Gender Discrimination Across U.S. States: What Has Changed Over the Past Thirty Years?

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ABSTRACT

This study examineschanges in the gender wage gap and level of gender discriminationin the United States over the period1980-2010 at the national and state levels. Usingdata from the U.S. Current Population Survey,this study applies theBlinder-Oaxaca Decomposition toseparate the explained and unexplained variations in the gender pay gap. The unexplained variationproxies the level of gender discrimination faced by U.S. workers. Thewage equation estimated utilizes the Heckman methodology to control for *sampleselection bias*. Results with and without sample selectivity controls are included in this paper.

This study reports the gender pay gap in the United States fell from 0.4357 log points over the period 1980-1984 to 0.2673 log points over the period 2005-2010. The narrowing in the gender pay gap is mainly attributable to a reduction in the level of gender discrimination, which decreased by 0.1539 log points in the United States over the thirty year period. Estimations conducted at the state level show the gender pay gap also narrowed for all states over the period 1980-2010. This study findswide variationsin the gender pay gap and level of discrimination at the state level. However, the variance in the gender pay gap and level of discrimination across U.S. states decreased significantly over the thirty year period, providing evidence that convergence is underway.

1.INTRODUCTION

The gender pay gap in the United Statesnarrowed substantially in the 1980's and early 1990's before slowing throughout the mid-1990's and 2000's. (Blau and Kahn, 2006; The Council of Economic Advisors, 1998).According to CPS data, the female to male gender pay ratio rose from0.6304 to 0.7233 over the period 1980-1994, while from 1995-2010 the pay ratio roseonly two percent to 0.7452. Severalreasons explain the closing gap over the past thirty years including increased labor mobility, commitment to the labor market, potential experience,and increases in education attainmentfor women. Many researchers conclude, however,the largest portion of the narrowing gender pay gapis attributable to reductions in gender discrimination (Blau and Kahn, 2006; Suh, 2010).

Although analysis of gender discrimination at the national level is a well-researched topic in the field of labor economics, little research examinesgender discrimination at the state level. Researchers posit that national-level policies have minimal impact on gender pay equality and that state level factors and labor market composition may have a large impact on the discrimination faced by workers in those states (Francois, 1997; Ryu, 2010). This suggests that wide variations in the gender pay gap and level of discrimination faced by workers may exist at the state level.

This analysis complements previous research on the topic of gender discrimination and the gender pay gap in two main ways. First, this paper analyzes gender discrimination over a thirty year period. Much of the research on this topic is cross-sectional and uses data from two points in time to analyze changes in discrimination. This study uses thirty years of data to analyze discrimination at six distinct, cross-sectional periods. This allows for the ability to provide more comprehensive analysis on the changes in gender discrimination and the gender pay gap.

Second, this paper provides analysis on the gender pay gap and level of gender discrimination at the state level. The goal of this analysis is to determine the level of the variation in discrimination across states and report how the variance changed over the past thirty years. In

addition, this paper provides a ranking of states by the level of gender discrimination and the magnitude of the gender pay gap faced by workers. This analysis provides policy makers with the ability to make comparisons across states and draw conclusions of why differences at the state level exist. Discrimination is an important topic for policy makers as it represents a possible underutilization of human capital, which can adversely affect a state's economic performance.

This analysis uses three decades of data (1980-2010) from the March Supplement of the Current Population Survey (CPS), published by the U.S. Census Bureau and Bureau of Labor Statistics. Due to the fact that this study analyzes gender discrimination at the state level, the sample size for smaller states (e.g. RI) is not large enough to produce robust results when conducting analysis using only one year of data. This becomes an even greater issue when controlling for all the explanatory variables present in the wage equation. Therefore, the analysis in this study is conducted over six distinct periods of time by pooling data (1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004, 2005-2010).[1]In order to pool the data, a significant assumption is made that changes in the gender pay gap and level of gender discrimination do not change significantly on a yearly basis.Analyzing U.S. estimates on a yearly basis supports this assumption. As such, focusing on five-year intervals provides an appropriate and efficient way to correct for the sample size issue in an effort to produce robust estimates.

The analysis of gender discrimination is conducted using the Blinder-Oaxaca Decomposition, a methodologythat allows for separating the explained and unexplained portions of a mean difference between two groups in a population, in this case the mean difference in hourly wages between males and females. Explained wage differentials are captured by explanatory variables in the wage equation such as educational attainment, number of children, experience, and industry/occupation.The unexplained component of the male-female differential is used as a proxy for gender discrimination. Specifically, the Oaxaca

[1] The periods 1980-1984, 1985-1989, 1990-1994, 1995-1999, and 2000-2004 each contain five years of data. The period 2005-2010 contains six years to include the most recent data available at the time this study was written.

Decomposition separates the wage gap into the components that can be explained by observed differences between men and women and that which cannot be explained.

This paper also utilizes the maximum likelihood estimation of Heckman's sample selection model to control for*sampleselection bias* caused by the omission of unemployed individuals from the wage equation. Although unemployed individuals are in the labor force, these observations are omitted from the wage equation because they do not have earnings. The Heckman methodology corrects for this bias,increasing the reliability of the results produced.

The remainder of the paper is structured as follows. Section 2 provides a literature review focusing on gender wage differentials and discrimination. Section 3 overviews the methodology used to conduct the analysis in this paper. Section 4 describes the data source used for this study. Section 5 presents and discusses the results of the analysis completed. Finally, Section 6 discusses the implications of the analysis conducted, limitations of the study, and areas for future research and improvement.

2.LITERATURE REVIEW

A substantial amount of research has been conducted to analyze gender differences in pay. One major goal of this research is to determine what observed factors can explain gender differences in pay and what portion of this gap can be attributed to gender discrimination.

Much of this research was conducted using the Blinder-Oaxaca decomposition technique (Blinder, 1973; Oaxaca, 1973). The Blinder-Oaxaca decomposition separates the wage differential into explained and unexplained components. The explained component represents the portion of the gender pay gap that can be accounted for by productivity differences between men and women (e.g. years of education, work experience) and the unexplained component represents the portion of the gap which cannot be accounted for. The unexplained portion of the wage differential is used as a measure of discrimination; however, this also

absorbs differences caused by omitted explanatory variables, which may biases the estimated coefficients and therefore the magnitude of discrimination (Jann, 2008).

Oaxaca (1994) uses the Blinder-Oaxaca Decomposition to conduct analysis of gender discrimination using 1988 CPS data, but also analyzes wage structures by conducting analysis using the pooled method. This methodology uses cross-product matrices as the weighting matrix in the regression to analyze wage structures as if wage discrimination did not exist. Oaxaca (1994) found that the male/female wage differential was about 35 percent, with nearly 32 percent of the differential being attributable to discrimination using the standard decomposition. However, the pooled estimates provided insight into the overpayment and underpayment of males and females respectively. This approach yielded results that concluded males are overpaid by 10 percent, females are underpaid by 11 percent and the remaining portion is attributable to male productivity advantage. This analysis fails to provide controls for *sample selection bias* and omits certain explanatory variables such as number of children from the wage equation.

Blau and Kahn (1994; 2000; 2006) write extensively on the narrowing in the gender pay gap in the United States over the past forty years. Blau and Kahn (1994) use a methodology to decompose the difference in the gender pay gap attributable to gender-specific factors and the portion attributable to changes in overall wage inequality. Using the Michigan PSID survey, they find that the log wage gap over the period 1975-1987 fell from 0.5040 log points to 0.3598 log points. Furthermore, when controlling for human capital and race characteristics, two thirds of the gender pay gap remained unexplained; however, when also controlling for industry, occupation and collective bargaining the unexplained gender pay gap fell from 0.2126 in 1975 to 0.1579 in 1987.Blau and Kahn (1994) conclude that during the 1970's and 1980's women were "swimming upstream" due to rising income inequality and adverse trends in wage structures. They find that wage inequality actually widened the gender log-wage gap by 0.07 log points. If there had been no gender specific improvements for women over this period, the female-male wage gap would have fallen from 60% in 1975 to 56% in 1987.

The authors find that substantial reductions in the unexplained portion of the gender pay gap as well as experience and occupational status, however, caused the pay gap to decrease over the period.

Blau and Kahn (2000) conduct further analysis to examine factors that can explain variations in the gender pay gapincluding occupational wage structure, household composition, qualifications caused by discontinuous working lives, and discrimination. Blau and Kahn (2000) suggest that industry differences in pay have been the largest contributor to the gender pay gap. Women historically avoided jobs with a large investment of skills because of a discontinuous working life (e.g. leaving work to raise children). In addition, occupations which have historically been occupied by females(e.g. teaching) tend to pay less and contribute significantly to the observed portion of the gender pay gap. However, Blau and Kahn (2000) conclude both trends have declined since the Equal Pay Act was passed in 1960. The composition of job opportunities for female college graduates is much more diversified than it was in the 1960's when the Equal Pay Act was passed. As an example, nearly 50 percent of female college graduates became teachers in 1960, whereas less than 10 percent became teachers in 1990. Women are now moving into traditionally male occupations, leading to a decrease in the gender pay gap. Furthermore, Blau and Kahn posit that wage inequality seems to have decelerated since the 1990's which may lead to further decreases in the gender pay gap, but labor market discrimination will prevent the gap from vanishing.

Barth and Dale-Olen (2009) posit that the male labor supply is more elastic than the female supply for given industries, thus explaining the differences in pay. If the labor supply of females is more inelastic they will earn less relative to productivity. One of the key variables introduced into this model is turnover rates of men and women in the workplace, used to determine whether a certain gender group is more likely to leave their job for a certain reason. Bart and Dale-Olen (2009) find that worker turnover is less sensitive to wages for women and thus one of the reasons employers are able to pay women less and exercise monopsonistic discrimination. This analysis provides one explanation for why female dominated jobs pay

less than male dominated jobs and makes the case for the inclusion of a worker turnover variable to be included in a model to describe the gender pay gap.

Ransom and Oaxaca (2010) find that the elasticity of labor supply for male and female employees is different, leading to profit-maximizing discrimination against female employees in companies that possess monopsony power. The authors use a unique data source for an individual firm, a regional grocery store, and find that women are less sensitive to wage differences, leading to the conclusion that the labor supply of women is more inelastic than that of men. This provides the firm with an incentive to discriminate against these female employees. Ransom and Oaxaca also posit that since women are less sensitive to pay, firms are more likely to fill low quality, low paying jobs with female employees. This paper provides further reasoning as to why women are still discriminated against by firms; however, the paper's limitations stem from the data used. Because this data is only for one firm, it is not reasonable to assume that the trends in gender elasticity are consistent with all industries; they could vary substantially by industry. In addition, this firm was unionized and therefore gender differences in pay for the same position could not be accurately estimated.

Amaram (2010) provides an overview of all of the factors that contributed to the narrowing gender wage gap over the past thirty years, providing discussion on explanatory variables that must be accounted for when assessing the magnitude of gender discrimination.He argues that enforcement of equal pay legislation has made it more difficult to rationalize the fact that pay differences are solely on the basis of gender. Amaram (2010) posits that choices in the job market and elsewhere, rather than discrimination, are the primary reasons for the wage gap in the 21st century. Similar to Blau and Kahn (2000), Araman (2010) concludes that women tend to choose careers that pay substantially less. He suggests that more emphasis on casual factors and their impact on the wage gap including experience, education, occupation, work patterns, marital status, and union affiliation is needed to assess whether gender discrimination still exists.

Suh (2010) conducted a cross sectional study using CPS data from March 1989 and March 2005 in order to analyze the causes of the gender wage gap over this period using the Blinder-Oaxaca Decomposition and Neumark Decomposition. He finds that the gender wage gap narrowed significantly over the period, with the majority of the gains being attributable to reductions in discrimination. Furthermore, Suh (2010) concludes that the explained portion of the wage gap is mainly attributable to hours worked and family income, while convergence in the level of education and experience between men and women narrowed the gender pay gap over this period. He also concludes that there exist large variations in the closing of the gender pay gap across industries, occupations, race, and location.

Weinberger and Kuhn (2010) conduct analysis on the gender pay gap over the period 1959-1999 to determine whether the decline in the gender pay gap is attributable to wage growth after labor market entry or relative earnings at the time of entry. Instead of using a panel dataset, the authors follow cohorts of individual age groups over the forty year period. Weinberger and Kuhn (2010) find that approximately one-third of the narrowing gap is attributable to wage growth after market entry, while the majority is attributable to factors present at the time of labor market entry. This is consistent with much of the literature including Suh (2010) which concludes discrimination reduction, rather than measured factors, explain the majority of the closing gender pay gap. The authors also conclude the female/male wage gap is narrower during initial entrance into the workforce, widens around the time most women have children (25-35 years old), and then narrows again until retirement. Weinberger and Kuhn (2010) also find that the female/male earnings ratio slopes for each successive age cohort were steeper, representing an overall closing of the gender pay gap. One of the limitations of this is the limited number of controls included in the regression analysis. Due to data limitations, the only controls used were experience and age.

Hegewitch, et al. (2010) discuss gender segregation in the labor market more in depth as a cause of the gender wage gap. Hegewitch, et al. (2010) discuss the trends in occupation segregation over the time period 1972-2009 and determine that not all occupations have shown a change in gender composition. They use the Index of Dissimilarity in order to

analyze the occupational trends over this time period. The index shows that progress toward gender integration is further along for those with a college degree, however it seems to be stalled for all workers in recent years. They find that there exists a correlation between percentage of female workers in occupations and level of earnings. Female dominated occupations have earnings between 66.9 percent and 79.8 percent of male dominated occupations when controlling for skill level. This study demonstrates the importance of controlling for occupation in a model that analyzes discrimination.

Ryu (2010) analyzes the effect of state policies and mechanisms on gender wage inequality. The author links state intervention policies to wage differentials in each of the 50 U.S. states to examine their effect on gender wage equality. He finds that female employees achieve more gender equity in states with progressive institutional environments. Using data from the 2000 census and the Heckman Two- Step, Ryu (2010) measures the wage gap between men and women when controlling for human capital characteristics.He also includes state-level fixed effects to analyze the effect of state level policies on the gender pay gap. Although there is some discussion on discrimination as a factor, it is not the major topic of the paper, nor is there any discussion of the gender pay gap or gender discrimination at the state level. Rather than completing this analysis for each individual state, Ryu estimates a model to state the "earning penalty" of a state being progressive or conservative. One of the drawbacks of this paper is the fact that it is not analyzing gender differentials over a period of time.

Flabbi (2010) argues that the traditional measures of productivity do not accurately depict actual productivity and uses a search model of the labor market with matching, bargaining, and employer's taste discrimination to determine what portion of the gap is attributable to unobserved productivity and how much is attributed to prejudice by employers. Flabbi (2010) finds that productivity is 6.5% lower for females than males;however, 50% of employers are prejudiced which leads to wage discrimination. The author concludes that two-thirds of the gender pay gap is still attributable to discrimination, while the other third is attributable to the productivity differences. Flabbi (2010) discusses that wage discrimination is present at unprejudiced employers as well because women's outside options are restricted due to

prejudiced employers. The major limitation of this study is the fact that analysis is only completed for one year, which prevents the ability to analyze how these differences in productivity change over time.

This paper aims to improve the literature on the topic of gender discrimination in three major ways. One issue is the fact thatprevious literature fails to provide a comprehensive method for analyzing gender discrimination over time. Blinder (1973), Oaxaca (1973), Oaxaca (1994), and Suh (2010) use the Oaxaca Decomposition to separate the explained and unexplained portions of the gender pay gapl; however, all of these studies fail to account for *sample selection bias*. Individuals who are unable to obtain a job and therefore do not have an observed wage are not included in any of these studies. This paper corrects for this bias by using the maximum likelihood estimation of Heckman's sample selection model. This approach turns the *sample selection bias* into an omitted variable bias which can be controlled for in the regression model.

Second, previous research on this topic rarely analyzes gender discrimination over more than two periods of time. Studies such as Blau and Kahn (1994; 2000) analyze the gender pay gap at two points in time, while studies such as Ryu (2010) and Flabbi (2010) only analyze gender discrimination at one point in time. This study will use six cross-sectional periods to report and analyze the gender pay gap over the past thirty years. This more comprehensive analysis allows for the ability to discuss trends in the narrowing gender pay gap over the past thirty years, identifying when the largest reductions occurred. In addition, unlike many of the studies that focus solely on the gender pay gap, this study will also decompose the gap to determine how level of discrimination changed over the thirty year period. Lastly, this study conducts analysis using data through 2010, providing recent and relevant information on the topic of gender discrimination.

Finally, the major contribution to the previous literature is the fact that this study will be conducted at the state level. All of the previous literature, with the exception of Ryu (2010), fails to provide any analysis of gender discrimination at the state level. However, Ryu

(2010)does not discuss the magnitude of the gender pay gap or level of gender discrimination at the state level. Furthermore, the purpose of the research conducted by Ryu (2010) is to examine state level policies rather than variations in the gender pay gap across states. This study will fill this gap in the literature, discussing magnitude of discrimination and level of variation across states over the past thirty years.

3. METHODOLOGY

The standard approach to examine wage discrimination is to estimate an equation where hourly earnings are regressed against personal and human capital characteristics. Consider the following

$$\ln(\mathrm{W}) = X\beta + \varepsilon\,, \tag{1}$$

whereWis a$N \times 1$ vector for hourly wage, X is a $n \times k$ matrix of predictors (explanatory variables), $\beta$is a vector of parameters, and ε is a vector of regression disturbances. We use the log specification of wages for this model, resulting in an estimate of earnings semi-elasticity. This is a more effective way of measuring responsiveness to changes in endowments because increases in wages are typically proportional to the previous wage level rather than absolute dollar increases for changes in endowments. Matrix X includes personal and human capital characteristics. The variables used in the wage equation are listed below.

Table 1: Wage Equation Variables

Name	Definition
Hourly Wage	= E/(W*H), where E= annual earning, W=average weeks worked in the past year, and H=usual number of hours worked per week
Gender	=1 if Female, =0 is male
High School	= 1 if High School is highest educational attainment, =0 otherwise
Some College	= 1 if Some College is highest educational attainment, =0 otherwise
Bachelor's Degree	= 1 if Bachelor's Degree is highest educational attainment, =0 Otherwise
Graduate Degree	= 1 if Graduate Degree Completed, =0 otherwise
Married	=1 if married, =0 otherwise
Children Under 6	=1 if person has children under 6, =0 otherwise
Children 6-18	=1 if person has children 6-18, =0 otherwise
Experience	= potential years of market experience (age - years of education - 6)
Experience Squared	= potential years of market experience squared
Black	=1 if respondent is Black/African American, =0 otherwise
Other Non-White	=1 if respondent is Non-White, =0 otherwise
Metropolitan	=1 if reside in a metropolitan statistical area, =0 otherwise
Occupation	=1 if in specified occupation, =0 otherwise
Industry	=1 if in specified industry, =0 otherwise
Private	=1 if works in private industry, =0 otherwise

OLS estimates for Equation (1) suffer from *sample selection bias*; individuals who are in the labor force but not employed are not included in the sample because they have zero earnings. The only individuals who are included in this analysis are those with an observed wagegreater than zero; therefore, individuals who are in the labor force, but unable to secure employment, are omitted from the sample.

Without correcting for this sample selection bias, the Guass Markov assumption stating the expected value of the error term must be equal to zero is violated. If the observed wage must be greater than zero, the error term must be greater than $-(x\beta)$[i.e., $\varepsilon > -X\beta$], thereby imposing a condition that violates the assumption of an error term with an expected value of zero (see Pencavel, 1986).

Toaccount for this bias, we follow themaximum likelihood estimation of Heckman's sample selection model(1979) to translate the sample selection bias into an omitted variable issue that can be corrected for by estimating an Inverse Mills Ratio (IMR). The Inverse Mills Ratio is

estimated using a probit modelthat assumes a value of 1 if the person has an observed wage and is in the labor force and 0 if the person does not have an observed wage but is still in the labor force. If we assume that each individual has a reservation wage for which they will accept a new position, we can develop a model that controls for these variations. The set of variables used in this model is similar to the set used in the wage equation; however, some variables are omitted as they would not impact a person's decision accept a position.Variables such as household income and home ownership are added to this model because they may represent factors that a person's decision to accept a job and impact their reservation wage. The variables used in the probit model are listed below.

Table 2: List of Labor Force Participation Variables

Name	Definition
Household Income	= ln-adjusted household income
Married	=1 if married, =0 otherwise
Children Under 6	=1 if person has children under 6, =0 otherwise
Children 6-18	=1 if person has children 6-18, =0 otherwise
Experience	=years of potential market experience (age - years of education - 6)
Experience Squared	= years of market experience squared
Metropolitan	=1 if reside in a metropolitan area, =0 otherwise
Rent Home	=1 if rent home, =0 otherwise
High School	= 1 if High School is highest educational attainment, =0 otherwise
Some College	= 1 if Some College is highest educational attainment, =0 otherwise
Bachelor's Degree	= 1 if Bachelor's Degree is highest educational attainment, = 0 otherwise
Graduate Degree	= 1 if Graduate Degree Completed, =0 otherwise

The resulting Inverse Mills Ratio from the probit model is added to the wage equation as an additional explanatory variable. The amended equation is

$$ln\,(W) = X\beta + \gamma IMR + \varepsilon \ . \qquad (2)$$

A statistically significant coefficient for the IMRsignifies that sample selectivity would bias estimates if it were not included as an explanatory variable.The Heckman Methodologycorrects for sample selectivity; however, it introduces heteroskedasticityinto our model, violating a second Guass Markov Assumption. To correct for heteroskedasticity we

follow the methodology suggested by White (1980) to produce robust variance-covariance estimates.

The next step in our analysis is to develop gender-specific wage equation models to evaluate the gender differences in pay. We develop two models using Equation (1),one using a sample of all males and the other of all females. This study follows the methodology proposed by Blinder (1973) and Oaxaca (1973). The Blinder-Oaxaca Decomposition takes the mean gender pay gap and separates the gap into explained and unexplained components. The unexplained component of the gap is used as a measure of gender discrimination (Jann, 2008). The Oaxaca Decomposition begins by defining R as the mean wage gap between men and women as shown below.

$$R = E(W_m) - E(W_f) \tag{3}$$

The gap between the mean wages of males and females can also be represented by

$$R = X_M B_M - X_F B_F, \tag{4}$$

where$X_M$and X_F are vectors of explanatory variables evaluated at the means for each gender. R can be further rearranged to better identify the contributions of group differences in predictors as a three-fold decomposition (see Windsborough and Dickinson (1971); Jones and Kelley (1984); Daymont and Andrisani (1984)). The rearranged equation is show below:

$$R = (X_M - X_F)\beta_F + X_F(\beta_M - \beta_F) + (X_M - X_F)(\beta_M - \beta_F) \ . \tag{5}$$

Equation (5) can be conveniently rewritten as:

$$R = E + C + I \tag{6}$$

The term $E = (X_M - X_F)\beta_F$ measures the differential that is due to differences in the predictors. For example, if women have a lower average level of education, this difference would be captured in *E* as a predictor of why women earn less than men.

$C = X_F(\beta_M - \beta_F)$measuresthe difference in the coefficients between men and women. This component represents the difference in the returns to endowments between men and women. For example, if the returns to an additional year of education were higher for men than for women, this difference would be captured in *C*.

Lastly, $I = (X_M - X_F)(\beta_M - \beta_F)$ is the interaction term between endowments and coefficients.

E is certainly not a measure of discrimination as it captures differences in productivity. This portion of the wage gap would disappear if the mean values for each characteristic were equivalent for men and women. *C* represents the portion of the wage gap that is attributed to differences in the returns to endowments, or coefficients. For example, if the coefficient on experience for males is higher than for females one would consider this to be discrimination. This phenomenon cannot be explained by the model and is therefore attributed to discrimination. Lastly, *I*, the interaction term, is also considered discrimination because it contains the differences in returns to endowments. This term will converge to zero as differences in coefficients converge to zero.

It is important to note the fact that the unexplained portion of the decomposition also captures effects of differences in unobserved variables that are omitted from the model. This demonstrates the importance of controlling for as many factors as possible in order to have the most accurate, least biased estimates of discrimination.

By combining the Blinder-Oaxaca Decomposition with the maximum likelihood estimation of Heckman's sample selection model, this paper aims to assess accurately the magnitude of gender discrimination across states. In addition, by including a comprehensive set of

explanatory variables, the model used in this paper aims to minimize omitted variable bias that has plagued previous studies. Finally, by conducting cross sectional analysis over six distinct periods in time, this research is able to analyze changes in the level of gender discrimination over the past 30 years.

4. DATA

The Current Population Survey has been chosen as the primary data source for the analysis in this paper. The CPS March Supplement is a survey conducted by the Census Bureau and Bureau of Labor Statistics, is administered on a yearly basis, and surveys more than 150,000 households in the United States. In addition, the CPS contains all of the explanatory variables necessary for this analysis.This research focuses on changes in gender discrimination over the past thirty years because of the significant differences in CPS data available before 1980. Consistency in survey questions and methodology is necessary to ensure accurate estimations in this study. Furthermore, a thirty year time period provides an excellent framework for analysis.

Pooling of the data is necessary to create a sample size large enough at the state level to produce robust results. For example the 2010 CPS survey contains only 1729 observations (ages 25-65) for the State of Rhode Island. When controlling for all of the industry, occupation, and personal characteristics,the sample size for one year of data is not a large enough sample to produce statistically robust results, leading us to pool the sample into five year groups. The strongest assumption made in order to pool this data is that discrimination does not change substantially over short periods of time. Analyzing U.S. estimates on a yearly basis supports this assumption. As such, focusing on five-year intervals provides an appropriate and efficient way to correct for the sample size issue in an effort to produce robust estimates. The analysis in this paper is completed for six distinct periods of time by

poolingfive consecutive years of data (1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004, 2005-2010).[2]

The 2010 CPS variables used in this study can be found in Appendix A.Appendix B contains descriptive statistics for selected explanatory variables and the sample size for the six datasets used in this paper. It is worth noting that the analysis in this paper considers information from about 1.9 million individuals in the United States.

5. RESULTS

This study produced two sets of results: one set of results omits controls for sample selectivity and one set ofresults controls for sample selection using the maximum likelihood estimation of Heckman's sample selection model. Both sets of results can be found in the Appendices; Appendix C contains results without sample selectivity controls and Appendix D contains results with sample selectivity controls. The results section is divided as follows. Section 5.1 compares the two sets of results, discussing the changes in the estimates when accounting for *sample selection bias*. Section 5.2 discusses the point estimates for individual states using the results without controls for sample selectivity. Finally, Section 5.3 examines the level of variation in the gender pay gap and level of gender discrimination across states over the past thirty years using results without controls for sample selectivity.

5.1 Comparison of Results With and Without Sample Selectivity Controls

Table 3 contains a comparison of the results controlling and not controlling for sample selectivity for the U.S for all six time periods. Chart 1provides a visual depiction of the difference in the gender pay gap estimates. The results in Table 3 suggest that sample selectivity has a small impact on the magnitude of the gender pay gap and the magnitude of

[2]The main challenge in the compilation of the data used for this project was the need to create extraction data scripts in order to assemble a dataset of variables needed for this analysis. This data extraction was conducted using scripts provided by the National Bureau of Economic Research through 1989; however, all of the scripts for 1980-1988 were written manually. This was a time consuming process of extracting household, family, and personal variables and then combining all three types for each record.

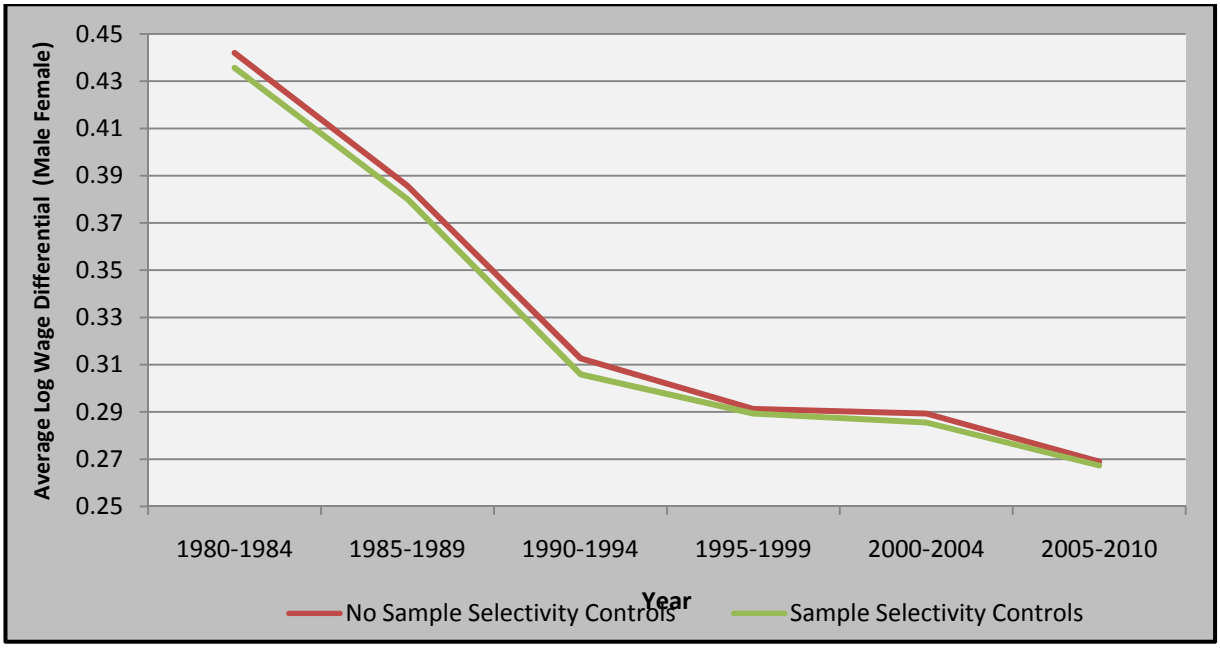
gender discrimination. For the U.S. model, not controlling for sample selection positively biased the results for all time periods, suggesting that the magnitude of the gender pay gap was overstated.[3]However, Chart 3 shows the difference between the two sets of results has decreased over time, suggesting that *sample selection bias* decreased over the past thirty years.

Table 3: Results With and Without Sample Selectivity Controls, U.S. Model

Year	Average Pay Gap (Male-Female)			Average Discrimination (Male-Female)		
	No Sample Selectivity	Sample Selectivity	Difference	No Sample Selectivity	Sample Selectivity	Difference
1980-1984	0.4420	0.4357	0.0064	0.3929	0.3868	0.0062
1985-1989	0.3857	0.3801	0.0056	0.3800	0.3747	0.0054
1990-1994	0.3127	0.3059	0.0067	0.3382	0.3318	0.0065
1995-1999	0.2913	0.2893	0.0020	0.2933	0.2914	0.0019
2000-2004	0.2893	0.2855	0.0038	0.2864	0.2827	0.0037
2005-2010	0.2690	0.2673	0.0017	0.2345	0.2329	0.0016

Source: Author's estimation using data from the Current Population Survey
Note: All estimates are reported in log-points.

Chart 1: Gender Pay Gap With and Without Sample Selectivity Controls, U.S. Model



Source: Author's estimation using data from the Current Population Survey.

[3]The Inverse Mills Ratio was statistically significant at the 5% level for the U.S. Model over all time periods.

Table 4lists the five states with the largest difference in the change in discrimination over the periods 1980-1984 and 2005-2010 between the two models. Table 5 displays the same information for the gender pay gap. Appendix E presents the information in Tables 4 and 5 for all states. It is important to note that the average difference between the two models for both the level of discrimination and magnitude of the gender pay gap is 0.01, meaning that the model estimates for the majority of states are consistent with the U.S. model. It is likely that the problem with the states listed below is a result of issues with the sample selection model. When conducting analysis on why these differences existed, it was determined that the number of censored observations (number of individuals in the labor force without an observed wage or unemployed individuals) as a proportion of those in the labor force was much higher than the unemployment rate for these states. This can cause the model to not perform as expected and appears to be a data collection error that cannot be corrected. It is possible that oversampling of unemployed individuals occurred in these states.

Table 4: Changes in Discrimination for Both Models: Selected States, 1980-2010

State	No Sample Selectivity Model	Sample Selectivity Model	Difference
	1980-1984 Discrimination Level - 2005-2010 Discrimination Level	1980-1984 Discrimination Level - 2005-2010 Discrimination Level	
MO	0.09	-0.02	0.12
NE*	0.06	-0.04	0.11
IL	0.19	0.10	0.09
OK	0.13	0.05	0.08
KS	0.26	0.18	0.08
Average	0.15	0.14	0.01

Source: Author's estimation using data from the Current Population Survey
Note: All estimates are reported in log-points.
* Estimations are conducted using 1985-1989 data due to issues with the 1980-1984 data (large number of censored observations).

Table 5: Changes in Gender Pay Gap for Both Models: Selected States, 1980-2010

State	No Sample Selectivity Model	Sample Selectivity Model	Difference
	1980-1984 Discrimination Level - 2005-2010 Discrimination Level	1980-1984 Discrimination Level - 2005-2010 Discrimination Level	
MO	0.15	0.04	0.11
NE*	0.15	0.06	0.09
IL	0.19	0.10	0.09
OK	0.17	0.09	0.08
KS	0.16	0.09	0.08
Average	0.16	0.15	0.01

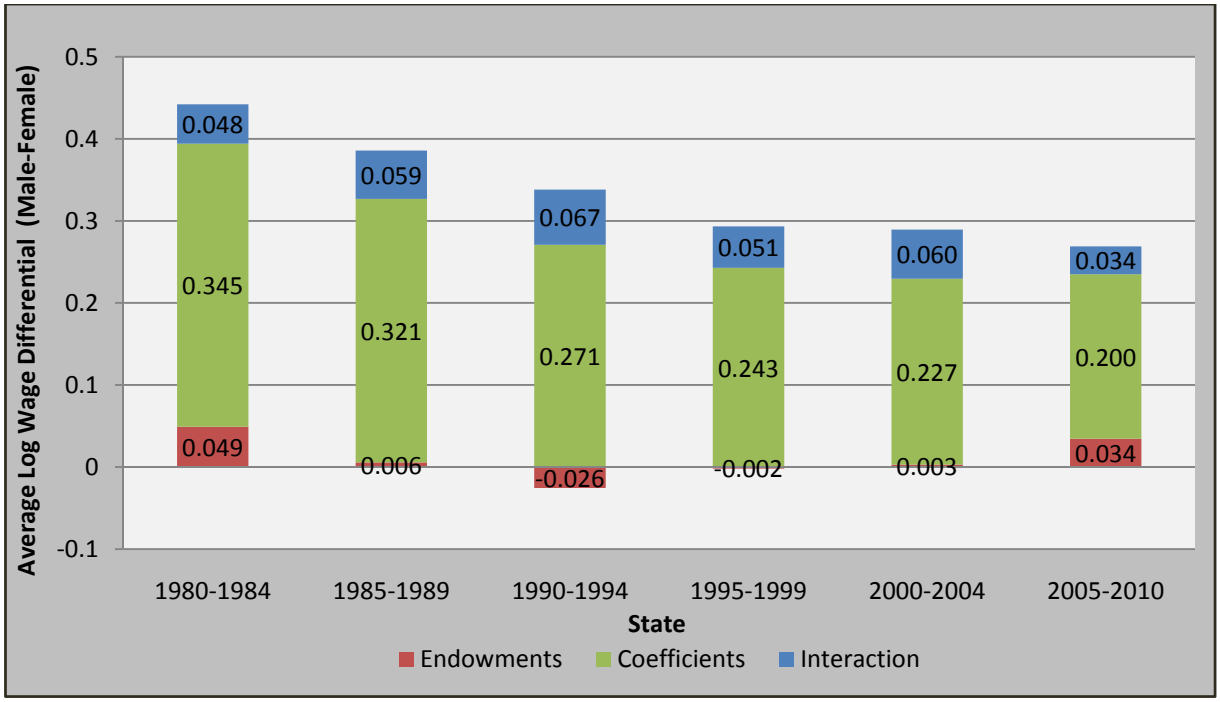
Source: Author's estimation using data from the Current Population Survey
Note: All estimates are reported in log-points.
* Estimations are conducted using 1985-1989 data due to issues with the 1980-1984 data (large number of censored observations).

The remainder of this section discusses results omitting controls for sample selection bias as these estimates appear to be more consistent over time. In addition, differences between the point estimates of the gender pay gap and level of discrimination for the two sets of results are not statistically significant for the majority of states.

5.2Analysis of National Level Gender Pay Gap and Discrimination

Chart 2 displays the decomposition components of the gender pay gap for the United States over the period 1980-2010. In the United States, the average gender pay gap fell 0.173 log points from 0.442 log points over the period 1980-1984 to 0.269 log points over the period 2005-2010. When isolating the portion of the gender pay gap that is regarded as discrimination, defined as the sum of coefficient and interaction terms, the results show a decrease of 0.159 log points over this thirty year period. The reduction in discrimination represented that largest proportion of the closing gender pay gap for the United States. The gender pay gap also narrowed minimally due to explained variations, or the endowment portion of the gender pay gap.

Chart 2: U.S. Gender Pay Gap Components, 1980-2010



Source: Author's estimation using data from the Current Population Survey.
Note: All estimates are reported in log-points.

One possible explanation for convergence in explained variation is the fact that the mean years of education for woman is now greater than that for men (See Appendix B). Women's mean years of education was slightly lower than the mean years of education for men over the period 1980-1984; however, over the period 2005-2010 the average years of education was 0.2 years higher for women than for men. The endowment component of the gender pay gap fell from 0.049 log points over the period 1980-1984 to 0.034 over the period 2005-2010.

The tables in Appendix C, displaying wage differentials for all states, support the existing literature that the narrowing of the gender pay gap seems to have slowed since the mid 1990's (Blau and Kahn, 2004). The United States gender pay gap fell by 0.129 log points over the period 1980-1994. However, over the period 1995-2010 the gender pay gap closed only 0.022 log points from a value of 0.291 log points over the period 1995-1999 to a value of 0.269 log points over the period 2005-2010.

While discrimination accounts for the largest proportion of the gender pay cap, it accounted for a slightly smaller proportion of the gender pay over the period 2005-2010 when compared to the results over the period 1980-1984. Over the period 1980-1984 discrimination accounted for 88.9% of the gender pay gap, while it accounted for only 87.2% of the gender pay gap over the period 2005-2010.

5.3 Analysis of State Level Gender Pay Gap and Discrimination

Table 6 reports the five states with the lowest and the five states with the highest wage differentials over the period 2005-2010; Table 7 reports the same results over the period 1980-1984 (See Table C1 in the appendix for information on all states 2005-2010 and Table C6 in the appendix for the period 1980-1984).

Table 6: States With Lowest/Highest Wage Differentials: 2005-2010

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Prediction	Difference	Blinder Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
Top Five States With Lowest Wages Differentials							
1	CA	3.052	2.853	0.200	-0.030	0.176	0.054
2	DE	3.036	2.818	0.218	0.025	0.165	0.029
3	VT	2.979	2.759	0.220	0.027	0.199	-0.006
4	NV	3.001	2.778	0.223	0.005	0.184	0.034
5	ME	2.937	2.713	0.225	-0.008	0.137	0.095
Top Five States With Highest Wages Differentials							
46	ID	2.940	2.618	0.322	0.163	0.251	-0.091
47	MI	3.096	2.765	0.331	0.120	0.220	-0.009
48	UT	3.073	2.694	0.379	0.129	0.255	-0.005
49	LA	3.033	2.639	0.394	0.176	0.281	-0.063
50	WY	2.986	2.587	0.398	0.081	0.272	0.045
	US AVG	3.030	2.761	0.269	0.034	0.200	0.034

Source: Author's estimation using data from the Current Population Survey
Note: All estimates are reported in log-points.

Table 7: States With Lowest/Highest Wage Differentials: 1980-1984

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Prediction	Difference	Blinder Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
Top Five States With Lowest Wages Differentials							
1	ND	2.661	2.316	0.344	0.003	0.243	0.098
2	AR	2.622	2.269	0.353	-0.071	0.342	0.082
3	SC	2.671	2.316	0.355	0.030	0.224	0.101
4	ME	2.713	2.353	0.360	0.062	0.282	0.016
5	NC	2.707	2.341	0.367	0.063	0.296	0.007
Top Five States With Highest Wages Differentials							
46	PA	2.979	2.465	0.514	0.073	0.386	0.054
47	IN	2.933	2.419	0.514	0.116	0.369	0.029
48	MI	3.039	2.521	0.518	0.101	0.357	0.059
49	UT	2.908	2.386	0.523	0.089	0.425	0.009
50	WY	2.917	2.378	0.538	0.106	0.394	0.038
	US AVG	2.897	2.455	0.442	0.049	0.345	0.048

Source: Author's estimation using data from the Current Population Survey
Note: All estimates are reported in log-points.

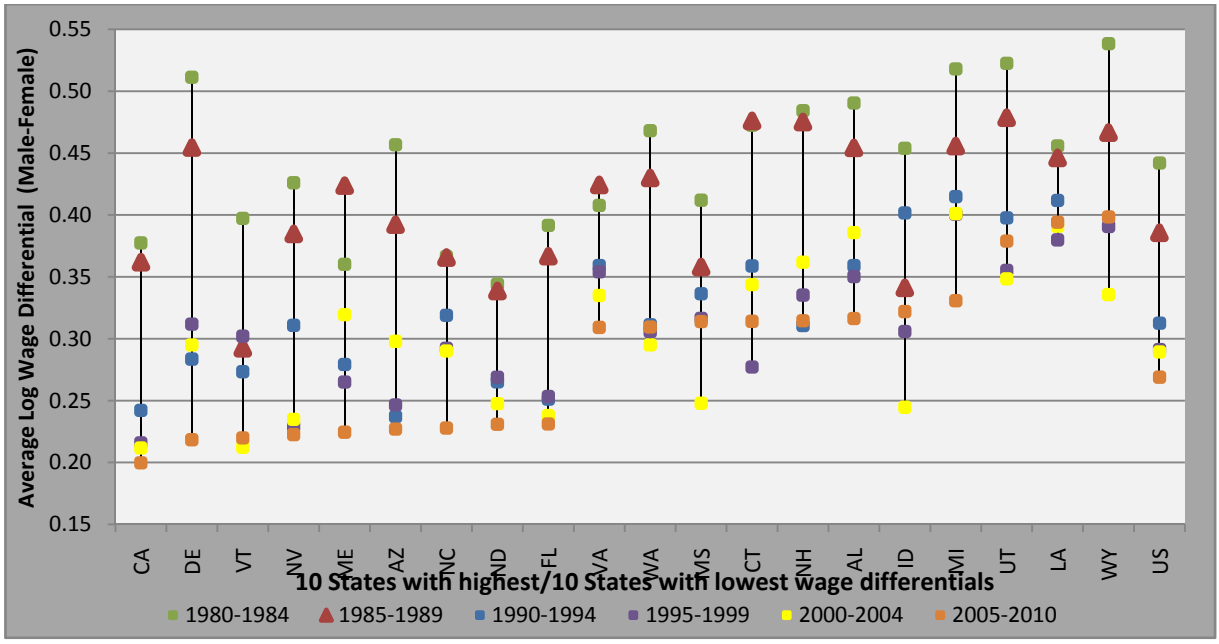
The estimates in these tables provide evidence of the significant variation in the gender pay gap across U.S. States. Over the period 1980-1984, Wyoming was the state that faced the largest gender pay gap of 0.538 log points. On the other hand, North Dakota was the state that had the lowest gender pay gap over this period of 0.344 log points. The difference between the estimates for these two states yields a sizeable range of 0.194 over the period 1980-1984. Over the period 2005-2010, Wyoming was still the state with the highest gender pay gap of .398 log points and California was the state with the lowest gender pay gap of .200 log points. The range between states remains close to its 1980-1984 level at.198 log points over the period 2005-2010. This information helps draw the conclusion that while the size of the gender pay gap narrowed for all states over the past thirty years, disparity across states still persists.

Upon further examination of the state level data, it is important to note there has been substantial movement amongst states that had the highest and lowest gender pay gap over the period 1980-1984. This information may provide useful insight to determine whether state level policies or labor market changes over the past thirty years resulted in significant changes

in the size of individual state's gender pay gap. Only one of the top five states facing the lowest gender pay gap over the period 1980-1984, Maine, is still in the top five over the period 2005-2010. One the other hand, three states, Michigan, Utah, and Wyoming,that faced the largest gender pay gap over the period 1980-1984 and are still in the bottom five over the period 2005-2010. This suggests that these states have made little progress in addressing the level of gender discrimination faced by workers over the past thirty years.

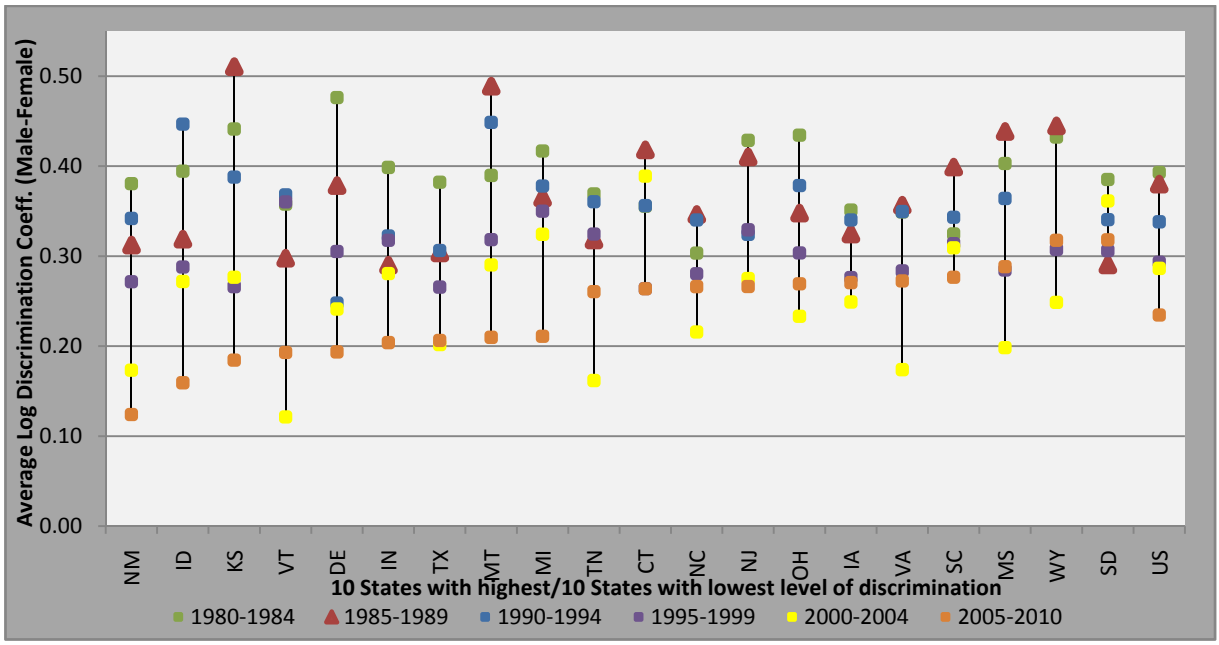
Table 8 displays the top five states with the largest reduction in discrimination and the five states with the smallest reduction in discrimination over the period 1980-2010. Table 9 displays the same information focusing on the gender pay gap as a whole. This information supports the conclusion that the level of the gender pay gap and gender discrimination decreased for all states over the period 1980-2010. Chart 3 and Chart 4 depict the finding that although all states experienced reductions in the gender pay gap and level of discrimination, there were wide variations in the narrowing of both over the past thirty years. A larger line represents a larger reduction in the gender pay gap/ level of discrimination over the thirty year period.

Chart 3: Wage Differential Trend: Selected States, 1980-2010



Source: Author's estimation using data from the Current Population Survey

Chart 4: Discrimination Level Trend: Selected States, 1980-2010



Source: Author's estimation using data from the Current Population Survey

Table 8: States With Lowest/Highest Discrimination Reduction

State	Rank 1980-1984 (1=Lowest Discrimination)	Rank 2005-2010 (1=Lowest Discrimination)	Discrimination Level 1980-1984	Discrimination Level 2005-2010	Difference
Top Five States With Smallest Discrimination Reduction					
NC	2	42	0.303	0.266	0.037
SC	4	47	0.325	0.276	0.048
ME	1	23	0.298	0.232	0.066
SD	22	50	0.385	0.318	0.067
RI	3	30	0.312	0.244	0.068
Top Five States With Largest Discrimination Reduction					
OR	47	10	0.459	0.216	0.243
CO	49	20	0.475	0.230	0.245
NM	19	1	0.381	0.124	0.257
KS	45	3	0.441	0.184	0.257
DE	50	5	0.476	0.194	0.282
US			0.393	0.235	0.158

Source: Author's estimation using data from the Current Population Survey
Note: All estimates are reported in log-points.

Table 9: States With Lowest/Highest Gender Pay Gap Reduction

State	Rank 1980-1984 (1=Smallest Gender Pay Gap)	Rank 2005-2010 (1=Smallest Gender Pay Gap)	Gender Pay Gap1980-1984	Gender Pay Gap 2005-2010	Difference
Top Five States With Smallest Gender Pay Gap Reduction					
LA	27	49	0.456	0.394	0.062
SC	3	22	0.355	0.269	0.086
MS	16	42	0.412	0.314	0.098
VA	15	40	0.408	0.309	0.099
RI	7	19	0.378	0.266	0.112
Top Five States With Largest Gender Pay Gap Reduction					
CO	38	21	0.486	0.269	0.218
WI	43	27	0.508	0.285	0.223
IN	47	28	0.514	0.286	0.228
AZ	28	6	0.457	0.227	0.230
DE	45	2	0.511	0.218	0.293
US			0.442	0.269	0.173

Source: Author's estimation using data from the Current Population Survey
Note: All estimates are reported in log-points.

Table 8 shows that Delaware is the state with the largest reduction in gender discrimination over the period 1980-2010, falling by .282 log points. Delaware's rank in terms of the level of discrimination faced changed from fifty, the state facing the largest level of discrimination, to number five over the period 2005-2010.In contrast, North Carolina experienced the smallest change in discrimination over the period 1980-2010 with a reduction of 0.037 log points.

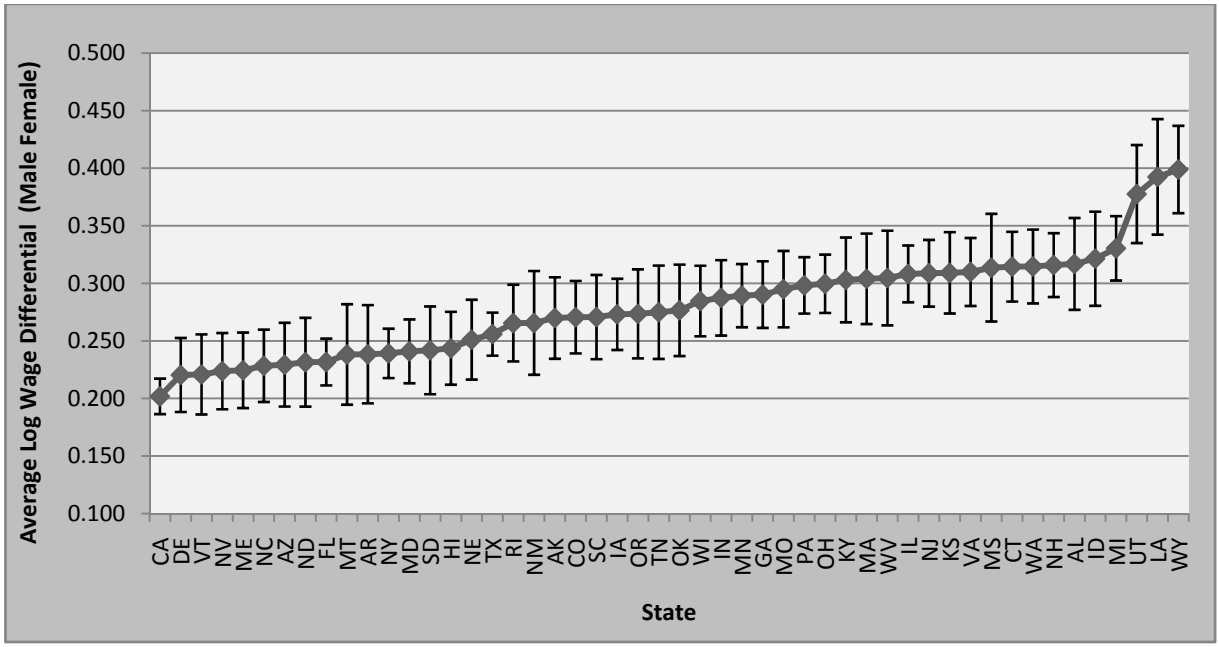
Table 9 shows that Louisiana was the state with the smallest decrease in the gender pay gap of .063 log points over the past thirty years. Delaware also experienced the largest reduction in the gender pay gap, decreasing .293 log points over the past thirty years. In terms of rank according to the gender pay gap, Louisiana moved from position twenty-seven over the period 1980-1985 to position forty-nine over the period 2005-2010. Delaware, on the other hand, moved from position forty-five to position two.

The gender pay gap rank order of states drastically changed over the past thirty years as shown in Table 7. Delaware was the state with the most favorable movement, ranking as number forty-five over the period 1980-1984 to number two over the period 2000-2005.

Three states, Louisiana, Mississippi, and Virginia experienced jumps in the opposite direction, falling twenty or more positions over this time period. Louisiana was ranked number twenty-seven over the period 1980-2985 and is now in position forty-nine. Virginia and Mississippi moved twenty-five and twenty-six spots respectively in an unfavorable direction. On average, each state's gender pay gap rank changed approximately ten positions over the past thirty years.

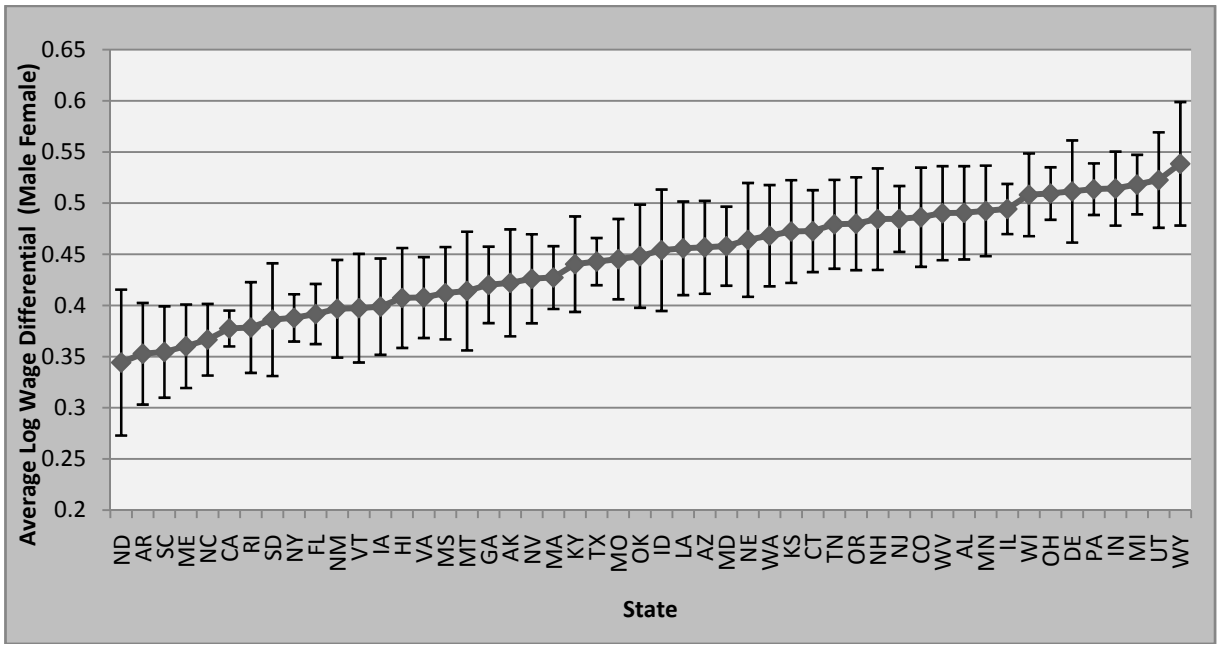
Charts 5 and 6 depict one on the limitations arising from this study, lack of precision in the point estimates of the gender pay gap. Chart 5 depicts the confidence interval for estimates over the period 2005-2010, while Chart 6 depicts the same information over the period 1980-1984. State gender pay gap confidence intervals over the period 2005-2010 are on average 0.07 log points, while the interval was on average .09 log points over the period 1980-1984.

Chart 5: Average Log Wage Differentials (Males - Females), 2005-2010



Source: Author's estimation using data from the Current Population Survey

Chart 6: Average Log Wage Differentials (Males - Females), 1980-1984

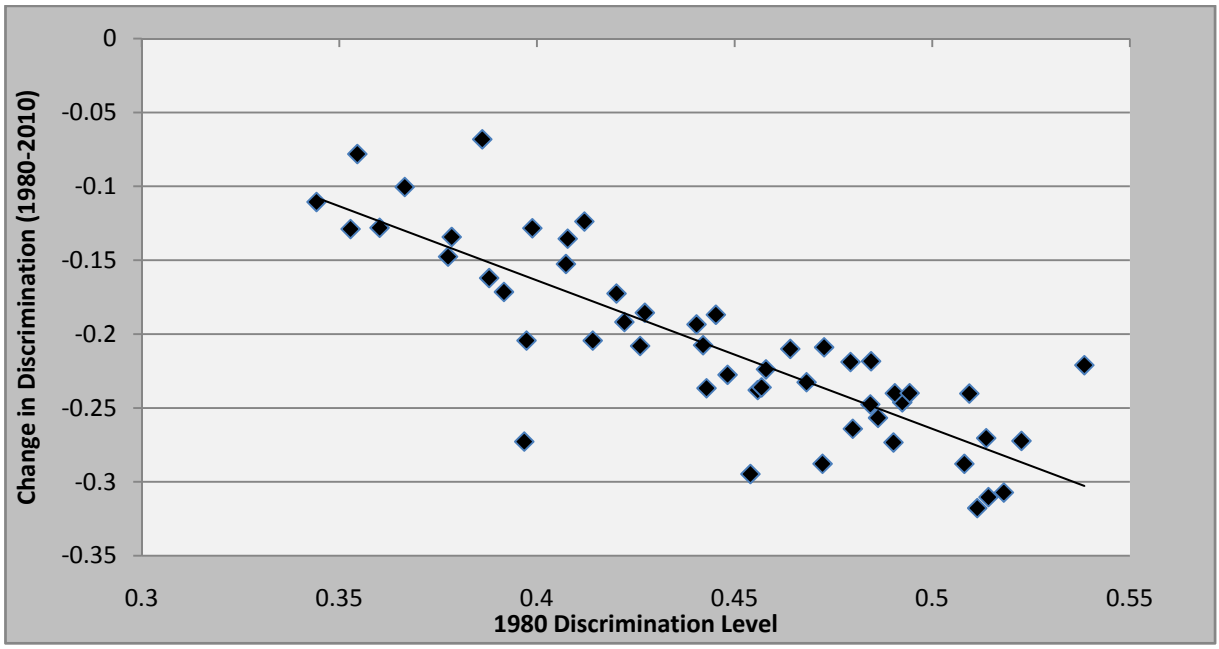


Source: Author's estimation using data from the Current Population Survey

5.4 Variations in the Gender Pay Gap and Gender Discrimination

The final goal of this paper was to determine whether there has been convergence in the variation of discrimination and the gender pay gap across U.S. States over the past thirty years. Chart 7visually depicts the fact that states with a larger level of discrimination over the period 1980-1984 experienced larger reductions in discrimination over the past 30 years. This pattern suggests that convergence may have occurred over the past thirty year as the states suffering from high levels of discrimination may have "caught up" or converged in relation to other states over the period 1980-2010.

Chart 7: Discrimination Reduction and Convergence, 1980-2010



Source: Author's estimation using data from the Current Population Survey

Analyzing the standard deviation of the discrimination coefficients over time is a more quantitative measure to determine whether convergence in the gender pay gap and level of discrimination among states has occurred. Table 10 shows that the variation in the gender pay gap and in the level of gender discrimination has decreased over the past thirty years. Despite the range between the states facing the highest and lowest gender pay gap remaining relatively constant, as described in Section 5.3, it appears that the variation in the level of gender discrimination and the gender pay gap decreased over the past thirty years.

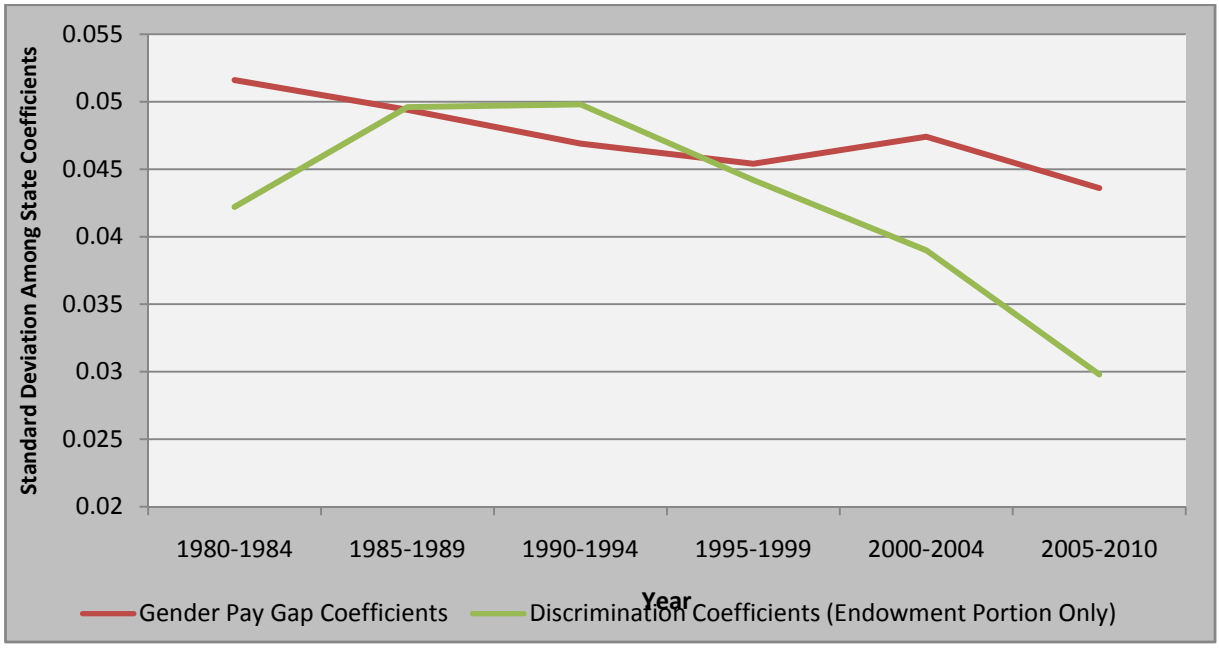
Table 10: Standard Deviation of State Gender Pay Gap and Discrimination Coefficients

	Standard Deviation of State Coefficients	
	Gender Pay Gap Coefficients	Discrimination Coefficients (Endowment Portion Only)
1980-1984	0.0516	0.0422
1985-1989	0.0494	0.0496
1990-1994	0.0469	0.0498
1995-1999	0.0454	0.0442
2000-2004	0.0474	0.0390
2005-2010	0.0436	0.0298

Source: Author's estimation using data from the Current Population Survey

Chart 8 provides a visual depiction of the standard deviation of the state gender pay gap and discrimination coefficients. The chart helps draw the finding that variation in the level of discrimination faced across U.S. States is converging faster than the pay gap itself. However, variation in both the gender pay gap and level of discrimination across U.S. States has converged over the past thirty years.

Chart 8: Standard Deviation of State Gender Pay Gap and Discrimination Coefficients



Source: Author's estimation using data from the Current Population Survey

6. CONCLUSION

This paper uses CPS data to examine the magnitude and trends of the gender pay gap and discrimination faced by workers across U.S. States. This paper provides evidence that the average hourly gender pay gap in the United States fell from 0.442 log points over the period 1980-1984 to 0.269 log points over the period 2005-2010. In other words, the female/male hourly pay ratio increased from 64.3% over the period 1980-1984 to 76.4% over the period 2005-2010. The Oaxaca methodology suggests that reduction in discrimination over this period accounted for the majority of the closing gender wage gap, decreasing by 0.159 log points over the thirty year period. Over the period 1980-1984 discrimination accounted for 88.9% of the gender pay gap, while it accounted for only 87.2% of the gender pay gap over the period 2005-2010. The explained portionof the wage gap narrowed over this period, accounting for 0.034 log points of the gender pay gap over the period 2005-2010, compared to 0.049 log points over the period 1980-1984.

This paper also provides a ranking of U.S. states in terms of the gender pay gap and level of discrimination. Some states experienced a large closing of the gender pay gap over the past thirty years, such as Delaware, where the gap closed by 0.293 log points. Louisiana, on the other hand, had the smallest reduction in the gender pay gap of 0.062 log pointsover the same period. Delaware is also the state with the largest reduction in discrimination, which decreased 0.282 log points from 1980-1984 to 2005-2010.

Analysis at the state level provides evidence that there is a significant amount of variation in discrimination across U.S. states. The difference between the state with the largest gender pay gap and the smallest gap was 0.194 log points over the period 1980-1984 and 0.198 log points over the period 2005-2010, suggesting that the range of the gender pay gap remained relatively constant over time. However, the variance in the level of discrimination across U.S. states decreased significantly over the thirty year period. The standard deviation in state discrimination coefficients fell from 0.0422 log points over the period 1980-1984 to 0.0298

over the period 2005-2010. This suggests that the level of discrimination across states has converged substantially over the past thirty years.

The main limitation of this study is the restriction imposed that the empirical model was the same across all U.S. states. An approach that would develop an empirical model for each could state improve the precision of the estimates. Moreover, unreliable estimates were obtained for a few states (e.g. Montana, Nebraska, Illinois) in the set of estimates using the Heckman correction for sample selection.Therefore, further investigation of these anomalies for approximately nine states is required.

This paper does provide measures of the magnitude of gender discrimination across states, but it does not aim to explain why there are large variations in discrimination. For example, three of states with the smallest gender pay gap (California, Maine, and Vermont) adopted state level family medical leave laws which may reduce the level of discrimination faced by workers in these states. On the other hand, a state like Michigan, which faced one of the largest gender pay gaps over the past thirtyyears, has a large male-dominated manufacturing sector. Therefore, areas for further research include developing a model which explains variations in the level of gender discrimination across the U.S. This type of analysis could provide important insights regarding the factors determining discrimination and what could be done to reduce discrimination across U.S. States.

APPENDICES

Appendix A:Description of 2010 CPS Variables Names and Descriptions

Household Record

Variable Description	Variable Name
1960 Census State Code	GESTCEN
Child care while working, anyone	HRPAIDCC
Children receiving free or reduced lunch prices	HFLUNCH
Disability Income	HDISVAL
Energy Assistance Income	HENGVAL
FIPS State Code	GESTFIPS
Food Stamps Value	HFDVALUE
Household earnings, total value	HHEARNVAL
Household Income	HOIVAL
Number of Persons in Household	H-NUMPER
Persons in Household age 5 to 18	HH5TO18
Public Assistance Income	HPAWVAL
Public Housing Project	HPUBLIC
Type of household	H-HHTYPE
Unemployment Compensation Income	HUCVAL
Wages and Salaries Value	HWSVAL

Personal Record

Variable Description	Variable Name
Adjusted Gross Income	AGI
Age	A-AGE
Childcare needed while parent worked	PAIDCCYN
Current earnings- Hourly Pay, value topcoded	A-HERNTF
Current earnings- Weekly Pay, value topcoded	A-WERNTF
Detailed reason for part-time	PRPTREA
Does… want a regular job now, either F/T or P/T	A-WANTJB
Duration of unemployment	A-WKSLK
Educational attainment	A-HGA
Family Type	A-FAMTYP
Full/part-time status	A-WKSTAT
Health Insurance Plan Type	HIEMP
Hourly Earnings	A-HRSPAY
Hours per week usually worked at all jobs	PEHRUSLT
Income, other (amount)	OI-VAL
Industry of longest job	INDUSTRY
Industry of longest job by detailed groups	WEIND
Industry of longest job by major industry group	WEMIND
Is… enrolled as either full-time or part-time student	A-FTPT
Major Industry code	A-MJIND
Major occupation code	A-MJOCC
Private Health Insurance, Including Dependents	COV-HI
Private health insurance plan coverage	HI-YN
Race	PRDTRACE
Reason for not working	RSNNOTW
Reason for unemployment	PRUNTYPE
Sex	A-SEX
Usual hrs worked per week	A-USLHRS
Wage and salary earnings, other, amount	WS-VAL
Weeks worked last year	WEWKRS

Appendix B: Descriptive Statistics

Table 1: Descriptive Statistics, 1980-2010 (Continues)

Variable	2005-2010				2000-2004			
	Male		Female		Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
% With Children Under 6	29.3%	62.7%	24.3%	55.9%	29.0%	62.0%	23.4%	54.4%
% With Children 6-18	63.7%	95.7%	67.8%	95.1%	64.2%	96.6%	69.3%	96.3%
Household Income	$ 91,083	$77,469	$85,626	$73,581	$78,261	$65,544	$73,159	$61,621
Age	42.7	10.4	42.8	10.4	42.1	10.1	42.0	10.0
Hourly Wage (adj for in	$ 26.84	$ 29.46	$20.00	$22.84	$26.34	$28.03	$19.31	$22.53
Years of Education	13.6	3.1	13.8	2.8	13.5	3.1	13.6	2.7
Years of Experience	23.1	10.6	22.9	10.8	22.6	10.4	22.4	10.5
% W/O High School Deg.	10.9%	31.1%	7.4%	26.2%	11.7%	32.2%	8.5%	28.0%
% With High School Deg.	47.0%	49.9%	46.2%	49.9%	48.5%	50.0%	50.0%	50.0%
% With Some College	9.3%	29.0%	12.2%	32.7%	8.6%	28.0%	11.1%	31.4%
% With Bachelor's Deg.	21.0%	40.7%	22.6%	41.8%	20.3%	40.2%	20.5%	40.4%
% With Graduate Deg.	11.8%	32.3%	11.6%	32.0%	10.9%	31.1%	9.8%	29.7%
% White/Caucasian	82.6%	37.9%	79.0%	40.8%	84.6%	36.1%	81.5%	38.9%
% Black	9.4%	29.2%	12.8%	33.4%	8.9%	28.5%	12.1%	32.6%
% Other Non-White	7.9%	27.0%	8.1%	27.3%	6.4%	24.5%	6.4%	24.4%
% Working In Private Ind.	85.9%	34.8%	78.9%	40.8%	86.1%	34.6%	79.2%	40.6%
% Renting Home	25.8%	43.8%	25.7%	43.7%	26.3%	44.0%	26.5%	44.1%
% Living in MSA	80.9%	39.3%	80.2%	39.9%	78.4%	41.1%	77.9%	41.5%
% Married	70.8%	45.4%	63.0%	48.3%	71.4%	45.2%	63.6%	48.1%
Observations	243831		227600		179492		165289	

Variable	1995-1999				1990-1994			
	Male		Female		Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
% With Children Under 6	27.5%	60.5%	22.8%	53.7%	29.3%	62.2%	24.1%	55.2%
% With Children 6-18	57.7%	93.9%	62.8%	94.8%	57.3%	93.5%	61.5%	93.2%
Household Income	$62,849	$51,739	$59,291	$48,899	$50,209	$31,774	$47,708	$31,573
Age	41.3	10.3	41.3	10.2	40.6	10.5	40.4	10.3
Hourly Wage	$23.86	$24.80	$17.28	$20.02	$22.19	$16.71	$16.05	$14.63
Years of Education	13.3	3.2	13.4	2.7	13.2	3.1	13.2	2.7
Years of Experience	21.9	10.7	21.9	10.7	21.4	11.0	21.2	10.9
% W/O High School Deg.	13.1%	33.7%	9.6%	29.5%	8.3%	27.5%	6.3%	24.3%
% With High School Deg.	49.8%	50.0%	53.1%	49.9%	36.6%	48.2%	37.9%	48.5%
% With Some College	7.9%	27.0%	9.9%	29.8%	22.1%	41.5%	25.5%	43.6%
% With Bachelor's Deg.	18.9%	39.2%	19.0%	39.3%	15.9%	36.6%	15.8%	36.5%
% With Graduate Deg.	10.3%	30.4%	8.4%	27.7%	12.3%	32.8%	10.6%	30.8%
% White/Caucasian	87.4%	33.1%	84.5%	36.2%	88.0%	32.5%	85.6%	35.1%
% Black	7.6%	26.5%	10.4%	30.6%	7.6%	26.5%	10.1%	30.1%
% Other Non-White	5.0%	21.7%	5.1%	21.9%	3.8%	19.2%	3.9%	19.3%
% Working In Private Ind.	85.8%	34.9%	79.6%	40.3%	84.4%	36.3%	78.6%	41.0%
% Renting Home	29.6%	45.6%	29.3%	45.5%	30.7%	46.1%	31.2%	46.3%
% Living in MSA	78.5%	41.1%	78.2%	41.3%	76.9%	42.1%	76.3%	42.6%
% Married	70.3%	45.7%	63.7%	48.1%	72.0%	44.9%	66.1%	47.3%
Observations	133190		120730		149656		133162	

Source: Author's compilation using data from the Current Population Survey

Table 1: Descriptive Statistics, 1980-2010 (Continued)

Variable	1985-1989				1980-1984			
	Male		Female		Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
% With Children Under 6	30.1%	63.4%	23.5%	54.6%	31.0%	64.4%	22.0%	52.9%
% With Children 6-18	59.3%	94.5%	62.7%	93.9%	67.7%	102.9%	70.1%	101.7%
Household Income	$40,945	$26,046	$38,650	$25,810	$30,105	$17,901	$28,083	$17,969
Age	40.4	10.9	40.0	10.7	40.7	11.3	40.3	11.1
Hourly Wage	$23.18	$17.64	$15.45	$13.90	$22.08	$14.67	$13.92	$12.64
Years of Education	13.1	3.1	13.1	2.6	12.9	3.2	12.8	2.7
Years of Experience	21.3	11.7	20.9	11.5	21.8	12.3	21.5	12.0
% W/O High School Deg.	10.0%	30.0%	7.8%	26.8%	19.8%	39.9%	16.3%	36.9%
% With High School Deg.	31.6%	46.5%	34.9%	47.7%	40.7%	49.1%	50.5%	50.0%
% With Some College	25.5%	43.6%	29.0%	45.4%	13.2%	33.8%	12.9%	33.5%
% With Bachelor's Deg.	14.1%	34.8%	13.3%	33.9%	13.6%	34.3%	11.4%	31.7%
% With Graduate Deg.	13.9%	34.6%	11.4%	31.8%	12.6%	33.2%	9.0%	28.6%
% White/Caucasian	88.9%	31.4%	86.2%	34.5%	89.7%	30.4%	86.8%	33.8%
% Black	7.7%	26.7%	10.4%	30.5%	7.4%	26.1%	9.9%	29.9%
% Other Non-White	3.2%	17.7%	3.4%	18.1%	2.9%	16.9%	3.3%	17.8%
% Working In Private Ind.	83.8%	36.8%	78.4%	41.2%	82.6%	37.9%	76.6%	42.4%
% Renting Home	29.5%	45.6%	30.7%	46.1%	27.0%	44.4%	28.5%	45.2%
% Living in MSA	72.4%	44.7%	72.3%	44.7%	57.8%	49.4%	57.8%	49.4%
% Married	74.8%	43.4%	67.4%	46.9%	78.1%	41.4%	67.0%	47.0%
Observations	146624		123657		153525		119261	

Source: Author's compilation using data from the Current Population Survey

Appendix C: Results Without Sample Selectivity Controls

Chart 1: Average Log Wage Differentials (Males - Females), 2005-2010

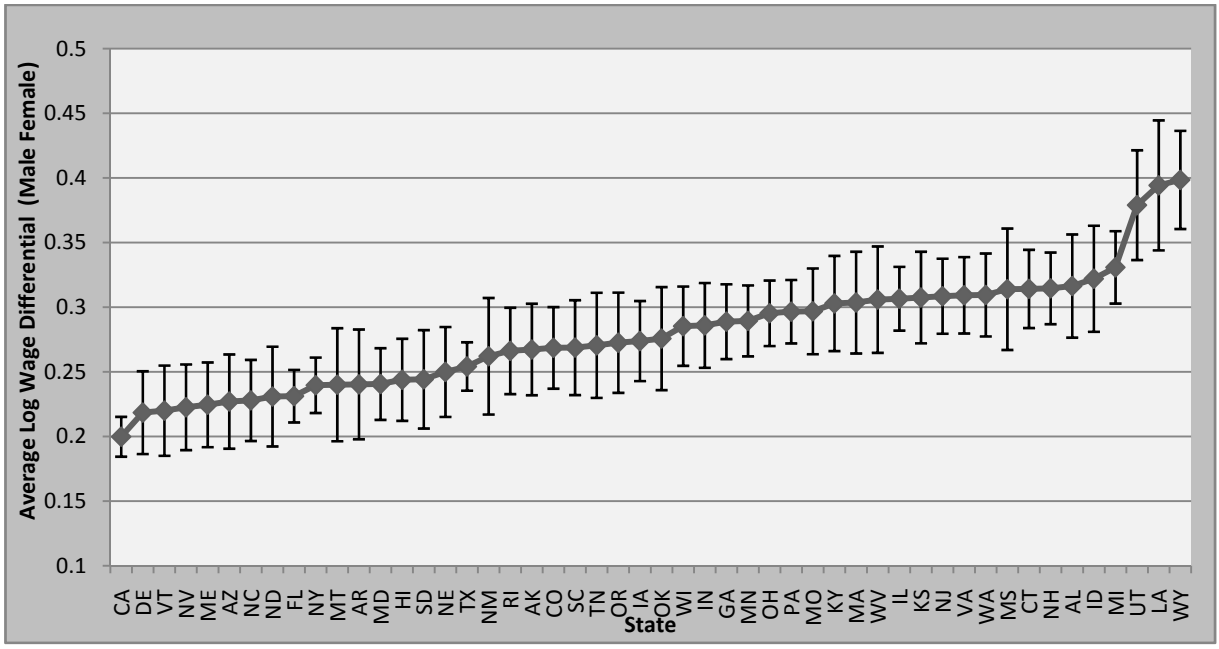


Chart 2: Components of Average Log Wage Differentials (Males-Females), 2005-2010

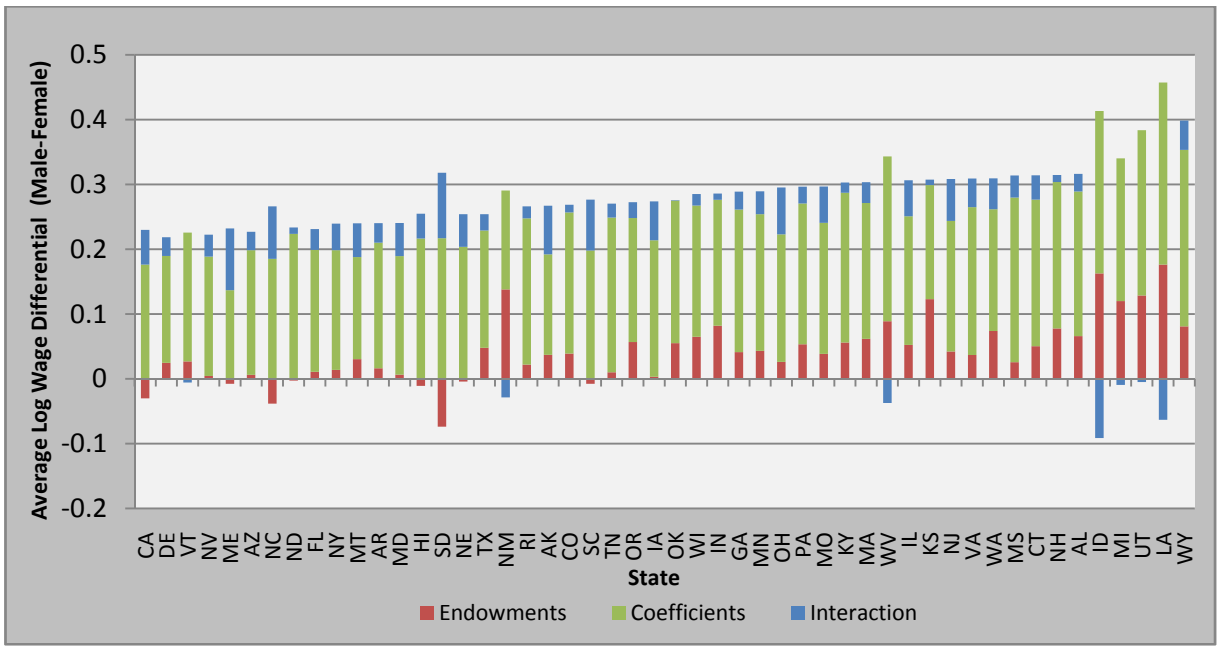


Table 1: Wage Differentials by State, 2005-2010

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	CA	3.052	2.853	0.200	-0.030	0.176	0.054
2	DE	3.036	2.818	0.218	0.025	0.165	0.029
3	VT	2.979	2.759	0.220	0.027	0.199	-0.006
4	NV	3.001	2.778	0.223	0.005	0.184	0.034
5	ME	2.937	2.713	0.225	-0.008	0.137	0.095
6	AZ	2.953	2.726	0.227	0.006	0.192	0.029
7	NC	2.917	2.689	0.228	-0.038	0.185	0.081
8	ND	2.852	2.621	0.231	-0.003	0.224	0.010
9	FL	2.970	2.739	0.231	0.011	0.188	0.032
10	NY	3.080	2.840	0.240	0.014	0.185	0.041
11	MT	2.832	2.592	0.240	0.030	0.158	0.052
12	AR	2.818	2.578	0.240	0.016	0.194	0.030
13	MD	3.176	2.935	0.241	0.006	0.183	0.051
14	HI	2.983	2.739	0.244	-0.011	0.216	0.038
15	SD	2.836	2.592	0.244	-0.074	0.217	0.101
16	NE	2.918	2.668	0.250	-0.004	0.204	0.050
17	TX	2.907	2.653	0.254	0.048	0.181	0.025
18	NM	2.915	2.653	0.262	0.138	0.153	-0.029
19	RI	3.129	2.862	0.266	0.022	0.226	0.019
20	AK	3.112	2.845	0.267	0.037	0.155	0.075
21	CO	3.120	2.852	0.269	0.039	0.218	0.012
22	SC	2.891	2.623	0.269	-0.008	0.198	0.078
23	TN	2.929	2.659	0.270	0.010	0.239	0.022
24	OR	3.004	2.731	0.272	0.057	0.191	0.024
25	IA	2.933	2.659	0.274	0.003	0.211	0.060
26	OK	2.920	2.644	0.276	0.055	0.220	0.001
27	WI	3.031	2.745	0.285	0.065	0.203	0.018
28	IN	3.001	2.716	0.286	0.082	0.194	0.010
29	GA	3.016	2.728	0.289	0.041	0.220	0.027
30	MN	3.111	2.821	0.289	0.043	0.211	0.035
31	OH	3.006	2.711	0.295	0.026	0.197	0.072
32	PA	3.065	2.768	0.297	0.053	0.217	0.026
33	MO	2.991	2.694	0.297	0.038	0.202	0.056
34	KY	2.928	2.625	0.303	0.056	0.231	0.016
35	MA	3.244	2.941	0.304	0.062	0.210	0.032
36	WV	2.906	2.600	0.306	0.089	0.254	-0.037
37	IL	3.088	2.781	0.307	0.052	0.199	0.056
38	KS	2.983	2.676	0.307	0.123	0.176	0.008
39	NJ	3.244	2.935	0.308	0.042	0.201	0.065
40	VA	3.146	2.837	0.309	0.037	0.228	0.044
41	WA	3.140	2.830	0.309	0.074	0.188	0.048
42	MS	2.878	2.564	0.314	0.026	0.254	0.034
43	CT	3.261	2.947	0.314	0.050	0.226	0.038
44	NH	3.176	2.861	0.315	0.078	0.226	0.011
45	AL	2.950	2.634	0.316	0.066	0.223	0.027
46	ID	2.940	2.618	0.322	0.163	0.251	-0.091
47	MI	3.096	2.765	0.331	0.120	0.220	-0.009
48	UT	3.073	2.694	0.379	0.129	0.255	-0.005
49	LA	3.033	2.639	0.394	0.176	0.281	-0.063
50	WY	2.986	2.587	0.398	0.081	0.272	0.045
	US AVG	3.030	2.897	2.897	2.897	2.897	2.897

Chart 3: Average Log Wage Differentials (Males - Females), 2000-2004

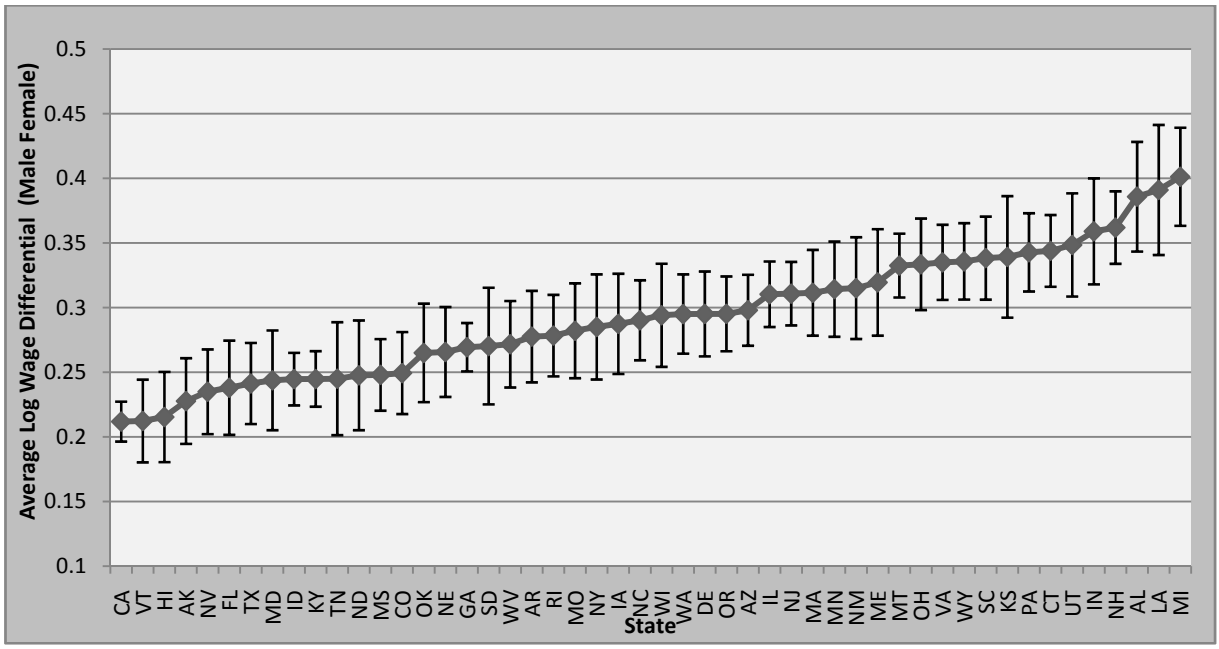


Chart 4: Components of Average Log Wage Differentials (Males-Females), 2000-2004

Table 2: Wage Differentials by State, 2000-2004

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	CA	3.052	2.840	0.212	0.021	0.172	0.019
2	VT	2.947	2.735	0.212	0.091	0.141	-0.020
3	HI	2.976	2.761	0.215	-0.023	0.149	0.089
4	AK	3.051	2.823	0.228	-0.142	0.150	0.220
5	NV	2.967	2.733	0.235	0.103	0.176	-0.044
6	FL	2.946	2.708	0.238	0.030	0.164	0.044
7	TX	2.899	2.658	0.241	0.040	0.177	0.024
8	MD	3.211	2.968	0.244	0.080	0.153	0.010
9	ID	2.824	2.579	0.245	-0.027	0.216	0.056
10	KY	2.928	2.684	0.245	0.072	0.181	-0.008
11	TN	2.949	2.704	0.245	0.083	0.148	0.013
12	ND	2.808	2.561	0.248	-0.004	0.219	0.033
13	MS	2.873	2.625	0.248	0.050	0.221	-0.023
14	CO	3.094	2.845	0.249	-0.007	0.217	0.039
15	OK	2.903	2.638	0.265	0.035	0.215	0.015
16	NE	2.931	2.665	0.266	0.035	0.206	0.025
17	GA	2.977	2.707	0.269	0.029	0.186	0.054
18	SD	2.849	2.579	0.270	-0.091	0.278	0.084
19	WV	2.838	2.567	0.272	0.166	0.201	-0.096
20	AR	2.842	2.565	0.278	-0.050	0.187	0.141
21	RI	3.110	2.831	0.278	0.062	0.187	0.030
22	MO	3.002	2.720	0.282	0.063	0.199	0.020
23	NY	3.104	2.819	0.285	0.039	0.210	0.035
24	IA	2.963	2.676	0.287	0.038	0.251	-0.002
25	NC	2.955	2.665	0.290	0.074	0.193	0.023
26	WI	3.034	2.740	0.294	-0.007	0.251	0.050
27	WA	3.102	2.807	0.295	0.051	0.206	0.038
28	DE	3.068	2.772	0.295	0.054	0.229	0.012
29	OR	2.989	2.694	0.295	0.022	0.192	0.081
30	AZ	3.013	2.715	0.298	-0.018	0.260	0.056
31	IL	3.112	2.801	0.310	0.057	0.224	0.029
32	NJ	3.250	2.939	0.311	0.036	0.193	0.082
33	MA	3.237	2.925	0.311	0.023	0.173	0.115
34	MN	3.172	2.857	0.314	0.054	0.237	0.024
35	NM	2.890	2.575	0.315	0.142	0.189	-0.015
36	ME	2.934	2.614	0.319	0.008	0.228	0.084
37	MT	2.808	2.475	0.333	0.042	0.256	0.034
38	OH	3.069	2.735	0.334	0.100	0.199	0.034
39	VA	3.137	2.802	0.335	0.161	0.239	-0.065
40	WY	2.898	2.562	0.336	0.087	0.266	-0.017
41	SC	2.983	2.645	0.338	0.029	0.278	0.031
42	KS	3.024	2.684	0.339	0.063	0.273	0.004
43	PA	3.135	2.792	0.343	0.104	0.241	-0.001
44	CT	3.270	2.927	0.344	-0.045	0.225	0.163
45	UT	3.017	2.668	0.348	0.126	0.229	-0.006
46	IN	3.067	2.708	0.359	0.078	0.248	0.032
47	NH	3.210	2.849	0.362	0.077	0.209	0.076
48	AL	3.004	2.619	0.386	0.042	0.318	0.026
49	LA	2.955	2.564	0.391	0.102	0.274	0.015
50	MI	3.155	2.754	0.401	0.077	0.236	0.089
	US AVG	3.006	2.897	2.897	2.897	2.897	2.897

Chart 5: Average Log Wage Differentials (Males - Females), 1995-1999

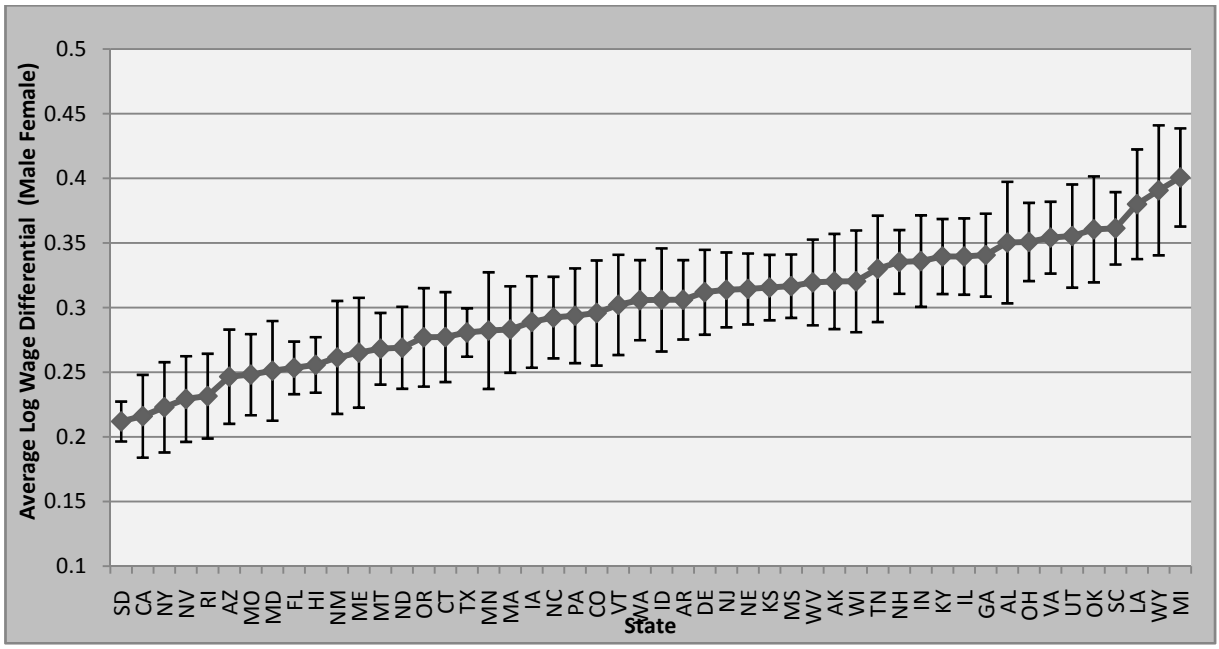


Chart 6: Components of Average Log Wage Differentials (Males-Females), 1995-1999

Table 3: Wage Differentials by State, 1995-1999

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	SD	2.649	2.437	0.212	-0.094	0.273	0.033
2	CA	2.887	2.671	0.216	-0.037	0.199	0.054
3	NY	2.969	2.746	0.223	-0.056	0.201	0.078
4	NV	2.884	2.655	0.229	0.017	0.198	0.014
5	RI	2.953	2.721	0.232	-0.064	0.236	0.059
6	AZ	2.810	2.563	0.247	-0.017	0.208	0.055
7	MO	2.838	2.590	0.248	-0.014	0.199	0.063
8	MD	3.075	2.824	0.251	0.006	0.244	0.001
9	FL	2.818	2.565	0.253	-0.020	0.226	0.048
10	HI	2.890	2.634	0.256	0.007	0.217	0.032
11	NM	2.722	2.461	0.261	-0.010	0.228	0.044
12	ME	2.790	2.525	0.265	-0.079	0.207	0.138
13	MT	2.668	2.399	0.268	-0.050	0.176	0.143
14	ND	2.713	2.444	0.269	-0.016	0.161	0.124
15	OR	2.895	2.618	0.277	-0.021	0.237	0.060
16	CT	3.112	2.835	0.277	0.013	0.169	0.095
17	TX	2.802	2.522	0.281	0.015	0.252	0.014
18	MN	2.959	2.676	0.282	0.021	0.222	0.040
19	MA	3.060	2.777	0.283	0.007	0.184	0.092
20	IA	2.801	2.512	0.289	0.013	0.290	-0.014
21	NC	2.874	2.581	0.292	0.012	0.265	0.015
22	PA	2.960	2.667	0.294	0.011	0.213	0.070
23	CO	2.949	2.653	0.296	0.054	0.259	-0.017
24	VT	2.835	2.533	0.302	-0.058	0.271	0.090
25	WA	2.985	2.679	0.306	-0.005	0.227	0.084
26	ID	2.776	2.470	0.306	0.018	0.313	-0.025
27	AR	2.704	2.398	0.306	0.044	0.260	0.002
28	DE	2.981	2.669	0.312	0.007	0.255	0.050
29	NJ	3.110	2.796	0.314	-0.016	0.222	0.108
30	NE	2.778	2.464	0.314	0.032	0.257	0.025
31	KS	2.856	2.540	0.315	0.049	0.324	-0.058
32	MS	2.756	2.439	0.317	0.032	0.157	0.128
33	WV	2.810	2.491	0.319	-0.016	0.269	0.067
34	AK	3.111	2.791	0.320	-0.044	0.242	0.122
35	WI	2.924	2.604	0.320	0.008	0.268	0.044
36	TN	2.847	2.517	0.330	0.005	0.249	0.075
37	NH	2.992	2.657	0.335	-0.015	0.271	0.080
38	IN	2.902	2.566	0.336	0.018	0.305	0.013
39	KY	2.876	2.536	0.340	0.047	0.304	-0.011
40	IL	3.028	2.688	0.340	-0.018	0.277	0.081
41	GA	2.937	2.596	0.341	0.053	0.300	-0.012
42	AL	2.866	2.516	0.350	0.059	0.300	-0.009
43	OH	2.980	2.630	0.351	0.047	0.256	0.048
44	VA	3.011	2.657	0.354	0.070	0.327	-0.043
45	UT	2.930	2.574	0.355	0.020	0.314	0.021
46	OK	2.838	2.477	0.360	0.029	0.275	0.057
47	SC	2.878	2.516	0.361	0.047	0.321	-0.008
48	LA	2.892	2.512	0.380	0.025	0.275	0.080
49	WY	2.805	2.414	0.391	0.083	0.244	0.064
50	MI	3.049	2.648	0.401	0.051	0.304	0.045
	US AVG	2.909	2.897	2.897	2.897	2.897	2.897

Chart 7: Average Log Wage Differentials (Males - Females), 1990-1994

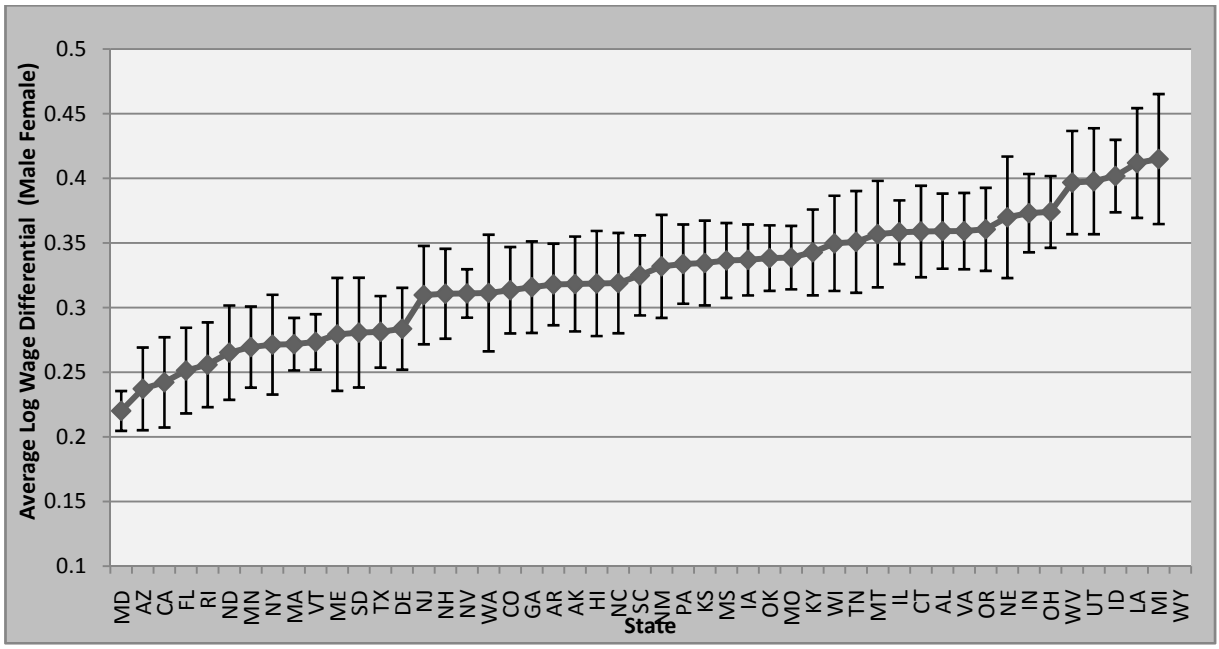


Chart 8: Components of Average Log Wage Differentials (Males-Females), 1990-1994

Table 4: Wage Differentials by State, 1990-1994

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	MD	3.012	2.792	0.220	-0.056	0.142	0.135
2	AZ	2.804	2.567	0.237	-0.020	0.160	0.096
3	CA	2.915	2.673	0.242	-0.054	0.241	0.055
4	FL	2.778	2.526	0.251	-0.025	0.233	0.044
5	RI	2.923	2.667	0.256	-0.070	0.239	0.086
6	ND	2.638	2.373	0.265	-0.055	0.296	0.024
7	MN	2.843	2.573	0.269	-0.040	0.194	0.115
8	NY	3.002	2.731	0.271	-0.063	0.241	0.094
9	MA	3.055	2.783	0.272	-0.022	0.203	0.091
10	VT	2.837	2.564	0.273	-0.095	0.239	0.129
11	ME	2.777	2.498	0.279	-0.088	0.320	0.047
12	SD	2.582	2.301	0.281	-0.060	0.348	-0.007
13	TX	2.744	2.463	0.281	-0.025	0.240	0.066
14	DE	2.923	2.639	0.284	0.036	0.218	0.030
15	NJ	3.111	2.801	0.310	-0.015	0.251	0.073
16	NH	2.993	2.682	0.311	-0.015	0.199	0.127
17	NV	2.881	2.570	0.311	-0.043	0.289	0.065
18	WA	2.967	2.656	0.311	0.020	0.240	0.052
19	CO	2.914	2.601	0.313	0.005	0.268	0.041
20	GA	2.872	2.556	0.316	-0.046	0.251	0.111
21	AR	2.672	2.354	0.318	-0.008	0.295	0.030
22	AK	3.091	2.773	0.318	-0.003	0.264	0.057
23	HI	2.987	2.668	0.319	-0.017	0.262	0.074
24	NC	2.816	2.497	0.319	-0.021	0.289	0.052
25	SC	2.793	2.468	0.325	-0.018	0.241	0.102
26	NM	2.751	2.419	0.332	-0.010	0.269	0.073
27	PA	2.917	2.584	0.334	-0.021	0.252	0.102
28	KS	2.822	2.487	0.334	-0.053	0.289	0.099
29	MS	2.655	2.319	0.336	-0.028	0.287	0.077
30	IA	2.706	2.369	0.337	-0.003	0.323	0.018
31	OK	2.754	2.416	0.338	-0.004	0.315	0.027
32	MO	2.815	2.476	0.339	-0.017	0.248	0.108
33	KY	2.817	2.474	0.343	-0.035	0.284	0.094
34	WI	2.888	2.538	0.350	0.022	0.299	0.028
35	TN	2.795	2.444	0.351	-0.010	0.281	0.080
36	MT	2.688	2.331	0.357	-0.092	0.297	0.152
37	IL	2.963	2.605	0.358	-0.009	0.304	0.064
38	CT	3.143	2.784	0.359	0.003	0.299	0.057
39	AL	2.776	2.417	0.359	-0.012	0.380	-0.009
40	VA	2.940	2.581	0.359	0.010	0.298	0.051
41	OR	2.885	2.525	0.361	0.014	0.287	0.060
42	NE	2.728	2.358	0.370	-0.020	0.336	0.055
43	IN	2.826	2.453	0.373	0.051	0.245	0.077
44	OH	2.938	2.564	0.374	-0.004	0.303	0.075
45	WV	2.775	2.379	0.397	0.027	0.309	0.061
46	UT	2.930	2.533	0.398	-0.003	0.303	0.098
47	ID	2.708	2.306	0.402	-0.045	0.387	0.059
48	LA	2.832	2.420	0.412	0.055	0.363	-0.006
49	MI	3.001	2.586	0.415	0.037	0.322	0.056
50	WY	0.000	0.000	0.000	0.000	0.000	0.000
	US AVG	2.887	2.897	2.897	2.897	2.897	2.897

Chart 9: Average Log Wage Differentials (Males - Females), 1985-1989

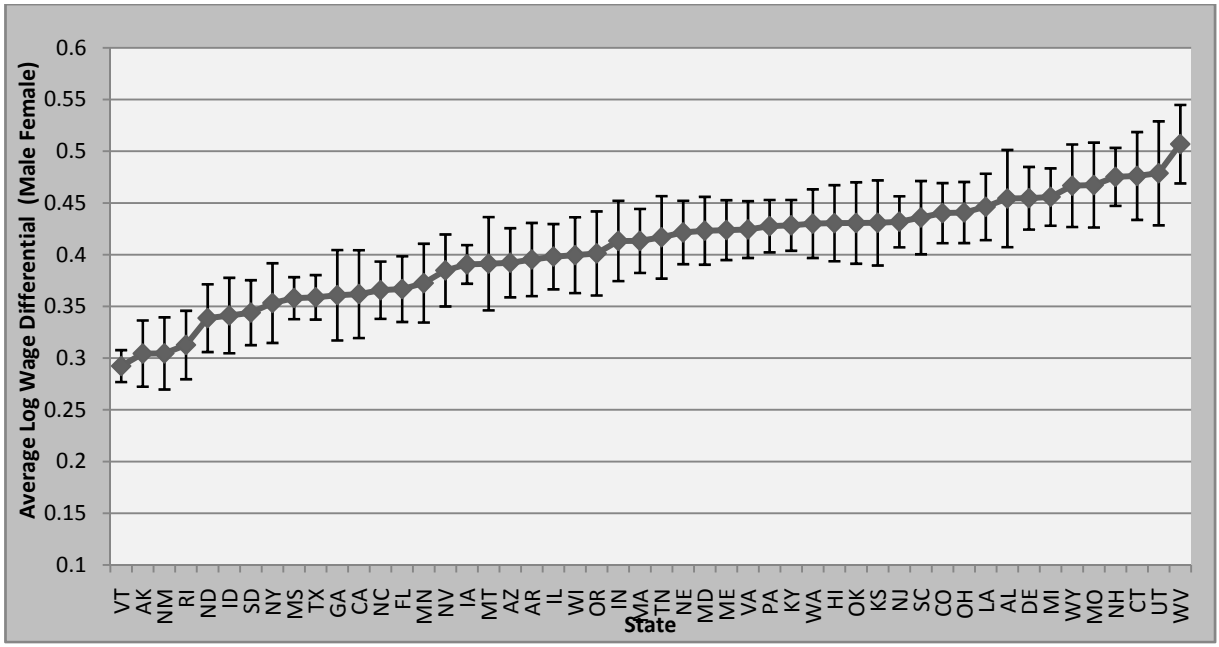


Chart 10: Components of Average Log Wage Differentials (Males-Females), 1985-1989

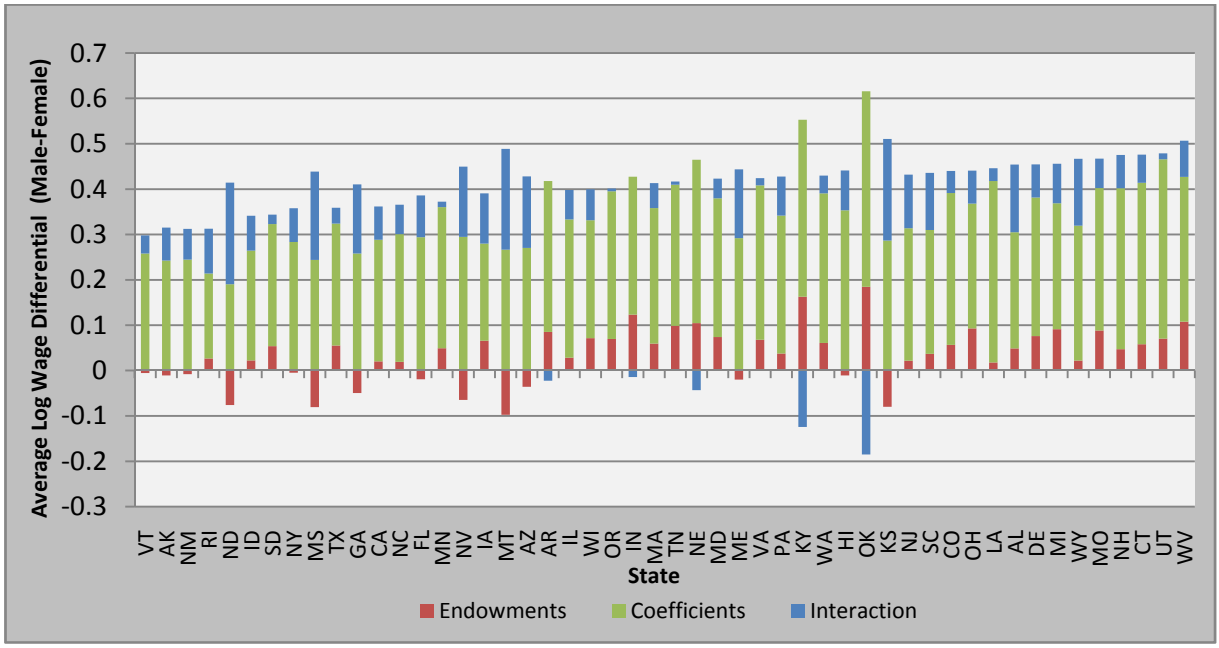


Table 5: Wage Differentials by State, 1985-1989

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	VT	2.756	2.463	0.292	-0.005	0.258	0.040
2	AK	3.214	2.910	0.304	-0.011	0.243	0.073
3	NM	2.752	2.447	0.305	-0.008	0.244	0.068
4	RI	2.904	2.592	0.313	0.027	0.187	0.099
5	ND	2.688	2.350	0.339	-0.076	0.190	0.224
6	ID	2.723	2.382	0.341	0.022	0.242	0.077
7	SD	2.621	2.277	0.344	0.054	0.269	0.021
8	NY	3.023	2.670	0.353	-0.005	0.283	0.075
9	MS	2.684	2.326	0.358	-0.081	0.244	0.195
10	TX	2.870	2.512	0.359	0.055	0.269	0.035
11	GA	2.866	2.505	0.361	-0.050	0.258	0.152
12	CA	3.015	2.653	0.362	0.020	0.268	0.074
13	NC	2.804	2.438	0.366	0.019	0.281	0.065
14	FL	2.833	2.467	0.367	-0.019	0.294	0.092
15	MN	2.932	2.559	0.372	0.049	0.311	0.012
16	NV	2.930	2.545	0.385	-0.065	0.295	0.155
17	IA	2.802	2.412	0.391	0.066	0.214	0.111
18	MT	2.767	2.376	0.391	-0.098	0.267	0.222
19	AZ	2.914	2.522	0.392	-0.036	0.270	0.158
20	AR	2.716	2.321	0.395	0.085	0.333	-0.023
21	IL	3.019	2.621	0.398	0.028	0.305	0.065
22	WI	2.916	2.517	0.400	0.071	0.260	0.068
23	OR	2.934	2.533	0.401	0.070	0.326	0.006
24	IN	2.895	2.481	0.413	0.123	0.304	-0.014
25	MA	3.053	2.640	0.413	0.059	0.299	0.055
26	TN	2.780	2.363	0.417	0.099	0.311	0.007
27	NE	2.805	2.384	0.421	0.105	0.360	-0.043
28	MD	3.080	2.657	0.423	0.074	0.306	0.043
29	ME	2.823	2.399	0.424	-0.020	0.292	0.152
30	VA	2.988	2.563	0.424	0.068	0.340	0.016
31	PA	2.964	2.536	0.428	0.038	0.304	0.086
32	KY	2.814	2.385	0.428	0.163	0.390	-0.125
33	WA	2.988	2.558	0.430	0.061	0.330	0.039
34	HI	2.981	2.550	0.430	-0.011	0.353	0.088
35	OK	2.850	2.419	0.431	0.185	0.431	-0.185
36	KS	2.924	2.493	0.431	-0.080	0.286	0.224
37	NJ	3.108	2.677	0.432	0.022	0.292	0.118
38	SC	2.865	2.429	0.436	0.037	0.273	0.126
39	CO	3.036	2.596	0.440	0.056	0.335	0.049
40	OH	2.997	2.556	0.441	0.093	0.275	0.073
41	LA	2.893	2.447	0.446	0.018	0.400	0.028
42	AL	2.799	2.345	0.454	0.049	0.256	0.149
43	DE	2.984	2.529	0.455	0.076	0.305	0.073
44	MI	3.036	2.581	0.456	0.091	0.278	0.087
45	WY	2.908	2.441	0.467	0.022	0.297	0.147
46	MO	2.907	2.439	0.467	0.088	0.314	0.065
47	NH	2.967	2.492	0.475	0.047	0.355	0.073
48	CT	3.141	2.665	0.476	0.058	0.356	0.062
49	UT	2.963	2.484	0.479	0.070	0.395	0.013
50	WV	2.877	2.370	0.507	0.108	0.319	0.080
	US AVG	2.933	2.897	2.897	2.897	2.897	2.897

Chart 11: Average Log Wage Differentials (Males - Females), 1980-1984

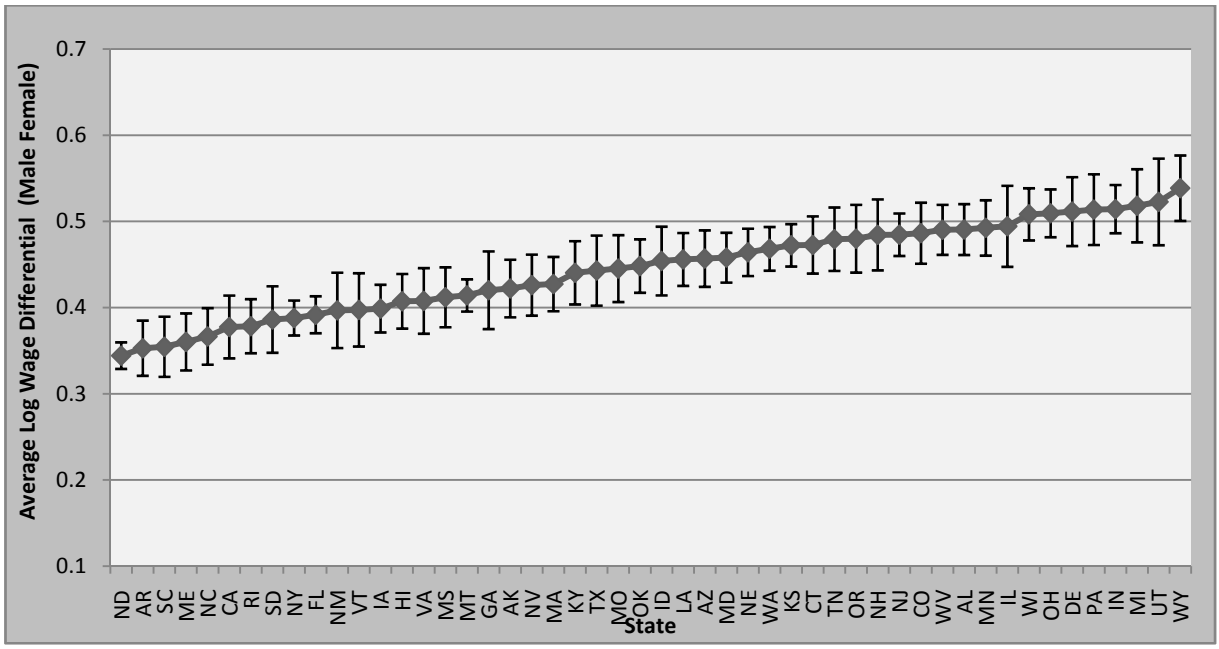


Chart 12: Components of Average Log Wage Differentials (Males-Females), 1980-1984

Table 6: Wage Differentials by State, 1980-1984

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	ND	2.661	2.316	0.344	0.003	0.243	0.098
2	AR	2.622	2.269	0.353	-0.071	0.342	0.082
3	SC	2.671	2.316	0.355	0.030	0.224	0.101
4	ME	2.713	2.353	0.360	0.062	0.282	0.016
5	NC	2.707	2.341	0.367	0.063	0.296	0.007
6	CA	2.960	2.582	0.378	0.046	0.294	0.038
7	RI	2.824	2.445	0.378	0.067	0.289	0.023
8	SD	2.640	2.254	0.386	0.001	0.355	0.030
9	NY	2.941	2.553	0.388	0.004	0.277	0.107
10	FL	2.753	2.361	0.392	0.044	0.319	0.029
11	NM	2.788	2.391	0.397	0.016	0.338	0.042
12	VT	2.699	2.302	0.397	0.040	0.328	0.030
13	IA	2.828	2.429	0.399	0.048	0.336	0.015
14	HI	2.895	2.488	0.407	-0.068	0.318	0.157
15	VA	2.890	2.483	0.408	0.059	0.310	0.039
16	MS	2.689	2.277	0.412	0.009	0.309	0.094
17	MT	2.765	2.351	0.414	0.024	0.313	0.077
18	GA	2.825	2.405	0.420	0.055	0.336	0.030
19	AK	3.188	2.766	0.422	0.022	0.356	0.044
20	NV	2.913	2.487	0.426	-0.010	0.337	0.099
21	MA	2.967	2.539	0.427	0.058	0.336	0.034
22	KY	2.822	2.382	0.440	0.092	0.334	0.015
23	TX	2.838	2.395	0.443	0.061	0.351	0.031
24	MO	2.867	2.421	0.445	0.093	0.343	0.009
25	OK	2.833	2.385	0.448	0.097	0.368	-0.017
26	ID	2.746	2.292	0.454	0.060	0.432	-0.037
27	LA	2.856	2.400	0.456	0.076	0.283	0.097
28	AZ	2.886	2.429	0.457	0.070	0.349	0.038
29	MD	3.064	2.606	0.458	0.051	0.359	0.048
30	NE	2.769	2.305	0.464	0.049	0.404	0.011
31	WA	3.001	2.533	0.468	0.040	0.326	0.102
32	KS	2.850	2.378	0.472	0.031	0.356	0.085
33	CT	3.016	2.544	0.473	0.117	0.324	0.031
34	TN	2.809	2.330	0.479	0.110	0.363	0.006
35	OR	2.911	2.431	0.480	0.021	0.383	0.076
36	NH	2.862	2.378	0.484	0.080	0.352	0.052
37	NJ	3.024	2.539	0.485	0.056	0.392	0.037
38	CO	2.941	2.455	0.486	0.011	0.382	0.093
39	WV	2.886	2.396	0.490	0.074	0.286	0.130
40	AL	2.798	2.307	0.491	0.064	0.337	0.090
41	MN	2.935	2.442	0.492	0.086	0.379	0.028
42	IL	3.046	2.551	0.494	0.048	0.402	0.044
43	WI	2.963	2.455	0.508	0.090	0.363	0.055
44	OH	3.000	2.490	0.509	0.075	0.346	0.089
45	DE	2.969	2.458	0.511	0.035	0.309	0.167
46	PA	2.979	2.465	0.514	0.073	0.386	0.054
47	IN	2.933	2.419	0.514	0.116	0.369	0.029
48	MI	3.039	2.521	0.518	0.101	0.357	0.059
49	UT	2.908	2.386	0.523	0.089	0.425	0.009
50	WY	2.917	2.378	0.538	0.106	0.394	0.038
US AVG	US AVG	2.897	2.455	0.442	0.049	0.345	0.048

Appendix D: Results With Sample Selectivity Controls

Chart 1: Average Log Wage Differentials (Males - Females), 2005-2010

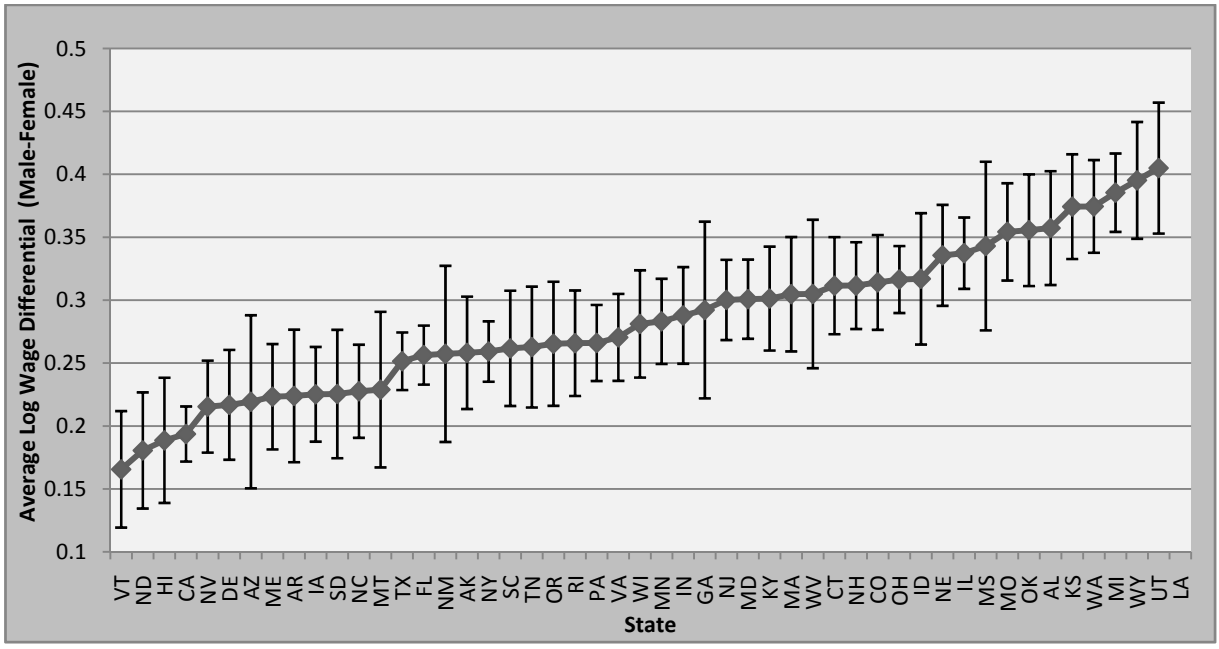


Chart 2: Components of Average Log Wage Differentials (Males-Females), 2005-2010

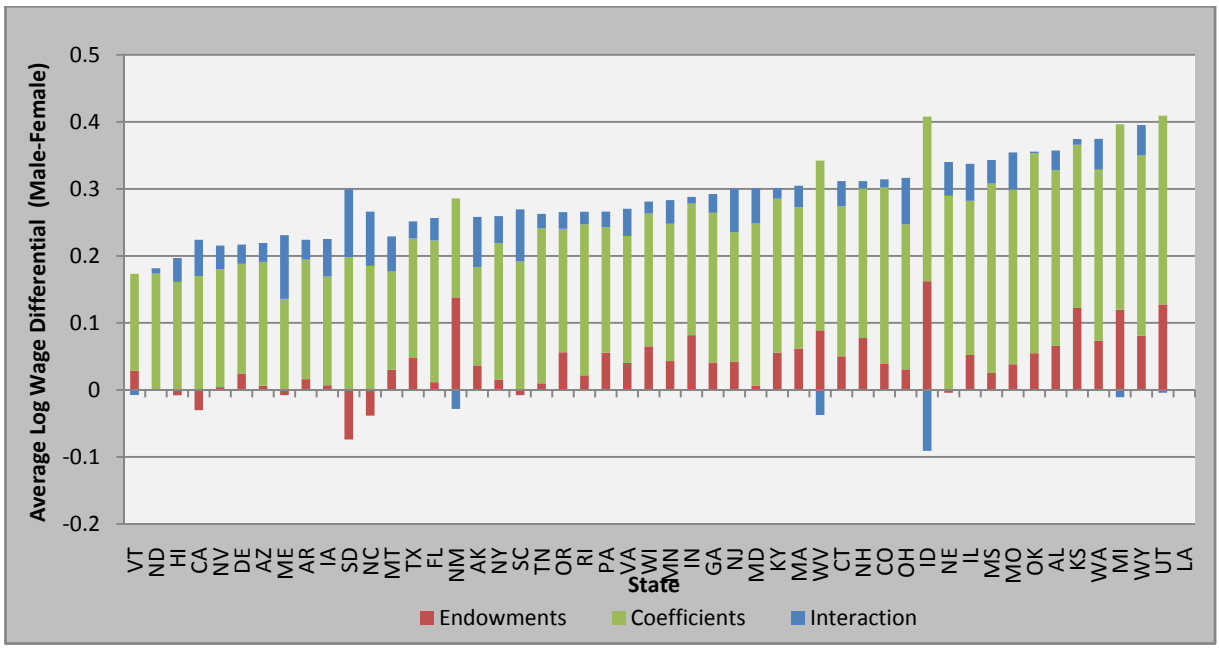


Table 1: Wage Differentials by State, 2005-2010

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	VT	2.962	2.797	0.166	0.029	0.144	-0.008
2	ND	2.846	2.665	0.181	-0.001	0.174	0.008
3	HI	2.982	2.793	0.189	-0.008	0.161	0.035
4	CA	3.040	2.847	0.194	-0.030	0.170	0.054
5	NV	2.988	2.773	0.215	0.004	0.176	0.035
6	DE	3.032	2.816	0.217	0.025	0.164	0.029
7	AZ	2.944	2.724	0.219	0.006	0.185	0.028
8	ME	2.931	2.707	0.223	-0.008	0.136	0.095
9	AR	2.799	2.576	0.224	0.016	0.178	0.030
10	IA	2.927	2.702	0.225	0.007	0.162	0.056
11	SD	2.813	2.588	0.225	-0.074	0.198	0.101
12	NC	2.907	2.679	0.228	-0.038	0.185	0.081
13	MT	2.819	2.590	0.229	0.030	0.147	0.052
14	TX	2.899	2.647	0.251	0.048	0.178	0.026
15	FL	3.012	2.756	0.256	0.011	0.212	0.033
16	NM	2.906	2.649	0.257	0.138	0.148	-0.028
17	AK	3.099	2.841	0.258	0.037	0.147	0.075
18	NY	3.126	2.866	0.259	0.015	0.204	0.040
19	SC	2.884	2.623	0.262	-0.008	0.191	0.078
20	TN	2.917	2.654	0.263	0.010	0.231	0.022
21	OR	2.988	2.722	0.265	0.056	0.184	0.025
22	RI	3.125	2.859	0.266	0.022	0.225	0.019
23	PA	3.059	2.793	0.266	0.056	0.187	0.023
24	VA	3.140	2.869	0.270	0.040	0.189	0.041
25	WI	3.025	2.744	0.281	0.065	0.198	0.018
26	MN	3.102	2.819	0.283	0.043	0.205	0.035
27	IN	2.994	2.707	0.288	0.082	0.196	0.010
28	GA	3.016	2.723	0.292	0.041	0.224	0.028
29	NJ	3.233	2.933	0.300	0.042	0.193	0.065
30	MD	3.235	2.934	0.301	0.006	0.242	0.052
31	KY	2.921	2.620	0.301	0.056	0.230	0.016
32	MA	3.242	2.937	0.305	0.062	0.211	0.032
33	WV	2.905	2.600	0.305	0.089	0.253	-0.037
34	CT	3.256	2.944	0.312	0.050	0.224	0.038
35	NH	3.165	2.854	0.312	0.077	0.223	0.011
36	CO	3.162	2.848	0.314	0.039	0.263	0.012
37	OH	3.066	2.750	0.316	0.031	0.217	0.069
38	ID	2.928	2.611	0.317	0.162	0.246	-0.091
39	NE	2.998	2.663	0.336	-0.004	0.290	0.050
40	IL	3.116	2.779	0.337	0.052	0.230	0.055
41	MS	2.903	2.560	0.343	0.025	0.283	0.035
42	MO	3.044	2.690	0.354	0.038	0.261	0.055
43	OK	2.989	2.633	0.356	0.055	0.298	0.002
44	AL	2.988	2.631	0.357	0.066	0.262	0.029
45	KS	3.041	2.667	0.374	0.122	0.243	0.009
46	WA	3.197	2.823	0.375	0.073	0.255	0.046
47	MI	3.147	2.762	0.385	0.120	0.277	-0.011
48	WY	2.975	2.580	0.395	0.081	0.269	0.046
49	UT	3.092	2.687	0.405	0.128	0.282	-0.004
50	LA	0.000	0.000	0.000	0.000	0.000	0.000
	US AVG	3.025	2.897	2.897	2.897	2.897	2.897

Chart 3: Average Log Wage Differentials (Males - Females), 2000-2004

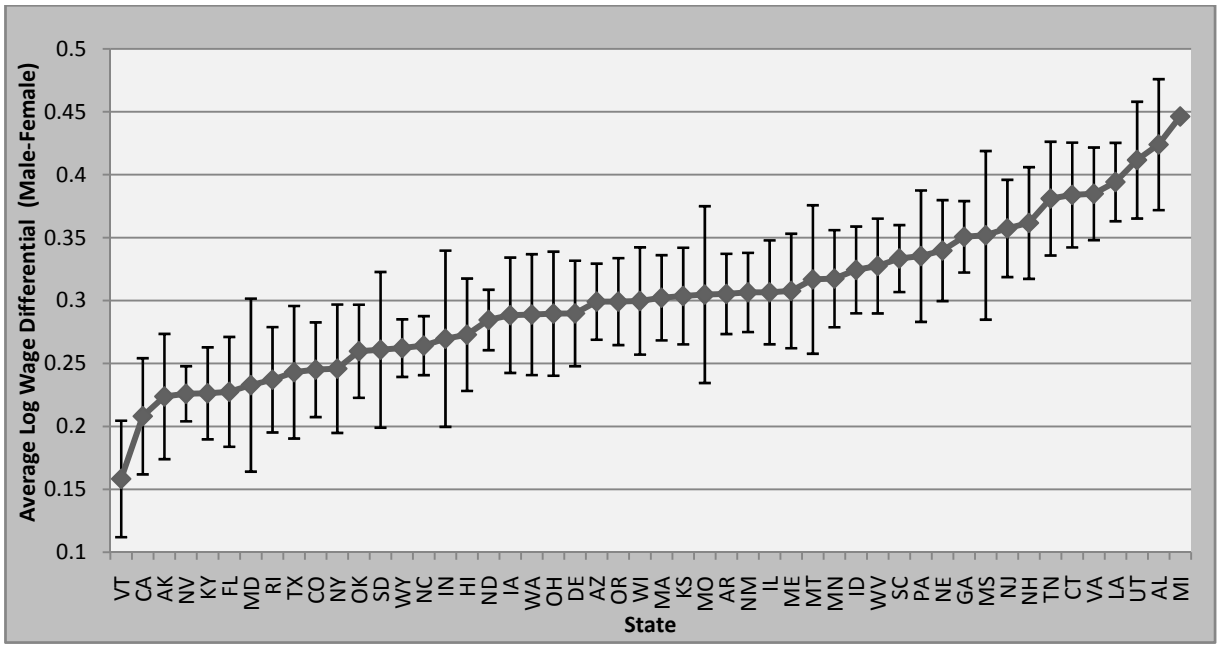


Chart 4: Components of Average Log Wage Differentials (Males-Females), 2000-2004

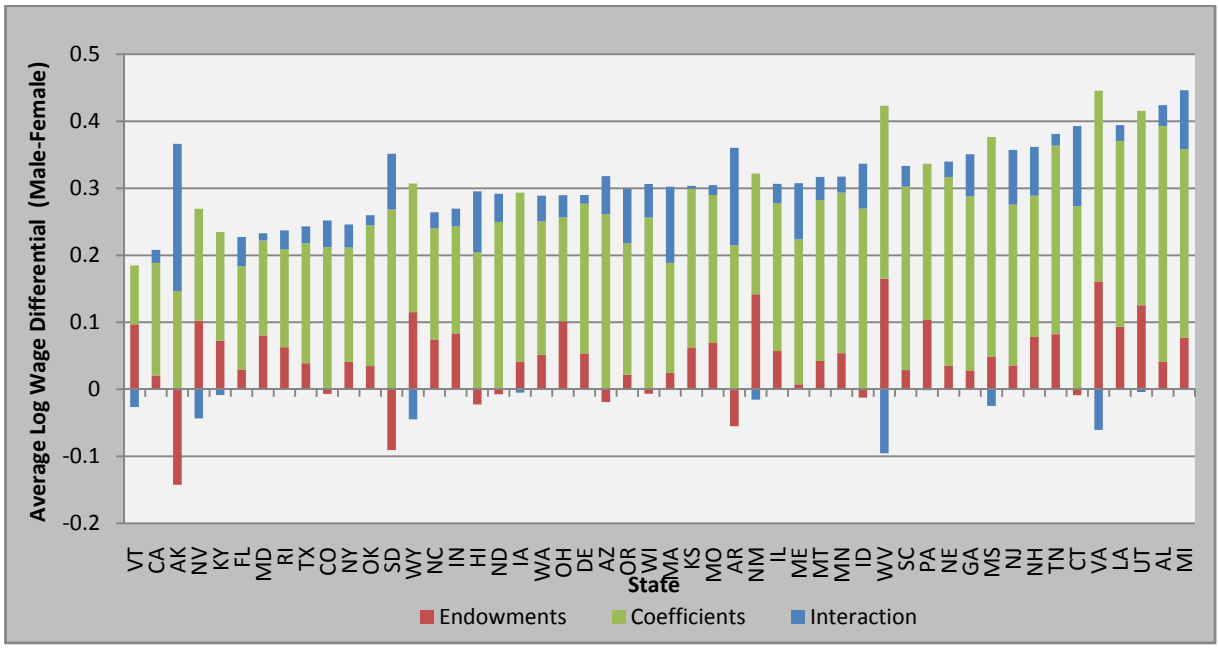


Table 2: Wage Differentials by State, 2000-2004

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	VT	2.933	2.775	0.158	0.097	0.088	-0.026
2	CA	3.039	2.831	0.208	0.021	0.168	0.019
3	AK	3.037	2.814	0.224	-0.143	0.147	0.220
4	NV	2.952	2.726	0.226	0.103	0.167	-0.043
5	KY	2.919	2.693	0.226	0.073	0.162	-0.008
6	FL	2.933	2.705	0.227	0.030	0.154	0.044
7	MD	3.198	2.966	0.233	0.080	0.142	0.011
8	RI	3.102	2.864	0.237	0.063	0.146	0.028
9	TX	2.890	2.647	0.243	0.039	0.179	0.025
10	CO	3.085	2.840	0.245	-0.007	0.212	0.040
11	NY	3.091	2.846	0.246	0.041	0.171	0.034
12	OK	2.891	2.631	0.260	0.035	0.210	0.015
13	SD	2.832	2.571	0.261	-0.091	0.268	0.083
14	WY	2.882	2.620	0.262	0.115	0.192	-0.045
15	NC	2.922	2.658	0.264	0.074	0.166	0.024
16	IN	3.015	2.746	0.270	0.083	0.160	0.027
17	HI	3.031	2.758	0.273	-0.023	0.205	0.091
18	ND	2.924	2.639	0.285	-0.007	0.250	0.042
19	IA	3.004	2.716	0.288	0.041	0.252	-0.005
20	WA	3.091	2.802	0.289	0.051	0.199	0.038
21	OH	3.054	2.765	0.290	0.101	0.155	0.033
22	DE	3.060	2.770	0.290	0.054	0.223	0.013
23	AZ	3.002	2.703	0.299	-0.019	0.261	0.057
24	OR	2.980	2.680	0.299	0.022	0.196	0.081
25	WI	3.034	2.734	0.300	-0.007	0.256	0.050
26	MA	3.227	2.925	0.302	0.024	0.164	0.114
27	KS	2.986	2.682	0.304	0.063	0.237	0.004
28	MO	3.072	2.767	0.305	0.069	0.221	0.015
29	AR	2.838	2.533	0.305	-0.055	0.215	0.145
30	NM	2.882	2.575	0.306	0.142	0.180	-0.015
31	IL	3.105	2.798	0.307	0.057	0.220	0.029
32	ME	2.916	2.608	0.308	0.008	0.216	0.084
33	MT	2.786	2.469	0.317	0.042	0.240	0.034
34	MN	3.166	2.849	0.317	0.054	0.240	0.024
35	ID	2.962	2.637	0.324	-0.012	0.270	0.067
36	WV	2.890	2.562	0.328	0.165	0.258	-0.096
37	SC	2.973	2.639	0.333	0.029	0.274	0.031
38	PA	3.123	2.788	0.335	0.103	0.233	-0.001
39	NE	3.005	2.665	0.340	0.035	0.282	0.023
40	GA	3.054	2.704	0.351	0.028	0.260	0.063
41	MS	2.962	2.610	0.352	0.049	0.328	-0.025
42	NJ	3.295	2.938	0.357	0.036	0.240	0.082
43	NH	3.250	2.889	0.362	0.078	0.211	0.073
44	TN	3.068	2.687	0.381	0.082	0.281	0.017
45	CT	3.360	2.976	0.384	-0.009	0.273	0.119
46	VA	3.180	2.795	0.385	0.161	0.285	-0.061
47	LA	2.952	2.558	0.394	0.093	0.277	0.024
48	UT	3.078	2.666	0.412	0.125	0.290	-0.004
49	AL	3.037	2.613	0.424	0.041	0.352	0.031
50	MI	3.199	2.753	0.446	0.077	0.282	0.088
	US AVG	2.998	2.897	2.897	2.897	2.897	2.897

Chart 5: Average Log Wage Differentials (Males - Females), 1995-1999

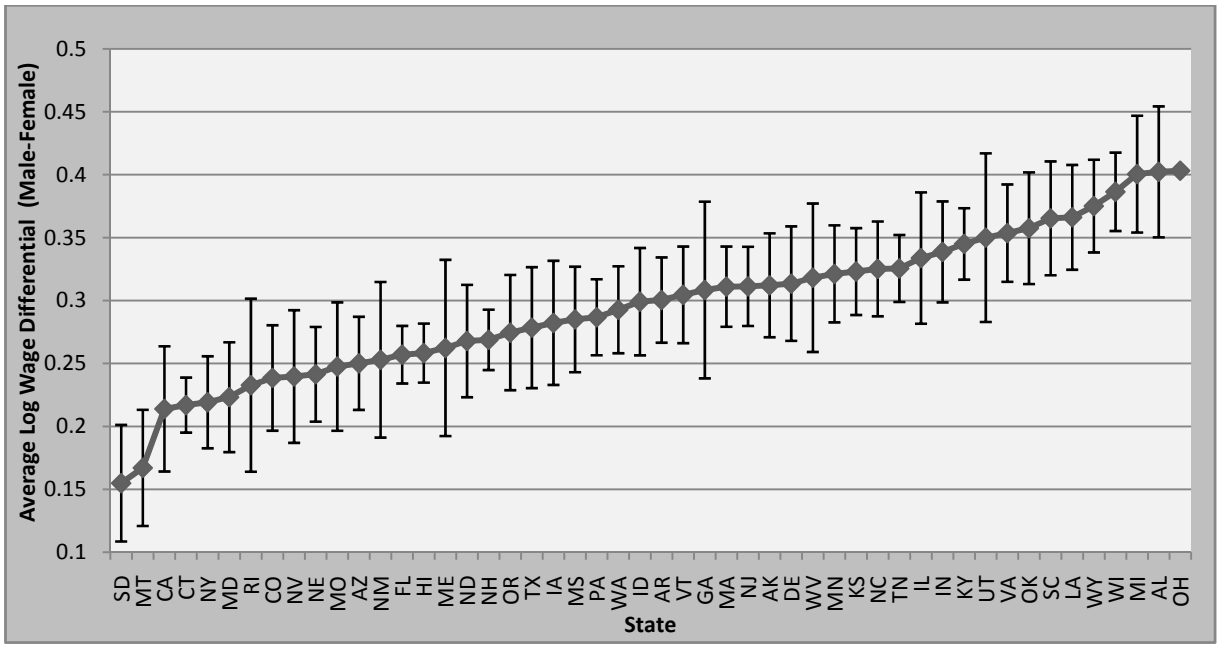


Chart 6: Components of Average Log Wage Differentials (Males-Females), 1995-1999

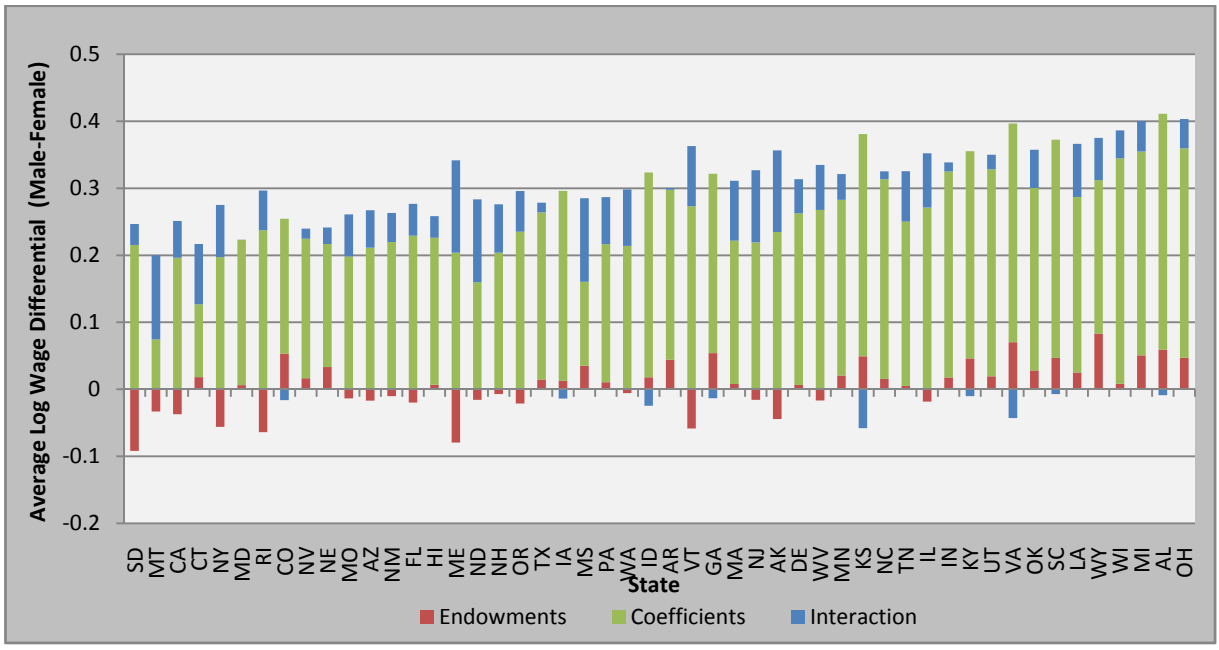


Table 3: Wage Differentials by State, 1995-1999

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	SD	2.632	2.477	0.155	-0.092	0.215	0.031
2	MT	2.665	2.497	0.167	-0.033	0.074	0.126
3	CA	2.877	2.663	0.214	-0.037	0.196	0.055
4	CT	3.098	2.881	0.217	0.018	0.109	0.090
5	NY	2.961	2.742	0.219	-0.056	0.197	0.078
6	MD	3.067	2.844	0.223	0.006	0.217	0.000
7	RI	2.952	2.719	0.233	-0.064	0.237	0.059
8	CO	2.946	2.708	0.239	0.053	0.201	-0.016
9	NV	2.879	2.640	0.240	0.016	0.208	0.015
10	NE	2.773	2.532	0.241	0.033	0.184	0.025
11	MO	2.832	2.584	0.248	-0.013	0.198	0.063
12	AZ	2.806	2.555	0.250	-0.017	0.211	0.056
13	NM	2.713	2.460	0.253	-0.010	0.220	0.044
14	FL	2.818	2.561	0.257	-0.020	0.229	0.048
15	HI	2.889	2.631	0.258	0.007	0.219	0.032
16	ME	2.785	2.522	0.262	-0.079	0.204	0.138
17	ND	2.702	2.435	0.268	-0.016	0.160	0.124
18	NH	2.986	2.717	0.269	-0.007	0.204	0.072
19	OR	2.882	2.608	0.275	-0.021	0.235	0.061
20	TX	2.795	2.516	0.279	0.015	0.249	0.014
21	IA	2.794	2.511	0.282	0.013	0.283	-0.014
22	MS	2.753	2.468	0.285	0.035	0.125	0.125
23	PA	2.951	2.664	0.287	0.010	0.206	0.070
24	WA	2.967	2.675	0.293	-0.006	0.214	0.084
25	ID	2.762	2.463	0.299	0.018	0.306	-0.024
26	AR	2.693	2.393	0.300	0.044	0.254	0.003
27	VT	2.832	2.527	0.305	-0.058	0.273	0.090
28	GA	2.926	2.618	0.308	0.054	0.268	-0.013
29	MA	3.123	2.812	0.311	0.008	0.214	0.089
30	NJ	3.106	2.794	0.311	-0.016	0.219	0.108
31	AK	3.099	2.787	0.312	-0.044	0.235	0.122
32	DE	2.979	2.666	0.314	0.006	0.256	0.051
33	WV	2.807	2.488	0.318	-0.017	0.268	0.067
34	MN	2.996	2.674	0.321	0.021	0.262	0.038
35	KS	2.847	2.524	0.323	0.049	0.332	-0.058
36	NC	2.935	2.610	0.325	0.015	0.298	0.012
37	TN	2.834	2.508	0.326	0.005	0.245	0.075
38	IL	3.022	2.688	0.334	-0.018	0.271	0.081
39	IN	2.896	2.557	0.339	0.018	0.307	0.014
40	KY	2.867	2.522	0.345	0.046	0.309	-0.010
41	UT	2.919	2.569	0.350	0.019	0.309	0.022
42	VA	3.006	2.652	0.354	0.070	0.326	-0.043
43	OK	2.825	2.467	0.358	0.028	0.272	0.057
44	SC	2.876	2.510	0.365	0.047	0.326	-0.007
45	LA	2.880	2.514	0.366	0.025	0.262	0.079
46	WY	2.787	2.412	0.375	0.083	0.229	0.063
47	WI	2.986	2.600	0.386	0.008	0.336	0.042
48	MI	3.046	2.646	0.401	0.051	0.304	0.046
49	AL	2.921	2.519	0.402	0.059	0.352	-0.009
50	OH	3.029	2.626	0.403	0.047	0.312	0.044
	US AVG	2.903	2.897	2.897	2.897	2.897	2.897

Chart 7: Average Log Wage Differentials (Males - Females), 1990-1994

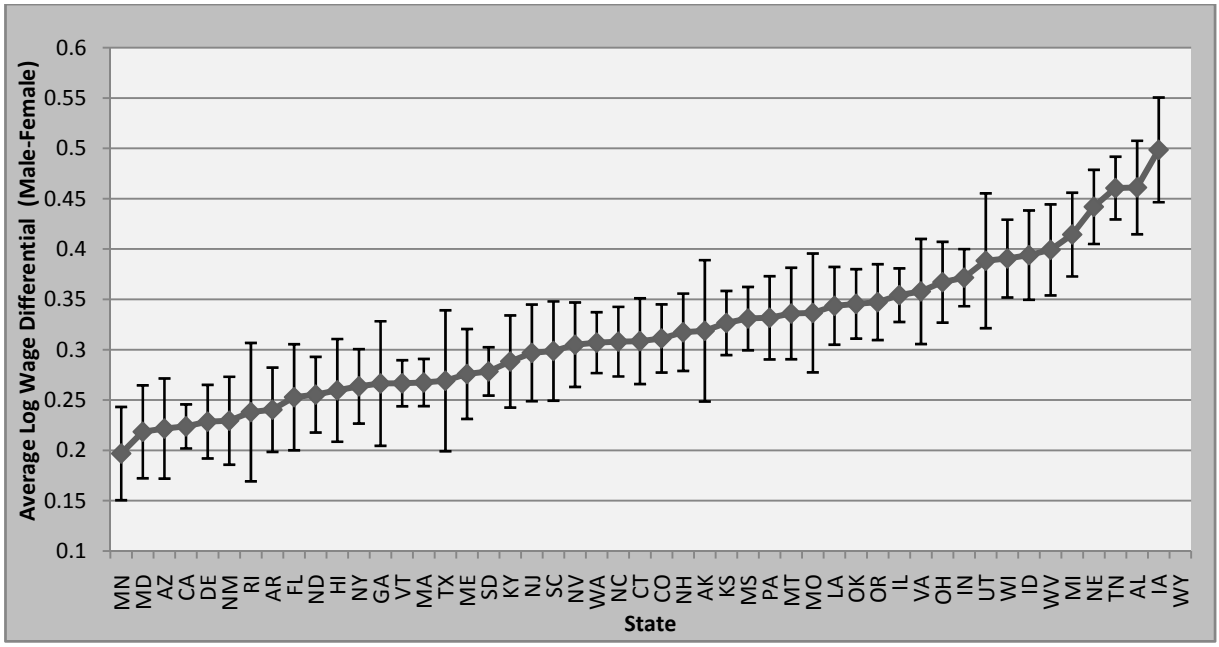


Chart 8: Components of Average Log Wage Differentials (Males-Females), 1990-1994

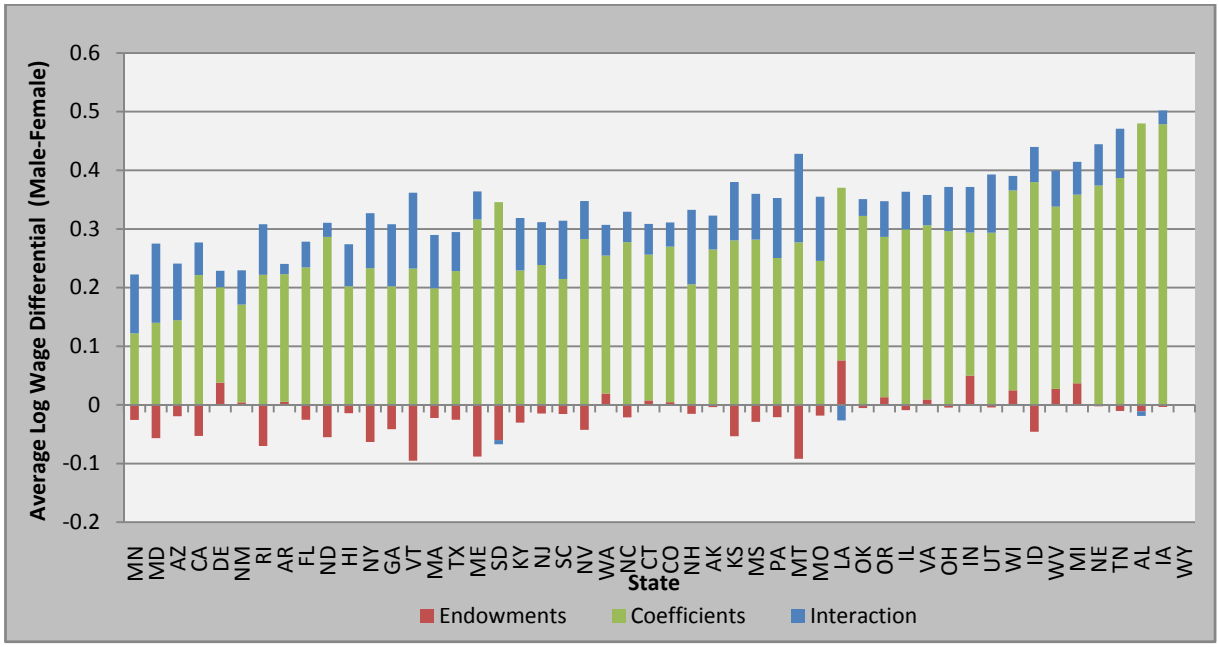


Table 4: Wage Differentials by State, 1990-1994

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	MN	2.831	2.634	0.197	-0.026	0.122	0.101
2	MD	3.005	2.787	0.218	-0.057	0.140	0.135
3	AZ	2.790	2.568	0.222	-0.019	0.144	0.097
4	CA	2.882	2.659	0.224	-0.053	0.221	0.056
5	DE	2.911	2.683	0.229	0.038	0.163	0.028
6	NM	2.740	2.511	0.229	0.004	0.167	0.058
7	RI	2.900	2.661	0.238	-0.070	0.222	0.086
8	AR	2.658	2.418	0.240	0.005	0.218	0.018
9	FL	2.774	2.521	0.253	-0.025	0.234	0.044
10	ND	2.625	2.370	0.255	-0.055	0.287	0.024
11	HI	2.974	2.715	0.260	-0.014	0.202	0.072
12	NY	2.988	2.724	0.264	-0.063	0.233	0.094
13	GA	2.857	2.591	0.266	-0.042	0.202	0.106
14	VT	2.824	2.557	0.267	-0.095	0.233	0.129
15	MA	3.043	2.775	0.267	-0.022	0.199	0.091
16	TX	2.722	2.453	0.269	-0.025	0.228	0.066
17	ME	2.762	2.486	0.276	-0.088	0.316	0.048
18	SD	2.580	2.302	0.278	-0.060	0.346	-0.007
19	KY	2.803	2.515	0.288	-0.030	0.229	0.090
20	NJ	3.094	2.797	0.297	-0.015	0.238	0.073
21	SC	2.785	2.486	0.299	-0.015	0.215	0.099
22	NV	2.863	2.558	0.305	-0.043	0.283	0.065
23	WA	2.952	2.645	0.307	0.019	0.235	0.053
24	NC	2.800	2.492	0.308	-0.021	0.277	0.052
25	CT	3.141	2.833	0.309	0.008	0.249	0.052
26	CO	2.902	2.591	0.311	0.005	0.265	0.041
27	NH	2.992	2.675	0.317	-0.015	0.206	0.127
28	AK	3.080	2.761	0.319	-0.004	0.265	0.058
29	KS	2.812	2.485	0.327	-0.054	0.281	0.100
30	MS	2.645	2.314	0.331	-0.029	0.282	0.078
31	PA	2.908	2.577	0.332	-0.021	0.250	0.102
32	MT	2.660	2.324	0.336	-0.092	0.277	0.151
33	MO	2.799	2.462	0.337	-0.018	0.246	0.109
34	LA	2.820	2.476	0.344	0.076	0.294	-0.027
35	OK	2.740	2.394	0.346	-0.005	0.322	0.029
36	OR	2.863	2.516	0.347	0.013	0.273	0.061
37	IL	2.955	2.600	0.354	-0.009	0.299	0.064
38	VA	2.933	2.575	0.358	0.009	0.297	0.052
39	OH	2.929	2.562	0.367	-0.005	0.296	0.075
40	IN	2.818	2.446	0.372	0.050	0.244	0.078
41	UT	2.913	2.524	0.388	-0.004	0.294	0.099
42	WI	2.974	2.583	0.391	0.025	0.341	0.025
43	ID	2.689	2.295	0.394	-0.046	0.380	0.060
44	WV	2.768	2.369	0.399	0.027	0.311	0.061
45	MI	2.999	2.584	0.414	0.037	0.322	0.056
46	NE	2.904	2.462	0.442	-0.002	0.374	0.070
47	TN	2.895	2.434	0.461	-0.010	0.387	0.084
48	AL	2.887	2.426	0.461	-0.011	0.480	-0.008
49	IA	2.858	2.359	0.499	-0.004	0.479	0.023
50	WY	0.000	0.000	0.000	0.000	0.000	0.000
	US AVG	2.873	2.897	2.897	2.897	2.897	2.897

Chart 9: Average Log Wage Differentials (Males - Females), 1985-1989

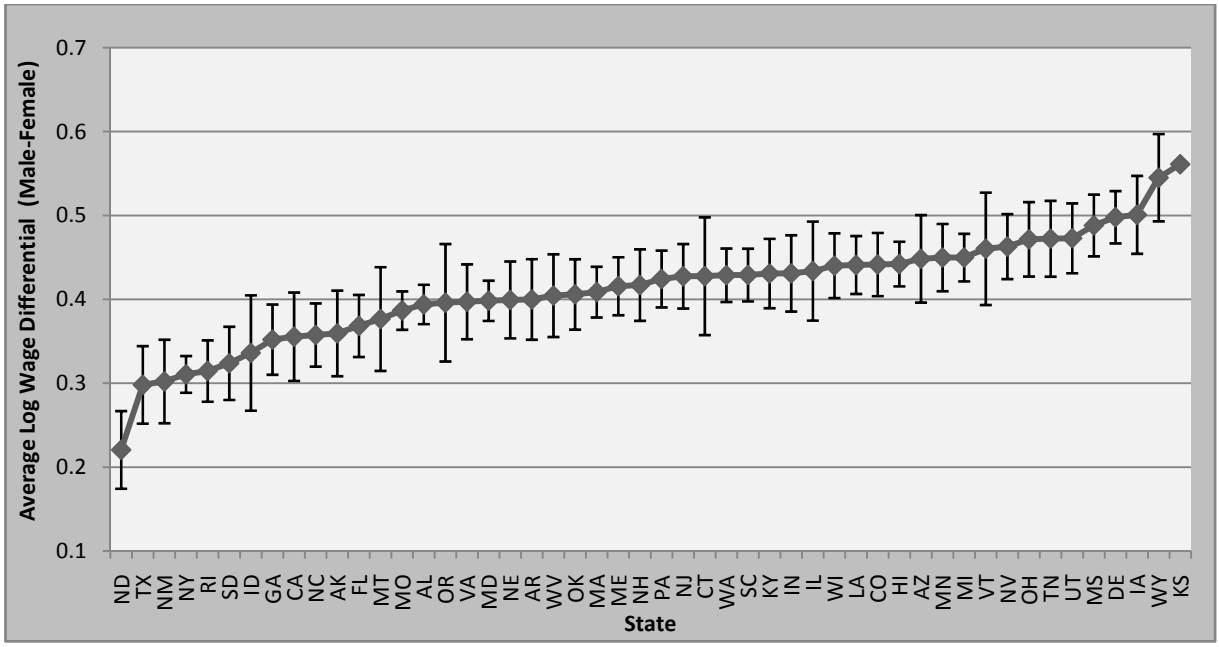


Chart 10: Components of Average Log Wage Differentials (Males-Females), 1985-1989

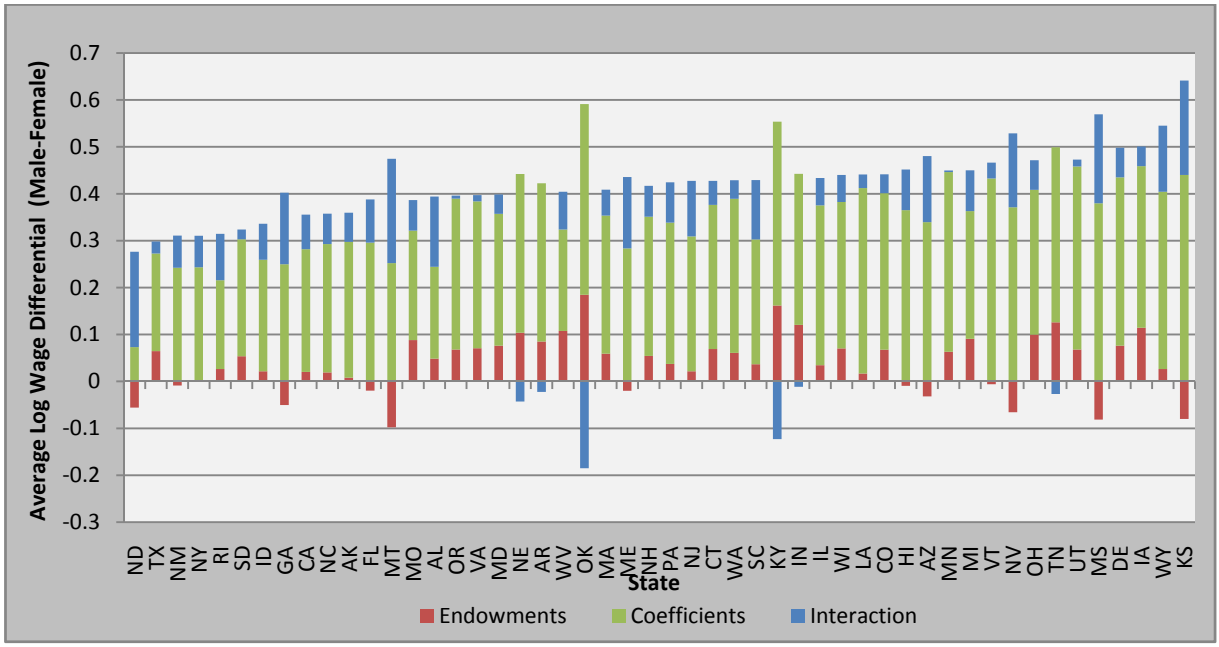


Table 5: Wage Differentials by State, 1985-1989

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
1	ND	2.671	2.450	0.221	-0.056	0.073	0.203
2	TX	2.866	2.568	0.298	0.065	0.208	0.025
3	NM	2.741	2.439	0.302	-0.009	0.242	0.069
4	NY	3.019	2.708	0.311	0.002	0.241	0.067
5	RI	2.902	2.587	0.315	0.027	0.189	0.099
6	SD	2.597	2.273	0.324	0.054	0.249	0.021
7	ID	2.714	2.378	0.336	0.022	0.238	0.077
8	GA	2.853	2.501	0.352	-0.050	0.250	0.153
9	CA	3.006	2.650	0.355	0.020	0.262	0.074
10	NC	2.795	2.438	0.358	0.019	0.274	0.065
11	AK	3.377	3.017	0.359	0.008	0.289	0.062
12	FL	2.829	2.461	0.368	-0.020	0.296	0.092
13	MT	2.747	2.371	0.377	-0.098	0.252	0.222
14	MO	2.899	2.513	0.387	0.088	0.233	0.065
15	AL	2.792	2.398	0.394	0.049	0.196	0.150
16	OR	2.913	2.517	0.396	0.068	0.322	0.006
17	VA	2.981	2.584	0.397	0.071	0.313	0.013
18	MD	3.075	2.676	0.398	0.076	0.281	0.041
19	NE	2.777	2.378	0.399	0.104	0.338	-0.043
20	AR	2.717	2.317	0.400	0.085	0.337	-0.022
21	WV	2.871	2.466	0.404	0.108	0.216	0.081
22	OK	2.824	2.418	0.406	0.185	0.407	-0.185
23	MA	3.048	2.640	0.409	0.059	0.294	0.055
24	ME	2.813	2.397	0.416	-0.020	0.284	0.152
25	NH	2.961	2.544	0.417	0.054	0.297	0.066
26	PA	2.960	2.536	0.424	0.037	0.301	0.086
27	NJ	3.102	2.674	0.428	0.021	0.288	0.118
28	CT	3.136	2.708	0.428	0.069	0.307	0.051
29	WA	2.987	2.558	0.429	0.061	0.328	0.040
30	SC	2.855	2.425	0.429	0.037	0.266	0.126
31	KY	2.805	2.374	0.431	0.162	0.392	-0.123
32	IN	2.892	2.461	0.431	0.121	0.322	-0.012
33	IL	3.101	2.667	0.434	0.034	0.341	0.058
34	WI	3.012	2.572	0.440	0.071	0.312	0.058
35	LA	2.881	2.440	0.441	0.017	0.395	0.029
36	CO	3.115	2.674	0.442	0.068	0.334	0.040
37	HI	3.065	2.623	0.442	-0.009	0.365	0.086
38	AZ	3.027	2.578	0.448	-0.032	0.339	0.141
39	MN	3.073	2.624	0.450	0.063	0.383	0.003
40	MI	3.030	2.580	0.450	0.091	0.272	0.087
41	VT	2.916	2.456	0.460	-0.006	0.433	0.034
42	NV	3.003	2.540	0.463	-0.066	0.371	0.158
43	OH	3.068	2.596	0.472	0.100	0.309	0.063
44	TN	2.886	2.414	0.472	0.126	0.373	-0.027
45	UT	2.949	2.476	0.473	0.068	0.390	0.015
46	MS	2.810	2.322	0.488	-0.081	0.380	0.190
47	DE	3.055	2.557	0.498	0.076	0.359	0.063
48	IA	3.000	2.499	0.501	0.114	0.344	0.042
49	WY	3.076	2.531	0.545	0.026	0.378	0.141
50	KS	3.050	2.489	0.561	-0.080	0.440	0.201
	US AVG	2.923	2.897	2.897	2.897	2.897	2.897

Chart 11: Average Log Wage Differentials (Males - Females), 1980-1984

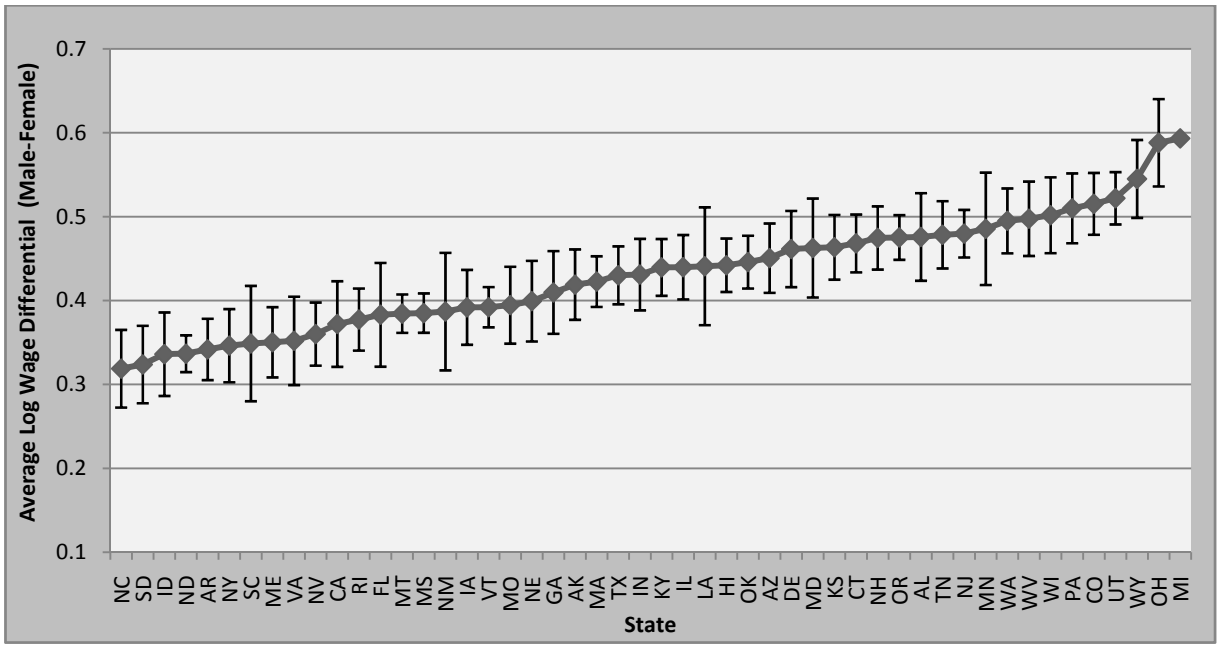


Chart 12: Components of Average Log Wage Differentials (Males-Females), 1980-1984

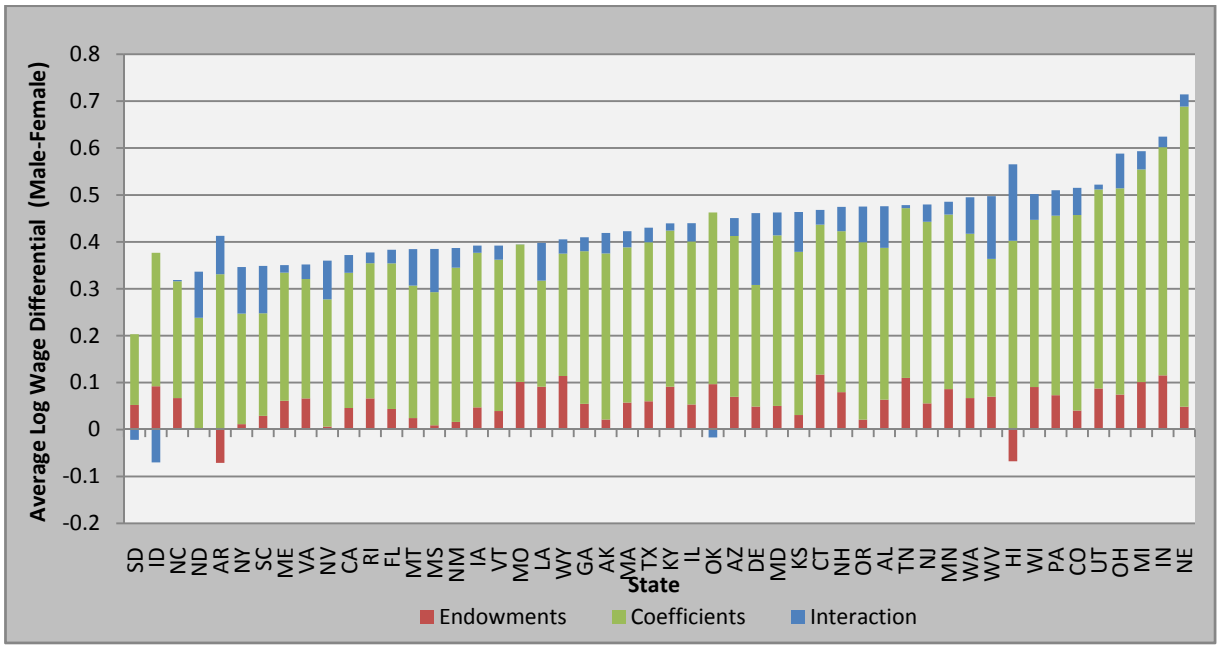


Table 6: Wage Differentials by State, 1980-1984

Rank (smallest difference=1)	State	Male Log Wage Prediction	Female Log Wage Predic.	Difference	Blinder-Oaxaca Decomposition		
					Endow.	Coeff.	Interaction
2	ID	2.721	2.415	0.307	0.092	0.285	-0.070
3	NC	2.695	2.376	0.319	0.067	0.249	0.003
4	ND	2.646	2.309	0.337	0.002	0.236	0.098
5	AR	2.609	2.268	0.342	-0.071	0.331	0.082
6	NY	2.937	2.591	0.346	0.011	0.236	0.099
7	SC	2.660	2.311	0.349	0.029	0.219	0.101
8	ME	2.697	2.347	0.350	0.061	0.273	0.016
9	VA	2.885	2.533	0.352	0.066	0.254	0.031
10	NV	2.903	2.543	0.360	0.006	0.271	0.083
11	CA	2.951	2.579	0.372	0.046	0.288	0.038
12	RI	2.821	2.444	0.377	0.066	0.288	0.023
13	FL	2.743	2.359	0.383	0.044	0.310	0.029
14	MT	2.734	2.350	0.384	0.024	0.283	0.078
15	MS	2.661	2.276	0.385	0.009	0.284	0.092
16	NM	2.778	2.391	0.387	0.016	0.329	0.042
17	IA	2.818	2.426	0.392	0.047	0.329	0.015
18	VT	2.692	2.300	0.392	0.040	0.323	0.030
19	MO	2.862	2.467	0.395	0.102	0.293	0.000
20	LA	2.842	2.445	0.398	0.091	0.226	0.080
21	WY	2.907	2.501	0.405	0.114	0.261	0.031
22	GA	2.813	2.403	0.410	0.055	0.325	0.030
23	AK	3.173	2.754	0.419	0.021	0.354	0.044
24	MA	2.961	2.538	0.423	0.058	0.331	0.034
25	TX	2.823	2.392	0.430	0.060	0.339	0.031
26	KY	2.816	2.376	0.440	0.091	0.333	0.016
27	IL	3.042	2.602	0.440	0.053	0.348	0.039
28	OK	2.825	2.379	0.446	0.097	0.366	-0.017
29	AZ	2.878	2.428	0.451	0.070	0.343	0.038
30	DE	2.965	2.503	0.461	0.049	0.259	0.153
31	MD	3.064	2.601	0.463	0.050	0.364	0.049
32	KS	2.841	2.378	0.464	0.031	0.348	0.085
33	CT	3.011	2.543	0.468	0.117	0.320	0.031
34	NH	2.849	2.374	0.475	0.080	0.343	0.052
35	OR	2.902	2.427	0.475	0.021	0.378	0.076
36	AL	2.781	2.305	0.476	0.064	0.324	0.089
37	TN	2.806	2.328	0.478	0.110	0.362	0.007
38	NJ	3.018	2.538	0.480	0.056	0.387	0.037
39	MN	2.928	2.442	0.486	0.086	0.372	0.027
40	WA	3.134	2.639	0.495	0.067	0.350	0.078
41	WV	2.883	2.385	0.498	0.070	0.294	0.134
42	HI	2.983	2.486	0.498	-0.067	0.402	0.163
43	WI	2.957	2.455	0.502	0.090	0.356	0.055
44	PA	2.974	2.464	0.510	0.073	0.383	0.054
45	CO	3.075	2.559	0.515	0.041	0.417	0.058
46	UT	2.904	2.382	0.522	0.087	0.424	0.010
47	OH	3.076	2.488	0.588	0.075	0.439	0.074
48	MI	3.113	2.520	0.593	0.101	0.453	0.039
49	IN	3.041	2.417	0.624	0.115	0.486	0.022
US AVG	US AVG	2.889	2.453	0.436	0.049	0.339	0.048

Note: The point estimates for SD and NE are nor reported because of large unexplained variations in the estimated discrimination coefficients. Further analysis for these two states are needed

Appendix E: Comparison of Results With and WithoutSample Selectivity Controls

Table 1: Comparison of Changes in Discrimination for Both Models, 1980-2010

	No Sample Selectivity Model	Sample Selectivity Model	
State	1980-1984 Discrimination Level- 2005-2010 Discrimination Level (in log points)	1980-1984 Discrimination Level- 2005-2010 Discrimination Level (in log points)	Difference
WY*	0.13	0.20	-0.08
HI*	0.19	0.25	-0.07
OH	0.17	0.23	-0.06
VT	0.16	0.22	-0.05
IA	0.08	0.13	-0.05
ND	0.11	0.15	-0.05
PA	0.20	0.23	-0.03
MI	0.21	0.23	-0.02
IN*	0.09	0.10	-0.02
WV	0.20	0.21	-0.01
TN	0.11	0.12	-0.01
AK	0.17	0.18	-0.01
AR	0.20	0.21	-0.01
NJ	0.16	0.17	0.00
OR	0.24	0.25	0.00
SC	0.05	0.05	0.00
AZ	0.17	0.17	0.00
KY	0.10	0.10	0.00
CA	0.10	0.10	0.00
ID*	0.16	0.16	0.00
RI	0.07	0.07	0.00
MN	0.16	0.16	0.00
SD*	-0.03	-0.03	0.00
CT	0.09	0.09	0.00
WI	0.20	0.20	0.00
NM	0.26	0.25	0.01
MA	0.13	0.12	0.01
NH	0.17	0.16	0.01
ME	0.07	0.06	0.01
TX	0.18	0.17	0.01
GA	0.12	0.10	0.01
MT	0.18	0.16	0.02
VA	0.08	0.06	0.02
UT	0.18	0.16	0.03
FL	0.13	0.09	0.03
LA*	0.21	0.17	0.04
CO	0.25	0.20	0.05
NC	0.04	-0.01	0.05
MD	0.17	0.12	0.05
AL	0.18	0.12	0.06
MS	0.11	0.06	0.06
DE	0.28	0.22	0.06
WA	0.19	0.13	0.07
NY	0.16	0.09	0.07
NV	0.22	0.14	0.08
KS	0.26	0.18	0.08
OK	0.13	0.05	0.08
IL	0.19	0.10	0.09
NE*	0.06	-0.04	0.11
MO	0.09	-0.02	0.12
AVG	0.15	0.14	0.01

* Estimations are conducted using 1985-1989 data due to issues with the 1980-1984 data (large number of censored observations).

Table 2: Comparison of Changes in the Gender Pay Gap for Both Models, 1980-2010

State	No Sample Selectivity Controls	Sample Selectivity Controls	
	1980-1984 Gender Pay Gap- 2005-2010 Gender Pay Gap	1980-1984 Gender Pay Gap- 2005-2010 Gender Pay Gap	Difference
WY*	0.07	0.15	-0.08
HI*	0.19	0.25	-0.07
OH	0.21	0.27	-0.06
VT	0.18	0.23	-0.05
ND	0.11	0.16	-0.04
IA	0.13	0.17	-0.04
PA	0.22	0.24	-0.03
MI	0.19	0.21	-0.02
IN*	0.13	0.14	-0.02
WV	0.18	0.19	-0.01
TN	0.21	0.22	-0.01
AK	0.15	0.16	-0.01
AR	0.11	0.12	-0.01
NJ	0.18	0.18	0.00
OR	0.21	0.21	0.00
AZ	0.23	0.23	0.00
SC	0.09	0.09	0.00
KY	0.14	0.14	0.00
CA	0.18	0.18	0.00
ID*	0.02	0.02	0.00
MN	0.20	0.20	0.00
RI	0.11	0.11	0.00
SD*	0.10	0.10	0.00
CT	0.16	0.16	0.00
WI	0.22	0.22	0.00
NM	0.13	0.13	0.01
MA	0.12	0.12	0.01
NH	0.17	0.16	0.01
ME	0.14	0.13	0.01
TX	0.19	0.18	0.01
GA	0.13	0.12	0.01
CO	0.22	0.20	0.02
VA	0.10	0.08	0.02
MT	0.17	0.16	0.02
UT	0.14	0.12	0.03
FL	0.16	0.13	0.03
WA	0.16	0.12	0.04
LA*	0.06	0.02	0.05
NC	0.14	0.09	0.05
DE	0.29	0.24	0.05
MD	0.22	0.16	0.06
AL	0.17	0.12	0.06
MS	0.10	0.04	0.06
NV	0.20	0.14	0.06
NY	0.15	0.09	0.06
KS	0.16	0.09	0.08
OK	0.17	0.09	0.08
IL	0.19	0.10	0.09
NE*	0.15	0.06	0.09
MO	0.15	0.04	0.11
AVG	0.16	0.15	0.01

* Estimations are conducted using 1985-1989 data due to issues with the 1980-1984 data (large number of censored observations).

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