (VMP_L) is equal to the additional revenue of one additional unit of output times the amount of additional output generated by one extra worker (Borjas, 2009).

If a firm is profit maximizing, its goal is to maximize revenues while minimizing costs. If a firm's costs are a function of capital and labor, its total cost function can be written as:

$$TC= r*K + w*L,$$

where r is the rent paid for capital, and w is the wage. Taking the partial derivative of the total cost function for the firm with respect to labor (holding capital constant) yields the marginal cost of labor (MC_L), which is simply the wage of the worker, and can be written as $MC_L=w$ (Borjas, 2009). A firm decides the optimum point at which to produce by setting marginal revenue product of labor equal to marginal cost of labor (if the assumption holds that capital is fixed). At the point where $VMP_L=MC_L$, the cost of one additional worker is equal to the value of the revenue the firm will get from that worker's additional output (Borjas, 2009). Setting the equations for marginal cost and marginal revenue equal to each other yields the following:

$$w=VMP_L=MR*MP_L.$$

Thus, a worker's wage is determined by the value of their marginal product of labor.

A worker does not necessarily have control over the marginal revenue associated with his or her production, but he or she is responsible for the marginal product of labor, which will affect the differences in the determination of wages. If a worker has a higher marginal product of labor, then he or she will have a higher wage than a worker with a lower marginal product of labor. What, then, determines a difference in marginal products of labor, and ultimately, a difference in wages? This is where human capital comes into play. The human capital model suggests that workers with more human capital will be more productive (i.e. have a greater MP_L), and will therefore receive a higher wage for their work (Borjas, 2009). A major determinant in a worker's ability is education, as workers with higher education (and higher degrees of human capital) are more productive and demand a higher wage.

Differences in human capital (or skills) explain differences in wages (Oaxaca, 1971). There are, however, cases in which persons with presumably the same skill set may receive different wages. This difference is the wage gap, first addressed by Becker (1971). A simple model of the labor supply of men and women illustrates Becker's theory at work.

In a perfectly competitive labor market, where there is no discrimination, men's and women's wages would be at w* (i.e., equilibrium). According to Becker, employers place a premium on women's wages if they are discriminatory by gender, acting as though women's labor is more expensive than that of men's, and will therefore hire fewer women or none at all (Becker, 1971). The difference between the equilibrium wage and the perceived wage is the wage gap, represented by *d (see Figure 2 in appendix)*. Becker proposes that increased competition will eliminate discrimination because it is inefficient (Becker, 1971). Employers essentially have two utility maximization problems: the employer wishes to maximize profits and maximize discrimination against women. If there is increased competition in the market, then there will be the incentive to lower costs, as other non-discriminatory firms may be hiring women, which will mean that they will have to recognize that women's labor costs are at the same level as men's.

According to the Oaxaca decomposition, the discrimination of the employer must decrease, or the difference in skills between men and women must decrease, in order to account for a smaller wage gap (Oaxaca, 1973). Skill, in the Oaxaca decomposition, can consist of the usual suspects of control variables on human capital: education, experience, age, race, number of children, marital status, and what region of the country in which they work. As explained previously, possible solutions for how women could close the gap between their wages and men's could include increasing their education and experience, and decreasing the number of children they have (or not staying home with them as long) (Altonji, 1999). An increase in the number of women attaining higher levels of education could even the playing field, in terms of the value of their human capital. A decrease in the number of children each woman has could lead to a decrease in the amount of time a woman spends at home before re-entering the workforce, indicating a change in preferences for women's market-home production. One variable that isn't listed in this vector of skill measurements is a proxy for physical strength, or a change in the labor market itself, from one that demands a higher level of physical strength, and therefore values men's human capital more than women's, to one that values cognitive abilities, lowering the barriers of women to enter (Altonji, 1999).

Estimation Technique

The Oaxaca decomposition, as mentioned previously, breaks down the measurement of the wage gap, or *d*, into three parts, which can then be classified as explained or unexplained discrimination:

$$\Delta w = (\alpha_M - \alpha_F) + (\beta_M - \beta_F)*s_F + \beta_M*(s_M - s_F) \text{ (Borjas, 2009).}$$

The second part, $\beta_M*(s_M-s_F)$, can account for the difference that is due to human capital differences, and the other, can be attributed to pure discrimination on the part of the employer $(\alpha_M - \alpha_F) + (\beta_M - \beta_F)*s_F$ (Oaxaca, 1973). Figure 3 *(see appendix)* illustrates this concept, though the x-axis only shows schooling as the proxy for skill, for simplicity's sake. The differing intercepts of the men's and women's earnings models, $(\alpha_M - \alpha_F)$, represent how employers may inherently value men's labor over that of women. The varying slopes of the earnings functions can then be broken down to account for differences in human capital. $(\beta_M - \beta_F)*s_F$ represents how much more an employer may value a male's skill set over that of a woman's (if the employer was non-discriminatory, this part of the equation would be equal to zero). The first two components of the equation, $(\alpha_M - \alpha_F) + (\beta_M - \beta_F)*s_{F,}$ make up the unexplained discrimination portion. $\beta_M*(s_M-s_F)$ is then the part of the wage gap that is attributable to differences in skills (i.e. explained discrimination), so that the higher the difference is between the skill sets of men and women, the steeper the men's earning function will be relative to women's (Borjas, 2009).[1]

This paper tests whether industries and occupations that are less labor-intensive will have a smaller wage gap than those that require a greater amount of physical strength. Presumably, men hold a comparative advantage over women in industries and occupations that require a greater degree of physical strength over cognitive ability. The function that represents this measurement is:

$$w=f(s,g,i),$$

[1] It is important to mention that the above equation is a simplified, univariate model of the Oaxaca. Because this study has several measures of human capital, the actual measure of the wage gap will be performed for each explanatory variable.

where w is the wage of a worker, which is a function of that worker's skills (s), gender (g), and the industry and occupation in which they are employed ($_i$). The variable s, in turn, is a vector that consists of all possible factors that could be used as a proxy for a worker's abilities: education, age, race, marital status, number of children, and region (where experience has been excluded as one would expect experience to be highly multicollinear with age). To measure the difference between men's and women's wages in a given industry, this study holds i constant, along with the other control variables, and allows sex to vary within each industry.

IV. Empirical Evidence

Summary Statistics

Data used in this analysis is from the Public Use Microdata Sample (PUMS), collected by the Bureau of Labor Statistics. The PUMS dataset contains a sample of responses from the American Community Survey (ACS), with variables from actual survey questions and variables derived from multiple survey questions. Each record in the dataset is representative of one person or household. Each year of data in the PUMS dataset contains information on one percent of the U.S. population. This study uses the most recent data available from PUMS, 2010. Table 4 *(see appendix)* presents the summary statistics.

The variables used to analyze the wage gap between men and women by industry are: age, the presence of children in the home, race, marital status, region and education. Data on experience was not available, so age functions as a measure of itself and as a proxy for this variable. Age is also squared in the regression to account for the non-linearity of this variable. Age, along with the dependent variable, log-wage, which was measured annually, are the only continuous variables in the regression analysis. Age is on a scale from 16 to 95, and wage is a continuous measure from $4 to $569,000 of yearly salary.

Because the remaining variables are categorical, the numerical interpretations of their respective means and standard deviations can be interpreted as the averages of the sample of the data. The variables for children present in the home serve multiple purposes. First, they indicate whether or not there are children living in the household. Secondly, they indicate if there are children that are above or below the age of schooling. The reference level for the child present variable is the level that indicates that no children under the age of 5 were present in the home. 18.5% of the sample reported having at least one child under 5 present in the home, while 81.5% of the sample reporting have no child under 5 present. The reference level for race is that of all other minority races (which encompasses American Indian, Alaska Native, Native Hawaiian, or a combination of races), so that there are coefficient estimates for white, black, and Asian workers. Almost 90% of the sample identified as white, 10% identified as black, and the last 10% was split between Asian or another race. For marital status, single is the reference level, with model estimates for married now and previously married (separated/divorced/widowed), and for education, the reference is some high school education attainment (consisting of the completion of Grade 9 through Grade 12), with estimates for high school (including high school diploma completion or GED certificate), some college (including completion of some college credits or an associate's degree), undergraduate (attainment of bachelor's degree), and post-undergraduate degrees (including master's, professional, or doctorate degrees). Almost 70% of the sample was currently married, 20.7% were single, and 9.3% were previously married. 7.9% of the sample reported having completed some high school, 26.9% having attained a high school diploma, 33.1% having completed some college, almost 20% having received their bachelor's degree, and 12.1% having completed some form of post-undergraduate study. The reference level for the region variable is the Midwest, with coefficient estimates for the Northeast, South, and West. 18.7% of the respondents were from the Northeast, 23% from the Midwest, 36.3% from the South, and 21.9% from the West. Levels for sex are male and female, which is split fairly evenly at 50.7% and 49.3%, respectively. Thus, the final regression used to measure the difference between men's and women's wages for each industry is:

$$Log(Wage)=\beta_0+\beta_1*Age+\beta_2*Age^2+\beta_3*Children\ Present +\beta_4*White+\beta_5*Black+\beta_6*Asian+\beta_7*Married+\beta_8*Previously\ Married+\beta_9*High\ School+\beta_{10}*Some\ College+\beta_{11}*B.A.+\beta_{12}*Post\text{-}undergrad+\beta_{13}*Midwest+\beta_{14}*South+\beta_{15}*West+e.$$

As such, the coefficient on age is expected to be positive, as one would expect that an individual would have greater human capital with increased age and experience. The squared-variable for age should be negative, as it accounts for the decreasing returns to wage as age increases. The coefficients for increased levels of education should be positive, as more education leads to increased ability for which one must be compensated. I expect that the race coded as “white” will have higher wages than the respective minorities listed. As for children present in the home, marital status, and region, the direction of these variables is unclear. Children present in the home might have a positive effect on wage if having children incentivized individuals to work harder, and earn more, to provide for their families. Gender and industry are dummy variables, so that a separate regression is run for each gender within each industry level, and the difference between each resultant coefficient shows that, holding all other variables constant, what the difference in the returns to that coefficient are for each sex.

Included in the appendix are tables of each categorical variable’s dummy levels and frequency, with the exception of industry and occupation, which have too many levels to represent. These industries are grouped into labor-intensive and non-labor intensive categories according to the framework defined in Ural, et al. (2009), who broke down the manufacturing sectors and service sectors into knowledge-based and non-knowledge-based industries, depending on R&D intensity and ratio of college grads. This format was used to group the industries included in this dataset, which were grouped according to the North American Industry Classification System (NAICS), in which each industry sector or subsector is placed into either a goods-producing industry or a service-producing industry. The four industry levels are: knowledge-based manufacturing, non-knowledge-based manufacturing, knowledge-based services and non-knowledge-based services. Theory, then, suggests that the knowledge-based groups have a smaller wage gap between men and women than the non-knowledge-based groups *(see appendix for a full description of the industry breakdown).*

Later, the analysis is re-run using occupation dummies (as a robustness test for industry), to see how dependent the results are on industry breakdown. These occupation levels are grouped according to the division proposed by Zveglich & Rodgers (1997), who define seven occupation levels: professional and technical, administrative and managerial, clerical, sales, service, agricultural, and production/transportation/laborers. Because there was such a small sample of agricultural workers, the agricultural group is combined with the production/transportation/laborers group to form six final occupation groups. Theory suggests that those groups that require a higher amount of cognitive human capital, like professional, technical, administrative, and managerial occupations should have smaller wage gaps than those that are more physically demanding, like service, production, transportation, and general labor.

Industry Wage Regression Results

Table 13 *(see appendix)* summarizes the results of the full-scale wage regressions with industry dummy variables. There is a regression for each sex in each industry group, for a total of eight regressions. The coefficients for each explanatory variable, along with its corresponding p-value, are reported. A coefficient that is significant at the 5% level is indicated with an asterisk (*) Tests for multicollinearity and heteroscedasticity showed no violations.

The results on the coefficients for age show that age has a greater return to log-wages for men and women in the service industries than in the manufacturing industries. In addition, it appears that age has a greater return for women in the manufacturing industries, whereas the results are mixed in the services industries. The effect of the squared age variable is greater for males than females, and is more prominent in the services industry than the manufacturing industry. This means that after a certain point, the returns to age (experience) decrease faster for service industry wages than manufacturing industry wages.

The presence of children under school age in the home has a positive effect across sex and industry, meaning that individuals with children under 5 have higher annual wages than those who have children greater than 5, or no children at all. Men have a higher return than women when a child under 5 is present in the home, which is consistent with previous literatures' findings.

White men have a higher annual wage than other minority races (a direction consistent with theory). This coefficient is higher in magnitude in manufacturing than in the services industry, indicating that the there is a smaller difference in racial wages in services. The effect of being white on the return to annual log-wages is actually negative for women in the services industry, meaning that white women, on average, have a lower log-wage than other minority women (though this result is not statistically significant). Black and Asian men, with negative differences, have on average, a lower return to log-wages, than black and Asian women. The effects of black and Asian as coefficients vary in terms of direction across sex and industry, and in terms of statistical significance.

The effect of current or previous marriage is positive for all industries and sex groups, meaning that those who are currently or previously married have higher wages than those who are single. The magnitudes of the coefficients for men are much higher than those for women, indicating that marriage has a greater effect on the wage for men than women, again in accord with previous literature. Additionally, it appears that people who live in the Northeast earn more than those in the other three regions, as the effect on Midwest, South, and West are negative.

Education has a positive effect across industry and sex as well, which is in line with theory. Each level of education, from high school diploma to post-undergrad schooling, has a positive effect, indicating that the returns to log-wages are higher for higher levels of education versus only some high school education. With the exception of college graduates in the knowledge-based services sector, the coefficient for each level of education for women is higher than that for men, indicating that the return to education for women is higher. The magnitude of the coefficients for education in the services industries are higher for knowledge-based than non-knowledge-based, which makes sense given that the division of industries between the two groups was based upon mean college attainment of workers. The returns to education, for all levels and both sexes, is higher for non-knowledge-based manufacturing than knowledge-based manufacturing, meaning that people with higher levels of education have higher returns for education versus lower levels of education in the less cognitively centric manufacturing group. The opposite effect is true in the services industry, as the coefficients for education are larger for the knowledge-based variables than the non-knowledge-based variables.

It is also important to keep in mind that these results could be skewed by the fact that there may just be more of one sex in a specific industry group than in others, so it could prove useful to look at the division of men and women between each industry category. Tables 14-17 *(see appendix)* provide such analysis. As shown, men make up the majority of the workforce for all industry groups with the exception of knowledge-based services, which exhibits a complete reversal of the sex distribution. Given that our theory suggests that women have a lower disadvantage in industries that are more cognitively-intensive, it is interesting that women make up the majority of the industry group that is defined as the most cognitively-intensive. Additionally, when compared to the manufacturing groups, women's participation in the non-knowledge-based service group is about 10% higher, also in accordance with theory. Because of this, it appears that labor market entry is easier for women in the services industry than the more labor-intensive manufacturing industry.

Oaxaca Decomposition Industry Results

Table 18 *(see appendix)* reports the results for this analysis, in exponential form, so values are in dollars rather than log-dollars. The differentials on the means analysis reports the mean wages for each sex in each industry group, and the difference is the multiplicative value of the men's wages over those of women's. The results show that the wage differential is greatest in the non-knowledge-based services industry, in which there is a 77.84% difference between the wages of men and women. The second largest wage differential is 53.58%, for the knowledge-based manufacturing industry, followed closely by that of the knowledge-based services industry, at 49.40%, and non-knowledge-based manufacturing, at 48.79%.

The explained percentage shows how much women's wages would change if, in that particular industry group, women were at the same "endowment" levels as men, meaning that they had the same mean levels of human capital. For knowledge-based manufacturing and non-knowledge-based services, women's wages would increase by 12.74% and 5.23%, respectively, leaving 36.23% and 69.00% of the wage gap "unexplained." Alternatively, the wages for women in non-knowledge-based manufacturing and knowledge-based services would actually decrease if they had the same endowments as men in those industry groups, resulting in a wage that is 98.27% and 99.63% of the previous wage level, respectively. Essentially, the wage would not change that much between men and women if their skill types were the same. In these two groups, 51.41% and 49.95% of the wage gap is left unexplained.

It is also interesting to point out that the explained component of non-knowledge-based manufacturing and knowledge-based services is minimal. These results suggest that almost the entire wage gap in these two groups is attributable to "unexplained" differences in men and women (i.e. discrimination). The result is similar for non-knowledge-based services. The only group in which differences in human capital plays a major role in explaining the difference in wage is knowledge-based manufacturing, where only 36.23% of the remaining wage gap is left unexplained, as compared to about 50% for non-knowledge-based manufacturing and knowledge-based services, and 69% in non-knowledge-based services.

From this analysis, the wage gap is the smallest in the knowledge-based manufacturing sector, and the largest in the non-knowledge-based services sector, with a close tie between the other two groups for second and third. There isn't a great difference between the wage gaps of either of the manufacturing groups and that of the knowledge-based services. Rather, these three groups have a much lower wage gap as compared to non-knowledge-based services. This is not completely in line with theory, as knowledge-based services should have a smaller wage gap, and non-knowledge-based manufacturing should have the largest wage differential, or at least one that is larger than that of knowledge-based manufacturing or knowledge-based services. However, it does show that the smallest wage-gap is a knowledge-based group, and the industry group with the largest wage gap is, in fact, a non-knowledge-based group. The ambiguity lies with the non-knowledge-based manufacturing and the knowledge-based service industry groups, and the similarities between them. Again, this result could be due to the distribution of men and women in each industry group, or how this study categorized the industries between the four levels. Additionally, this could also be due to the fact that occupation is not accounted for in this analysis, which may play a bigger part in determining a wage gap than the industry in which the occupation is categorized. An analysis of this data by occupation rather than industry could potentially show a different wage-scheme.

Occupation Wage Regression Results

Table 19 provides the results of the occupation wage regressions. Overall, the results are in line with those found in the industry regressions. Age has a positive effect for all occupation groups and all sexes. The returns to age are higher for men than for women in all occupation groups. The effect of the squared age term does not vary much throughout. Again, the effect of children present in the home is positive and greater for men than women in all categories. The results for race are more mixed than they were with industry. In professional/technical, clerical, and services, white women tend to make less than other minorities, while white men make more than minority men. An opposite trend occurs with black men. Black men in every occupation group make less than other minorities, while black women earn more. The effect of the Asian race coefficient varies in direction and significance by sex and occupation. Like the industry regressions, the effect of current or previous marriage results in a higher wage than for single people, and its effect is greater for men than women, and the returns to education increase as the level of education increases. These coefficients are much larger for the professional, technical, administrative, and managerial careers than for the production, transportation, and labor careers, which is in line with theory. The effect of Midwest, South, and West are once again negative, indicating that those who work in the Northeast have the greatest returns to wage.

Like the industry results, these results for occupation could be dependent on the distribution of men and women in each occupation group. Tables 20-25 *(see appendix)* give the division of men and women in each occupation group. Surprisingly, women hold a majority of the positions in the data for professional/technical positions, at 65.87%. Men hold greater than 50% of the jobs for administrative/managerial and sales, and more than 80% in the most physically intense category, production/transportation/labor/agriculture (PTLA). Women hold more than 50% of the positions in service, and more than 70% in clerical, which is also in line with theory, as these positions tend to be less physically strenuous. These distributions could also affect the results of the Oaxaca decomposition.

Oaxaca Decomposition Occupation Results

The results of the Oaxaca decomposition by occupation are in Table 26 *(see appendix).* The largest wage gap is in administrative/managerial positions, in which men's wages are almost double that of women's. Similarly, the men make 95.97% more than women in annual salary. These two large wage gaps are then followed by professional/technical (85.79%), PTLA (71.96%), service (68.36%), and finally clerical, with the smallest wage gap (25.05%). Even though the administrative/managerial category has the largest wage gap, it also has the largest percentage due to explained differences in human capital, 27.29%. The next closest are sales and professional/technical, at 15.43% and 10.78%, respectively. The production and service groups have almost none of the wage gap attributable to differences in human capital. Clerical actually shows that if women had the same skill set as men, they would have a wage 90.42% of what it is now. The final unexplained wage gap is largest in sales (69.77%), followed by PTLA (68.38%), professional/technical (67.71%) and service (67.12%). The smallest is once again clerical, with 38.30% of the wage gap left unexplained.

This result is in line with theory, as I expected the occupations that require less human capital attainment to have the largest level of discrimination. The surprising result is that of professional/technical, which has one of the largest wage gaps, and one of the largest levels of unexplained discrimination. Also, it is interesting that administrative/managerial has the highest wage gap, but the highest percentage due to differences in skill, resulting in the lowest unexplained wage gap portion. This result indicates that there is a severe difference in human capital between men and women in administrative/managerial jobs. The opposite is true of the lower level jobs, like PTLA, which had almost none of the gap due to differences in skill. This makes sense because, as we do not have a measure of the difference in physical strength, or perceived physical capacity on the part of the employer, that difference must be included in the unexplained portion of the wage gap.

V. Conclusion

This analysis contributes to the existing literature by providing a measure of the wage gap between men and women by industry and occupation for the U.S. in the year 2010. It also provides a decomposition of each wage gap measure, which allows for a comparison of explained and unexplained portions by industry and occupation. The results of this analysis show that, overall, the larger wage gaps between men and women exist in industries and occupations that require a greater degree of physical strength than cognitive ability (in line with theory). For industry, non-knowledge-based manufacturing has the largest unexplained wage gap, and likewise for the occupation groups for sales and production/transportation/labor/agriculture. These groups do not have the largest wage difference, what they have in common is that very small percentages of the gap could be explained away by differences in human capital. This result is in line with theory because, as there was no covariate included in the regressions for physical strength, that difference would be picked up in the industry/occupation dummies, and thus if physical strength made an impact on wage, would be included in the unexplained portion of the wage gap. This unexplained wage gap could be the result of actual, unmeasured differences in abilities between men and women, or a perceived difference in the capabilities of men and women on the part of the employer.

Limitations exist that could explain why the results for my regressions for my knowledge-based categories for industry and occupation were not completely in line with theory. As with any regression, the model is limited by the covariates included for human capital. Any other variable that may account for a difference in wages between men and women that were not included in the regressions is included in the unexplained portion of the wage gap difference. Additionally, the results are extremely dependent on the division of observations into industry and occupation groups. Future studies could improve upon this research by either doing a more in-depth breakdown of industry and occupation, or by including occupation and industry in the same regression, to compare the differences in wages by occupation within a given industry group. It could also be true that industry and occupation may not be the best proxy to show the difference in physical strength and cognitive ability. If an individual measure of physical strength was available for use in analysis, it may be a better covariate to include in the regressions to see if it captures any of the discrimination in the explained portion of the wage gap.

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VII. Appendix

Figure 1

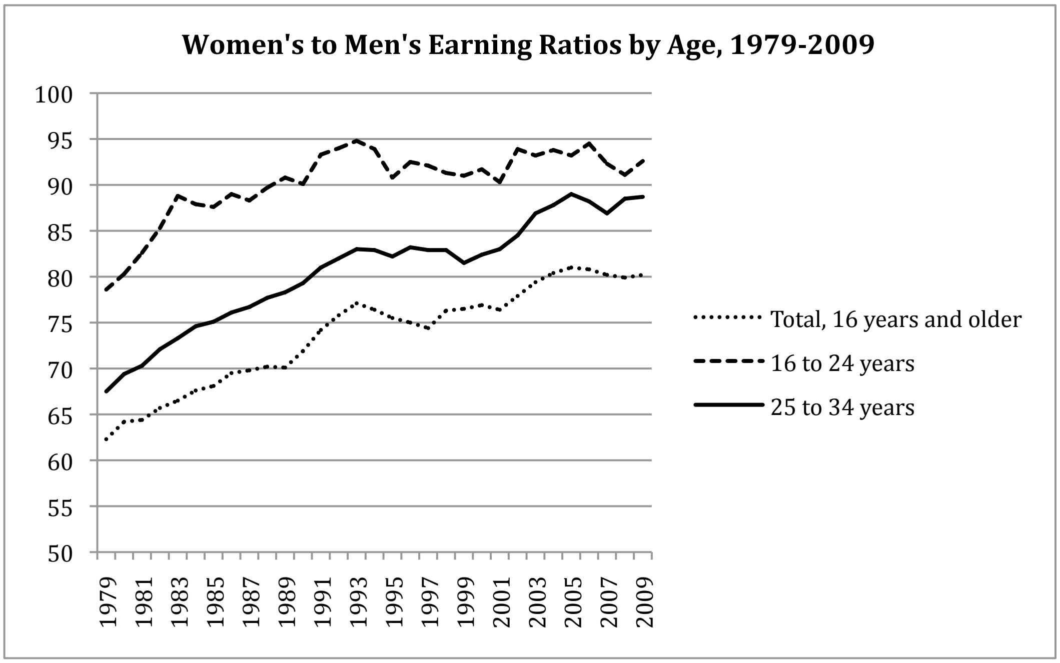

Figure 2

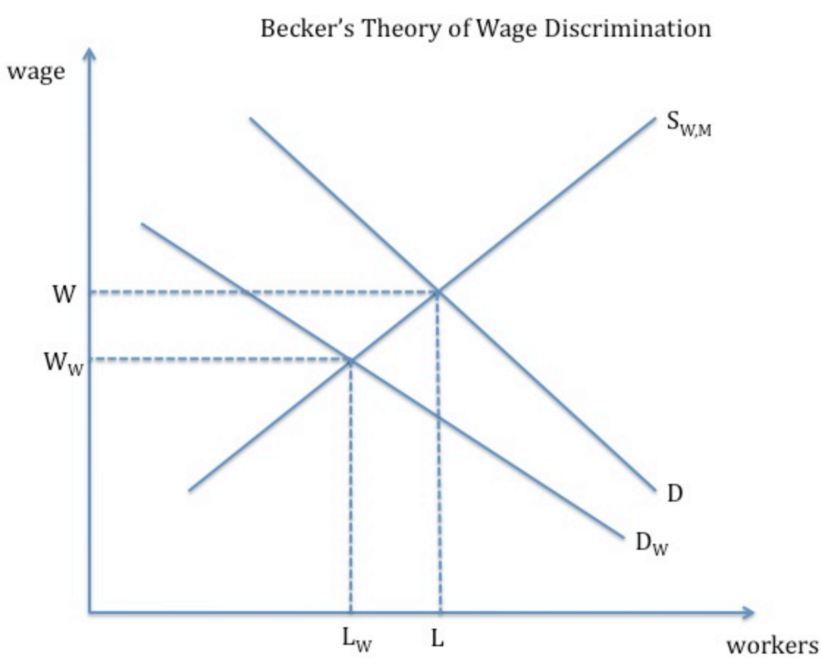

Figure 3

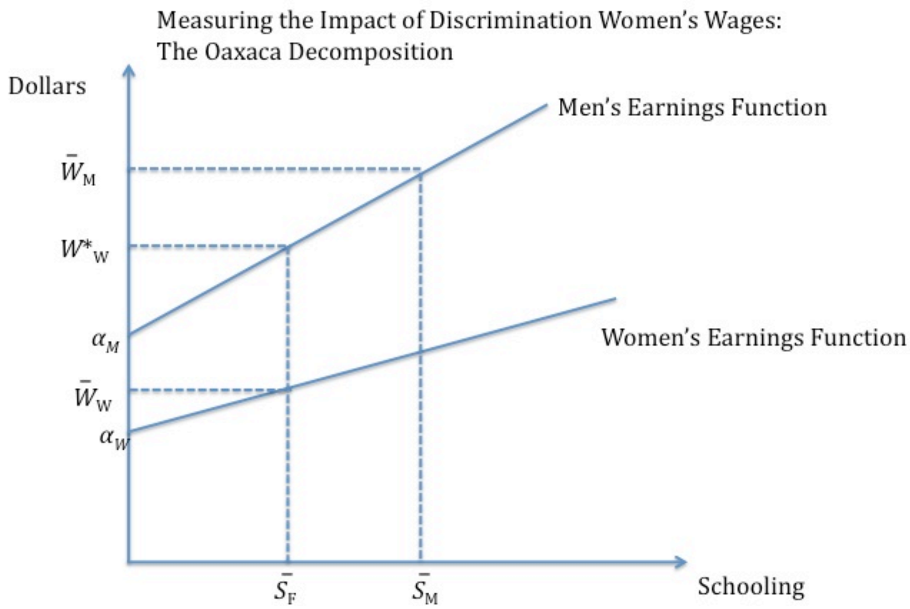

Table 4

Summary Statistics				
Variable	Obs	Mean *Std. Dev*	Min	Max
Age	1128837	42.39368 *14.08599*	16	95
Children Present	1128837	2.979389 *1.091152*	1	4
Race	1128837	1.735822 *1.902494*	1	9
Wage (yearly)	1128837	43199.98 *50643.94*	4	569000
Marital Status	1128837	2.02124 *1.64233*	1	5
Sex	1128837	1.492564 *.4999449*	1	2
Industry	1128837	6358.97 *2599.189*	170	9870
School	1128837	18.63109 *2.630261*	12	24
Occupation	1128837	4238.83	10	9830

		2554.247		
Region	1128837	2.613989 *1.024591*	1	4
Log(Wage)	1128837	10.0817 *1.289343*	1.386294	13.25164
Child Under 5 Present	1128837	.1841603 *.3876151*	0	1
No Child Under 5 Present	1128837	.8158397 *.3876151*	0	1
White	1128837	.7997975 *.400152*	0	1
Black	1128837	.0909201 *.2874956*	0	1
Asian	1128837	.0500568 *.2180623*	0	1
Other Race	1128837	.0592256 *.2360465*	0	1
Married	1128837	.6996351 *.4584169*	0	1
Previously Married	1128837	.0927158 *.2900339*	0	1
Single	1128837	.2076491 *.4056243*	0	1
Male	1128837	.5074364 *.4999449*	0	1
Female	1128837	.4925636 *.4999449*	0	1
Some HS	1128837	.0793923 *.2703502*	0	1
High School	1128837	.2683966 *.4431253*	0	1
Some College	1128837	.3311036 *.4706105*	0	1
B.A.	1128837	.1998721 *.3999042*	0	1
Post-undergrad	1128837	.1212354 *.3264008*	0	1
Northeast	1128837	.1871439 *.3900272*	0	1
Midwest	1128837	.2309696 *.4214532*	0	1
South	1128837	.3626405 *.4807625*	0	1
West	1128837	.219246 *.4137358*	0	1
Knowledge-based	1128837	.030286	0	1

Manufacturing		*.1713733*		
Non-knowledge-based Manufacturing	1128837	.1026304 *.3034757*	0	1
Knowledge-based Services	1128837	.5663891 *.4955731*	0	1
Non-knowledge-based Services	1128837	.2952304 *.4561465*	0	1
Professional/ Technical	1128837	.2147299 *.410635*	0	1
Administrative/ Managerial	1128837	.1793102 *.383612*	0	1
Clerical	1128837	.1907671 *.3929061*	0	1
Sales	1128837	.0663462 *.2488863*	0	1
Service	1128837	.1272859 *.3332931*	0	1
Production/ Transportation/ Laborers/ Agricultural	1128837	.2104396 *.407621*	0	1
Age-squared	1128837	1995.639 *1223.822*	256	9025

Table 5

Children Present Summary Statistics	**Freq.**	**Percent**	**Cum.**
Under 5 years only	207,887	18.42	18.42
5 to 17 years only or no children	920,950	81.58	100.00
Total	1,128,837	100.00	

Table 6

Race Summary Statistics	**Freq.**	**Percent**	**Cum.**
White	902,841	79.98	79.98
Black or African American alone	102,634	9.09	89.07
Asian alone	56,506	5.01	94.08
Two or more major race groups	66,856	5.92	100.00
Total	1,128,837	100.00	

Table 7

Marital Status Summary Statistics	Freq.	Percent	Cum.
Married	789,774	69.96	69.96
Previously Married	104,661	9.28	79.24
Single	234,402	20.76	100.00
Total	1,128,837	100.00	

Table 8

Sex Summary Statistics	Freq.	Percent	Cum.
Male	572,813	50.74	50.74
Female	556,024	49.26	100.00
Total	1,128,837	100.00	

Table 9

Educational Summary Statistics	Freq.	Percent	Cum.
Some HS	89,621	7.94	7.94
HS/GED	302,976	26.84	34.78
Some College	373,762	33.11	67.89
Bachelor’s Degree	225,623	19.99	87.88
Masters/PH.D/Doctorate Degree	136,855	12.12	100.00
Total	1,128,837	100.00	

Table 10

Region Summary Statistics	Freq.	Percent	Cum.
Northeast	211,255	18.71	18.71
Midwest	260,727	23.10	41.81
South	409,362	36.26	78.08
West	247,493	21.92	100.00
Total	1,128,837	100.00	

Table 11

Sex Summary Statistics	Freq.	Percent	Cum.
Male	572,813	50.74	50.74
Female	556,024	49.26	100.00
Total	1,128,837	100.00	

Description 12: Industry/Occupation Breakdown

Knowledge-manufacturing industries (KBMHT) consist of the following industries: electronical machinery, communication equipment, office/accounting/computing machinery, and motor vehicles. The low-tech (non-knowledge-based) manufacturing industries (KBMLT) includes the following industry groups: chemicals, rubber/plastic products, nonmetallic mineral products, metals, fabricated metal products, non-electrical machinery, precision instruments, other transport equipment, furniture/manufacturing, food/beverages/tobacco, textiles/apparel/leather, wood/paper products, printing, petroleum refineries/products, and recycling. Knowledge-based service industries include communications, financial services, business services, education services, health services/social work, and culture/recreation/entertainment. Low-level service industries include electricity/gas/water supply, construction, wholesale/retail trade, hotels/restaurants, transport/storage, real estate activities, and all other services and industries.

Occupation was broken down into 6 sub-groups: professional/technical, administration/managerial, clerical, service, sales, and production/transportation/labor/agriculture. Because the occupation groups were still broken down by industry code, the occupations had to be created manually (and at times, subjectively). Industries included in professional and technical were those that require some form of professional certification or technical skill, like business, finance, communications, engineering, computers, science, law, education, and medicine. Apart from the management industry, managerial/administrative included any job code that had the code words “manager,” “supervisor,” or “administrator,” regardless of the industry code. Clerical included any job description for clerical or secretarial work. Service included the following industries: entertainment, public service, food service, and all other jobs that offer a service as a product. Sales included both the sales industry codes, as well as any job description with the code word “sales.” The production/transportation/labor/agriculture consists of, but is not limited to, the following industry codes: machine operators, forestry workers, extraction workers, operators, construction, installers, repairers, transportation, mechanics, assemblers, processors, tenders, millers and setters, loaders, and agricultural workers.

Table 13

Full-scale Wage Regression Results (Industry)	Knowledge-based Manufacturing		Non-knowledge-based Manufacturing		Knowledge-based Services		Non-knowledge-based Services	
Variable Name	Male	Female	Male	Female	Male	Female	Male	Female
Constant	6.852392* (0.000)	6.681744* (0.000)	6.117804* (0.000)	5.754485* (0.000)	4.968812* (0.000)	5.431597* (0.000)	5.675081* (0.000)	5.459942* (0.000)
Age	.1223147* (0.000)	.1226181* (0.000)	.1488766* (0.000)	.1589362* (0.000)	.1910354* (0.000)	.1627721* (0.000)	.171067* (0.000)	.1659904* (0.000)
Age^2	-.0012531* (0.000)	-.0012402* (0.000)	-.0015442* (0.000)	-.001653* (0.000)	-.0020059* (0.000)	-.0017059* (0.000)	-.0018068* (0.000)	-.0017323* (0.000)
Child Present	.0360133* (0.009)	.0159776 (0.527)	.1229063* (0.000)	.0184717 (0.234)	.1486939* (0.000)	.0773441* (0.000)	.1439201* (0.000)	.0603558* (0.000)
White	.1453206* (0.000)	.1405321* (0.000)	.1224733* (0.000)	.0429257 (0.067)	.0417638* (0.000)	-.0032327 (0.662)	.0762973* (0.000)	-.0084489 (0.520)
Black	-.0471037 (0.135)	.0635999 (0.189)	-.1281772* (0.000)	.0335975 (0.259)	-.1434882* (0.000)	.0442666* (0.000)	-.128532* (0.000)	.0360755* (0.028)
Asian	-.0158817 (0.581)	.0540282 (0.247)	-.0340193 (0.107)	.1060721* (0.001)	.0084877 (0.474)	.1095011* (0.000)	-.1059413* (0.000)	.0137335 (0.467)
Married	.4928409* (0.000)	.1910113* (0.000)	.5197982* (0.000)	.2311135* (0.000)	.617804* (0.000)	.1970943* (0.000)	.5431964* (0.000)	.1300542* (0.000)
Prev. Married	.2466442* (0.000)	.0956398* (0.007)	.2206824* (0.000)	.215574* (0.000)	.2760743* (0.000)	.2013805* (0.000)	.2041609* (0.000)	.1431362* (0.000)
High School	.252891* (0.000)	.3420361* (0.000)	.3992369* (0.000)	.4108911* (0.000)	.4948456* (0.000)	.5669605* (0.000)	.3389095* (0.000)	.4257028* (0.000)
Some College	.498855* (0.000)	.5090468* (0.000)	.5680984* (0.000)	.6115537* (0.000)	.7359147* (0.000)	.8092555* (0.000)	.4597002* (0.000)	.5283709* (0.000)
B.A.	.9759785* (0.000)	1.068888* (0.000)	1.008084* (0.000)	1.108078* (0.000)	1.141272* (0.000)	1.138492* (0.000)	.7966975* (0.000)	.810942* (0.000)
Post-undergrad School	1.22562* (0.000)	1.398938* (0.000)	1.352553* (0.000)	1.499913* (0.000)	1.450714* (0.000)	1.46523* (0.000)	.8653644* (0.000)	1.018654* (0.000)

Midwest	-.139841* (0.000)	-.1286353* (0.000)	-.1441977* (0.000)	-.115205* (0.000)	-.2178285* (0.000)	-.156903* (0.000)	-.1262702* (0.000)	-.1007721* (0.000)
South	-.0622728* (0.000)	-.137759* (0.000)	-.0072849 (0.429)	-.087808* (0.000)	-.1089008* (0.000)	-.0983525* (0.000)	-.0755395* (0.000)	-.0409883* (0.000)
West	.0972742* (0.000)	.1479541* (0.000)	-.0367686* (0.000)	-.110415* (0.000)	-.0869229* (0.000)	-.0625039* (0.000)	-.0314889* (0.000)	.0276528* (0.006)
F-stat	987.94	242.20	3,262.48	851.12	16,145.36	11,482.50	7,741.80	2,693.33
Adj. R^2	0.3700	0.2873	0.3672	0.2879	0.4945	0.3054	0.3557	0.2473
Number of Observations	25,211	8,977	84,317	31,536	247,596	391,765	210,344	122,923
p-values in parentheses								
*Significant at 5% level								

Table 14

Knowledge-based Manufacturing	Freq.	Percent	Cum.
Male	25,211	73.74	73.74
Female	8,977	26.26	100.00
Total	34,188	100.00	

Table 15

Non-knowledge-based Manufacturing	Freq.	Percent	Cum.
Male	84,317	72.78	72.78
Female	31,536	27.22	100.00
Total	115,853	100.00	

Table 16

Knowledge-based Services	Freq.	Percent	Cum.
Male	247,596	38.73	38.73
Female	391,765	61.27	100.00
Total	639,361	100.00	

Table 17

Non-knowledge-based Services	Freq.	Percent	Cum.
Male	210,344	63.12	63.12
Female	122,923	36.88	100.00
Total	333,267	100.00	

Table 18

Industry Decomposition Results (Exponential)	Knowledge-based Manufacturing	Non-knowledge-based Manufacturing	Knowledge-based Services	Non-knowledge-based Services
Differential on Means:				
Males	48496.51	34687.57	30421.68	25324.54
Females	31576.69	23312.38	20362.58	14240.55
Difference	1.535833	1.487946	1.493999	1.77834
Decomposition:				
Explained (%)	1.127387	.9827232	.9963008	1.052251
Unexplained (%)	1.362295	1.514105	1.499547	1.690035

Table 19

Full-scale Wage Regression Results (Occupation)	Professional/ Technical		Administrative/ Managerial		Clerical		Sales		Service		Production/ Transportation/ Laborers/ Agricultural	
Variable Name	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Constant	5.4264* (0.000)	6.4011* (0.000)	5.29508* (0.000)	5.019* (0.000)	5.0155* (0.000)	5.7030* (0.000)	5.3489* (0.000)	5.1737* (0.000)	4.9059* (0.000)	5.4360* (0.000)	5.8481* (0.000)	5.7301* (0.000)
Age	.17019* (0.000)	.13172* (0.000)	.17946* (0.000)	.18539* (0.000)	.19513* (0.000)	.16242* (0.000)	.17792* (0.000)	.17496* (0.000)	.19646* (0.000)	.15850* (0.000)	.16600* (0.000)	.15401* (0.000)
Age^2	-.00177* (0.000)	-.00140* (0.000)	-.0018* (0.000)	-.00191* (0.000)	-.00207* (0.000)	-.00172* (0.000)	-.00187* (0.000)	-.00184* (0.000)	-.00209* (0.000)	-.0016* (0.000)	-.00177* (0.000)	-.00158* (0.000)
Child Present	.09345* (0.000)	.04886* (0.000)	.12221* (0.000)	.04866* (0.000)	.16205* (0.000)	.06925* (0.000)	.19962* (0.000)	.0777* (0.000)	.19694* (0.000)	.10365* (0.000)	.13025* (0.000)	.04424* (0.002)
White	.08585* (0.000)	-.00979* (0.422)	.11111* (0.000)	.05576* (0.000)	.01092 (0.531)	-.04722* (0.000)	.08845* (0.001)	.03902 (0.144)	.00721 (0.631)	-.05303* (0.000)	.0764* (0.000)	.01777 (0.344)
Black	-.0804* (0.000)	.03500* (0.014)	-.1664* (0.000)	.01613 (0.388)	-.1190* (0.000)	.03154* (0.000)	-.17411* (0.000)	.00778 (0.815)	-.11348* (0.000)	.06830* (0.000)	-.12393 (0.000)	.13401* (0.000)
Asian	.20488* (0.000)	.2771* (0.000)	-.08005* (0.000)	-.03585 (0.097)	-.03747 (0.107)	.05531* (0.000)	-.17719* (0.000)	-.0277 (0.475)	-.2176* (0.000)	.00490* (0.000)	-.01587 (0.313)	.22045* (0.000)
Married	.56831* (0.000)	.14074* (0.000)	.66652* (0.000)	.22495* (0.000)	.55942* (0.000)	.15902* (0.000)	.71182* (0.000)	.30345* (0.000)	.59483* (0.000)	.05194* (0.000)	.51621* (0.000)	.1362* (0.000)
Prev. Married	.36436* (0.000)	.1972* (0.000)	.37925* (0.000)	.17463* (0.000)	.25939* (0.000)	.19904* (0.000)	.34395* (0.000)	.3093* (0.000)	.18913* (0.000)	.08809* (0.000)	.18399* (0.000)	.12237* (0.000)
High School	.67624* (0.000)	.4016* (0.000)	.41738* (0.000)	.40833* (0.000)	.54792* (0.000)	.61038* (0.000)	.45350* (0.000)	.4846* (0.000)	.49086* (0.000)	.46797* (0.000)	.34699* (0.000)	.34053* (0.000)
Some College	.83614* (0.000)	.69962* (0.000)	.67283* (0.000)	.70103* (0.000)	.6381* (0.000)	.67817* (0.000)	.58102* (0.000)	.60587* (0.000)	.6547* (0.000)	.56462* (0.000)	.44496* (0.000)	.3760* (0.000)

B.A.	1.0857* (0.000)	.96533* (0.000)	1.0896* (0.000)	1.221* (0.000)	1.005* (0.000)	.89147* (0.000)	.98274* (0.000)	.94087* (0.000)	.87457* (0.000)	.73376* (0.000)	.4759* (0.000)	.49721* (0.000)
Post-undergrad School	1.3421* (0.000)	1.2846* (0.000)	1.2882* (0.000)	1.4423* (0.000)	1.176* (0.000)	1.0603* (0.000)	1.0903* (0.000)	1.0050* (0.000)	.84149* (0.000)	.71492* (0.000)	.4527* (0.000)	.67768* (0.000)
Midwest	-.13969* (0.000)	-.11653* (0.000)	-.20501* (0.000)	-.16769* (0.000)	-.16942* (0.000)	-.14852* (0.000)	-.18016* (0.000)	-.15678* (0.000)	-.13493* (0.000)	-.10008* (0.000)	-.12842* (0.000)	-.09684* (0.000)
South	-.03746* (0.008)	-.10513* (0.000)	-.09438* (0.000)	-.07909* (0.000)	-.08322* (0.000)	-.09944* (0.000)	-.13845* (0.000)	-.09587* (0.000)	-.09267* (0.000)	-.03471* (0.002)	-.08092* (0.000)	-.12319* (0.000)
West	-.02490* (0.000)	-.07734* (0.000)	-.05114* (0.000)	.01338 (0.234)	-.08814* (0.000)	-.06148* (0.000)	-.12080* (0.000)	-.0471* (0.015)	-.00345 (0.779)	.01430 (0.254)	-.05899* (0.000)	-.08020* (0.000)
F-stat	2,653.78	2,387.15	6,003.05	4,190.12	3,264.74	2,543.01	1,830.60	924.44	4,328.14	2010.44	5,642.28	646.07
Adj. R^2	0.3248	0.1831	0.4401	0.4169	0.4312	0.2019	0.4127	0.2788	0.5023	0.2753	0.3001	0.1941
Number of Observations	82,719	159,676	114,530	87,882	64,572	150,773	39,061	35,833	64,325	79,360	197,389	40,163
p-values in parentheses												
*Significant at 5% level												

Table 20

Professional/Technical	Freq.	Percent	Cum.
Male	82,719	34.13	34.13
Female	159,676	65.87	100.00
Total	242,395	100.00	

Table 21

Admin./Managerial	Freq.	Percent	Cum.
Male	114,530	56.58	56.58
Female	87,882	43.42	100.00
Total	202,412	100.00	

Table 22

Clerical	Freq.	Percent	Cum.
Male	64,572	29.99	29.99
Female	150,773	70.01	100.00
Total	215,345	100.00	

Table 23

Sales	Freq.	Percent	Cum.
Male	39,061	52.16	52.16
Female	35,833	47.84	100.00
Total	74,894	100.00	

Table 24

Service	Freq.	Percent	Cum.
Male	64,325	44.77	44.77
Female	79,360	55.23	100.00
Total	143,685	100.00	

Table 25

Prod./Labor/Trans./Ag.	Freq.	Percent	Cum.
Male	197,389	83.09	83.09
Female	40,163	16.91	100.00
Total	237,552	100.00	

Table 26

Occupation Decomposition Results (Exponential)	Professional/ Technical	Administrative/ Managerial	Clerical	Sales	Service	Production/ Transportation/ Laborers/ Agricultural
Differential on Means:						
Males	49403.97	44918.39	25553.4	30988.6	15325.47	23174.89
Females	26591.43	22471.08	20434.09	15812.58	9102.772	13477.15
Difference	1.857891	1.998942	1.250528	1.959743	1.683605	1.719569
Decomposition:						
Explained (%)	1.107822	1.272939	.9042267	1.154339	1.007407	1.021192
Unexplained (%)	1.677066	1.570336	1.38298	1.697719	1.671226	1.683885