EXPLAINING UTAH'S GENDER GAP IN WAGES

by

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ABSTRACT

Women earn less than men, and the disparity between men's and women's wages in Utah is larger than the same disparity at the national or regional levels. Little is known as to why Utah has a larger wage gap than the nation or its neighbors. In this paper, we use Oaxaca-Blinder decomposition to decompose the wage gap in Utah, the Intermountain region, and the nation into a part that can be attributed to differing endowments between men and women and a part due to men and women being rewarded differently in the labor market, due to factors including discrimination. We compare these differentials across time (from 1992 to 2014) and geographic regions. Using pooled CPS March data from 2009 to 2014, we find that at the national level, women earn 82% of what men earn; among similarly qualified individuals, women earn 97% of what men earn. In Utah, these figures are 74% and 86%, respectively. Utah's earnings gap is larger than the nation's due to both more discrimination and a larger endowment effect for Utah. Furthermore, since 1992, inequality due to discrimination has decreased in Utah, but inequality due to differing endowments has increased, unlike the national trend where both causes decreased.

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INTRODUCTION

On average, women earn less than men. Is this due to earnings discrimination against women? Do employers see a male and female employee differently based on their sex, and pay them differently as a result? Or are women less qualified than men or prefer occupations that pay less but are desirable for reasons other than pay? These questions are harder to answer, and researchers have been discussing them at the national level for decades. The gender gap has led to the creation of research and econometric techniques that, while applicable to a number of other topics, were originally designed to answer this question.

While there has long been research on the national gender gap in earnings, there is not nearly as much research on Utah's gender gap in wage. Few researchers have examined the wage gap at the state level. Yet this wage gap is starting to see increased scrutiny. Utah has a larger wage gap than the rest of the nation, and this concerns many Utahns. More people are calling for something to be done.

This paper, which is intended to serve as a follow-up to an earlier paper published by Voices for Utah Children (2015), is intended to address an issue that the previous paper only passingly discussed: labor market wage discrimination against women. We wish to repeat the wage gap analysis often performed at the national level, but with Utah as the focus. There are three questions this paper tries to answer:

1. How much of Utah's wage gap can be attributed to labor market discrimination, and how much is due to measurable differences between men and women's attributes?
2. How does Utah's wage gap compare to the wage gaps observed at the national and regional levels, and why are they different?
3. How has Utah's wage gap changed over time?

We often repeat the same analysis for Utah at the national level and for the Intermountain region, Utah's neighbors. But the focus of this paper is on Utah. We begin the paper with a literature review, discussing research into Utah's wage gap and the decomposition of wage gaps into an endowment effect (the part of the gap due to different characteristics of men and women) and a returns effect (the part that could be attributed to discrimination). Next, we discuss the data we used. We then discuss the methodology used. We use linear regression and the Heckman selection bias correction to estimate men's and women's wage functions, and Oaxaca-Blinder decomposition to decompose the wage gap into a part attributable to differences in men's and women's attributes and a part attributable to discrimination. We present our results, and then launch a discussion on the findings and their limitations. We then conclude.

LITERATURE REVIEW

On average, men earn more than women. In the nation, women earn $0.79 for every dollar earned by men (Voices for Utah Children, 2015). This number has been improving over time, yet a large gap still persists.

Another undeniable fact is that Utah's wage gap is worse than the rest of the nation. Utah has the fourth largest gap, with Utah women earning $0.70 for every dollar earned by Utah men. Utah's wage gap has never been better than the nation's, and it has been closing at a much slower rate than the national wage gap (Voices for Utah Children, 2015). In recent years, Utah's wage gap has seen increasing attention, and the state of Utah is facing increased scrutiny for its large wage gap (Institute for Women's Policy Research, 2014a; Institute for Women's Policy Research, 2014b; Langston, 2014; Frohlich, Kent, & Hess, 2014; Voices for Utah Children, 2015).

While there is no argument over these figures themselves, what these figures mean is less clear. Do they represent discrimination against women, or women making less due to differences between men and women in many factors such as being less educated, less experienced, less attached to the labor force or burdened by family commitments, etc., compared to men. Standard economic theory, first put forth in Gary Becker's 1957 book *The Economics of Discrimination*, holds that discrimination is not sustainable in a market environment. Market forces would eventually result in a non-discriminatory equilibrium (see Sowell (2011)). Firms in a competitive market able to discriminate against women by paying them less than what equivalent men would earn have effectively implemented the equivalent of a cost-saving technological advance, giving them a competitive edge over firms not doing so. They would then hire *only* women, increasing the demand for female workers while decreasing the demand for male workers. The upward pressure on female wages and the downward pressure on male wages would eventually result in equalization of both genders' wages.

However, even if the market equilibrium is non-discriminatory, nothing requires that an economy actually be in equilibrium. “Equilibrium” is an analytical tool, not a description of the present state of the economy. We may still be approaching the non-discriminatory equilibrium, and the neoclassical theory cannot give a timeframe for how long it would take for this equilibrium to be reached. It could take decades, and may see setbacks along the way. After all, the causes of discriminatory behavior go beyond economic motives. Furthermore, this analysis requires that markets be competitive, which rarely holds in a real economy. If a firm has some market power, such as monopolists or monopsonists[1] in the labor market, they may not face the same pressures that result in the equalization of male and female wages.

The fact that the wage gap between men and women has been slowly closing for decades may lend credibility to the idea that, while the economy will eventually reach a non-discriminatory equilibrium, we are not there yet. There could still be discrimination, although we would expect to see it shrinking over time. We may wonder, though, how much of the wage gap is due to discriminatory behavior and how much is due to women being, in some sense, inferior workers compared to men on average. This question is ultimately an empirical question, and empirical methods can be employed to try to answer it.

Oaxaca-Blinder (OB) decomposition is a common method for trying to break the wage gap into a discriminatory and non-discriminatory part, and it is the method we use in this paper. The difference between men’s and women’s mean wages are broken into a

[1] A monopsonist is similar to a monopolist, but while a monopolist is the sole seller of a good, a monopsonist is the sole buyer (the U.S. military is a monopsonist in the military equipment market, for example). Thus a labor market monopsonist is the only firm hiring workers in that labor market, as could happen in small communities built around one firm, like a mining town.

difference due to differing endowments between men and women and a difference due to men and women having different wage equations, with the latter difference being associated with discrimination. OB decomposition works only at the mean of the wage distributions; the rest of the distribution is effectively ignored. There are other decomposition methods that do account for the rest of the wage distribution, but we do not use those methods since we are only interested in the mean difference. (We discuss the OB decomposition method in greater depth later.)

OB decomposition was originally devised for analyzing the gender wage gap. Oaxaca (1973) developed the decomposition method to quantify the wage gap between men and women and found that a sizeable portion could be attributed to discrimination. Blinder (1973) used the same method to decompose not only the wage gap between genders but also between whites and blacks. Another common decomposition method (although not nearly as common as OB decomposition) is the Juhn-Murphy-Pierce (JMP) decomposition, which operates on the entire distribution of men's and women's wages, allowing for decompositions of quantiles and changes in the wage gap. This method was employed by Blau and Kahn (1997) to see why the gap continued to close in the 1980s even though overall income inequality increased. Some do not use decomposition at all, and simply add a dummy[2] variable for gender and interpret its coefficient as being the wage gap associated with discrimination; this method, though, is a cruder measure of discrimination because it does not allow for men and women to face different wage functions.

[2] Also known as a binary variable; it equals one when a certain characteristic is true, and zero otherwise.

More recent studies have avoided identifying labor market discrimination in wages for women in general, if not declaring it to be miniscule to nonexistent. O'Neill and O'Neill (2005) used National Longitudinal Survey of Youth (NLSY) data to conclude that the part of the wage gap between men and women that could be attributed to discrimination ranges from $0.07 to nothing, depending on choice of the "nondiscriminatory" alternative wage scheme (where the choices are either men's or women's estimated wage functions). Likewise, the CONSAD Research Corporation, in a report sponsored by the U.S. Department of Labor, concluded that labor market discrimination cannot be quantified using decomposition methods on cross-sectional data (namely, the Current Population Survey Outgoing Rotation Group (CPS-ORG) data) since we cannot eliminate the possibility that the part of the wage gap that is "unexplained" (which is the part often attributed to discrimination) is due to some variable we cannot measure, such as actual (as opposed to potential) work experience (CONSAD Research Corporation, 2009). They used a number of models to decompose the wage gap, and estimates of "discrimination" varied considerably depending on the model chosen. Polachek (2004; 2007) criticizes common methods of decomposition and claims they cannot give a good depiction of the form of discrimination. Not only will these methods have a tendency to overestimate the part of the wage gap due to wage discrimination, they falsely legitimize the part of the wage gap that can be attributed to observable factors such as education. He notes that women frame their decisions for investing in their own human capital in the context of discrimination. This means that women could have less human capital than men *because* of discrimination.

Recent studies often seek to identify specific factors that contribute to the wage gap. Some of these factors include the share of females in firm management (Hirsch, 2013), the growing importance of overwork in pay (which women are not as inclined to do) (Cha & Weeden, 2014), differential human capital investment between men and women (Polachek, 2004; Polachek, 2007), and occupational dissimilarity (Hegewisch & Hartmann, 2014). There is growing attention to the pay gap associated with motherhood. Researchers have noticed discriminatory behavior against mothers while searching for a job (Correll, Benard, & Paik, 2007) and experiencing a "motherhood penalty" in pay while fathers experience a "fatherhood bonus" (Budig, 2014). Polachek (2004; 2007) is skeptical of the notion that employers discriminate against mothers but does note that their investment in human capital could be inhibited. Waldfogel (1998) lends credibility to this idea: she discovered that women who utilize maternity leave and return to work soon after giving birth to a child don't see a "motherhood penalty."

Recent research still claims to find evidence for wage discrimination. Eric van Tol, in his Master's thesis, used both OB and JMP decomposition on American Community Survey (ACS) data to examine racial and gender pay gaps, and found that most of the gap in the United States is not due to observable differences between men and women, such as education (van Tol, 2013). In fact, these factors work *in favor* of women at the national level! While van Tol found that this was not the case in Utah, most of Utah's wage gap still could not be attributed to observed factors. Fortin, Lemieux, and Firpo (2010) used the same dataset O'Neill and O'Neill (2005) used, but unlike the latter, found statistically significant evidence for discrimination when using a (arguably superior) counterfactual wage function in the OB decomposition different from the male or female wage functions.

Discrimination, as measured by decomposition methods, is decreasing over time. Bar et. al. (2013) found discrimination decreasing between the 1970s and the 1990s. Jarrell and Stanley (2004) conducted an extensive literature review and meta-regression analysis on 49 studies of the gender gap and made an estimate for the contemporary magnitude of discrimination and when it would close. Their meta-regression suggested that in 2003, women made $0.062 less than men per hour because of wage discrimination, and that this gap was closing at a rate of $0.006 a year.

Some researchers have tried to address the issue of selection bias and its relationship to the gender gap in wages when using cross-sectional data. Selection bias occurs when the probability individuals enter the labor force is not independent of that individual's characteristics which could also impact the individual's wages. This will impact the estimates of the coefficients of the wage equation. In the context of this problem, the women who enter the labor force may be more motivated or have greater skill than women in general. The opposite could be true as well.

Usually there is not only evidence for the existence of selection bias, but changing selection bias over time. Most use the Heckman two-step method (Heckman, 1979) for controlling for selection bias, such as Bar et. al. (2013) and Khitarishvili (2009); researchers employing this method estimate the probability that an individual enters the labor force, then uses that probability to add an additional variable, the inverse Mills ratio, to the wage equation, thus producing a wage equation corrected for selection bias. This is the method we use for correcting for selection bias. Machado (2012), though, devised an alternative method for addressing selection bias. Using this method, she examined the gender gap in educational and age cohorts and found evidence for a shift from positive to negative selection over time when using CPS data from 1976 to 2005. Bar et. al., though, found that selection bias shifted towards positive selection from the 1970s to the 1990s. Khitarishvili, when examining the gender gap in wages in Georgia (the country), found no evidence for selection bias among Georgian women but negative selection among Georgian men. In their literature analysis, Jarrell and Stanley (2004) concluded that, while being aware of and attempting to control for selection bias represents an improvement in research methods, the need to do so is decreasing over time, perhaps because of decreasing discrimination. (We describe the selection bias problem in more detail in the Methodology section.)

EMPIRICAL MODEL

The typical method for calculating the gender gap in wages is to divide the median wages of women by the median wages of men. This method says nothing about why the gap between men and women exists. This gap could exist due exclusively due to labor market discrimination against women, but this interpretation of the gap ignores other relevant factors. Those who claim there is no discrimination against women can argue that women differ in a number of ways that will result in women earning less. Women could be less educated or less experienced than men. They may voluntarily choose lower-paying occupations. Women may decide to focus more on their domestic role and are thus more prone to leave the labor force sporadically or less likely to enter to begin with. These are valid objections to interpreting the wage gap as being due purely to discrimination.

These reasons for casting doubt on labor market discrimination's role in the wage gap do not rule out its presence. What we would like to be able to do is take two workers who are identical in every aspect save their gender and see if there is a difference in pay. The difference would be deemed discriminatory. Obviously this cannot be done since we cannot ensure that two individuals are identical in every way but gender, but we could try to instead estimate what men's and women's wages would be if the two groups were rewarded for their qualifications similarly. We would have both women's observed wages along with women's wages if they were paid the same as men. We would then conclude that the difference between these two wages is discriminatory. (We call this the "returns effect.") Additionally, we could take the estimated wages of a man and a woman with differing qualifications and examine the difference between their predicted wages under our hypothetical, non-discriminatory wage scheme. This difference would be deemed due to differences in the individuals' qualifications or endowments. (We call this the "endowment effect.")

This is the basic idea behind Oaxaca-Blinder (OB) decomposition (Fortin, Lemieux, & Firpo, 2010). When performing OB decomposition, one estimates a wage equation for both men and women, along with a wage equation if they were paid the same, used to estimate the "counterfactual" wage. OB decomposition takes the following form:

$$\overline{W}_M - \overline{W}_F = \underbrace{(\bar{X}_M - \bar{X}_F)\tilde{\beta}}_{\text{Endowment Effect}} + \underbrace{\left[\left(\hat{\beta}_M - \tilde{\beta}\right)\bar{X}_M + \left(\tilde{\beta} - \hat{\beta}_F\right)\bar{X}_F\right]}_{\text{Returns Effect}}$$

$\bar{W}_M - \bar{W}_F$ is the difference between men's and women's log wages, or men's wage premium. $\bar{X}_M$ and $\bar{X}_F$ are vectors representing men's and women's mean characteristics (thus it contains information about average education levels, average ages, the percent of workers in particular occupations, and so on). $\hat{\beta}_M$ and $\hat{\beta}_F$ are the estimated wage function coefficients of men and women or returns to each attribute, respectively, and $\tilde{\beta}$ is the "counterfactual" wage function coefficients according to which both men and women would be paid if they were rewarded in the same way.

Many researchers do not estimate a third equation, and instead assume that either in the absence of discrimination, women would be paid like men or men would be paid like women; in other words, $\tilde{\beta} = \hat{\beta}_M$ or $\tilde{\beta} = \hat{\beta}_F$. We find this approach unsatisfactory in this context; women might be underpaid for certain skills, or men overpaid, and choosing the counterfactual to be either the male or female wage equation would remove this effect. As suggested by Oaxaca and Ransom (1994), a wage gap should account for both a wage penalty to the disadvantaged group and a bonus to the privileged group. We therefore estimate a "pooled" wage equation, which includes both men and women in the sample and takes the same form as the male or female wage equation save for an additional dummy variable for gender. This is similar to what Oaxaca and Ransom recommended, while adding the variable for gender helps account for potential omitted variable bias described by Jann (2008).

The first term of this OB decomposition is the "endowment effect[3]"; this represents the difference in wages that we can attribute to observable differences in the

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[3] There are numerous names for this term; another common one is "explained effect."

mean characteristics of men and women. One might think of this as the part of the wage gap that we could attribute to differences in men's and women's qualifications or attributes.

The second term is the "returns effect[4]." This is the portion of the wage gap that can be attributed to men and women being rewarded for their endowments differently. The returns effect captures discrimination. Unfortunately, though, it will also capture the effects of unobserved or unobservable differences between men and women. More seriously, if the omitted variable is correlated with any of the other observed variables, that variable's influence on the wage gap will be captured here. This is due to omitted variables' influence on the estimates of the coefficients of the wage equation (often called omitted variable bias). The more we do to control for unobserved differences between men and women, the more this effect will represent discrimination alone.

We can do all we can to avoid omitting variables, but there will still likely be important effects that we fail to capture and result in bias. This could be due to limitations of our data source or to factors that are impossible to observe and quantify in a meaningful way. In the context of estimating gender wage discrimination, our regressions used for estimating the wage gap may be biased because women do not participate in the labor force the same way men do. Women, in general, tend to be less attached to the labor force and are more likely to assume domestic roles. In addition, women may not have developed their human capital to the same degree men have, perhaps due to women leaving the labor force and sacrificing on-the-job training and experience in order to raise

[4] Like the endowment effect, this also goes by multiple names. Other common names include "treatment effect" or "unexplained effect."

families. Thus naïve measures underestimate what women's wages would be if they had similar human capital to men, and their estimates of the gender gap are thus too large.

Or perhaps, in some instances or specific time periods, we are underestimating the gap. Perhaps those women who participate in the labor force are unusually skilled, and thus their wages tend to be higher. In comparison, the larger population of women is not as skilled as those who are working, and if we could observe their wages, they would be lower. Under this scenario, if we could account for working women's unusually high skill level, we would actually see a larger wage gap.

Both of these potential problems have a common theme: women enter the labor force differently than men, and these differences may influence the raw wage gap, making it either larger or smaller than it would be if these factors were not present. Economists call this problem "selection bias." If the women entering the labor force tend to have lower levels of human capital (in ways not captured by education and age), motivation, labor force attachment, salary negotiation skills, or other unobservable characteristics, we would call this phenomenon negative selection. On the other hand, if they tend to have high human capital, motivation and so on, we would observe positive selection. In the presence of negative selection, the wage gap estimated by OLS is biased upward; in the case of positive selection, OLS will yield an underestimate of the wage gap.

Fortunately, there are econometric methods that allow us to obtain this more accurate wage gap. In this paper, we use the Heckman correction[5]. This method estimates the probability that a woman enters the labor force (or, more exactly, the study

[5] James Heckman won the Nobel Prize in 2000 for developing this procedure (Nobel Media AB, 2014).

population) using a probit model. This probability is then used to calculate the inverse Mills ratio for that particular individual, which is added as an additional variable to the wage equation. The new wage equation is used to estimate what the true gender gap in wages is. This estimate of the wage gap effectively represents what the gender gap is after removing the effects of selection bias (Heckman, 1979).

In this report, we want to examine the change of the gender gap over time. We also want to explain why Utah has a larger gender gap than the nation; in other words, what explains the difference in the wage gap between Utah and the Intermountain region, or between Utah and the rest of the nation? A basic approach would be to take the difference between the respective endowment and returns effects. There are problems with this method, though; they only work if women's endowments and the counterfactual returns do not change between regions or across time (Bilginsoy, 2013). Kim (2010) and others proposed a solution to this. The decomposition of the difference of wage gaps between two groups, regardless of whether they separated by region or by time, can be represented as:

$$\Delta(\bar{W}_M - \bar{W}_F)$$

$$= \underbrace{\left(\frac{\bar{X}_M^1 + \bar{X}_M^0}{2}\right)\Delta\left(\hat{\beta}_M - \tilde{\beta}\right) + \left(\frac{\bar{X}_F^1 + \bar{X}_F^0}{2}\right)\Delta\left(\tilde{\beta} - \hat{\beta}_F\right)}_{\text{Pure returns effect difference}}$$

$$+ \underbrace{\left(\frac{\left(\hat{\beta}_F^1 + \hat{\beta}_F^0\right) - \left(\tilde{\beta}^1 + \tilde{\beta}^0\right)}{2}\right)\Delta\bar{X}_M + \left(\frac{\left(\tilde{\beta}^1 + \tilde{\beta}^0\right) - \left(\hat{\beta}_F^1 + \hat{\beta}_F^0\right)}{2}\right)\Delta\bar{X}_F}_{\text{Returns interaction}}$$

$$+ \underbrace{\left(\frac{\tilde{\beta}^1 + \tilde{\beta}^0}{2}\right)\Delta(\bar{X}_M - \bar{X}_F)}_{\text{Pure endowment effect difference}} + \underbrace{\left(\frac{(\bar{X}_M^1 + \bar{X}_M^0) - (\bar{X}_F^1 + \bar{X}_F^0)}{2}\right)\Delta\tilde{\beta}}_{\text{Endowment interaction}}$$

The superscripts 0 and 1 are used to identify the two groups of workers (in this paper, they could be groups of workers separated by geography or by time), and Δ represents the difference in some value between these groups. This formula allows us to separate the pure difference in returns effects and the pure difference in endowment effects from accounting interactions between returns and endowments. The sum of the first two terms represents the difference in the returns effects, with the first term representing the part of the difference due exclusively to differences in the returns effect. The sum of the third and fourth terms represent the difference in endowment effects, with the third representing the part of the difference due exclusively to differences in the endowment effect. The other two terms are interaction terms that capture the differences due to changing means and wage functions; they are not interesting on their own, so we will not discuss their meanings here.[6]

In this paper, we use the following wage function:

$$
\begin{aligned}
log(wage_i) &= \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i \\
&+ \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} vet_i \\
&+ \boldsymbol{\beta_{11}} \cdot \boldsymbol{occ}_i + \boldsymbol{\beta_{12}} \cdot \boldsymbol{ind}_i + \beta_{13} overwork_i + \beta_{14} public_i + \varepsilon_i
\end{aligned}
$$

(Note that bolded variables indicate vectors, in this case vectors of dummy variables for occupation and industry groups, with the first group serving as the baseline.)We use $\log(wage_i)$ [7] because we assume that wages follow a lognormal

[6] For a discussion on the interpretation of these interaction effects, see Bilginsoy (2013) or Kim (2010).
[7] Here, log is the natural log; in other words, $\log(wage_i) = \ln(wage_i)$.

distribution. By using this variable, we interpret coefficients as the percentage increase in wages for a unit change in that variable. Furthermore, this allows us to calculate the male wage premium by subtracting women's average log wage from men's log wages. This difference is interpreted as the percentage by which men out-earn women. ε_i is the error term. Our independent variables are: age and age^2, for age and age squared; $nohsdeg$, $somecoll$, $assoc$, $bachelor$, and $graduate$ which is a dummy variables for having less than a high school education, some college but no degree, an associate degree, a bachelor degree, and a graduate degree, respectively; $notwhite$, a dummy for indicating if the individual is not white; $notcitizen$, a dummy indicating an individual is not a U.S. citizen; vet, a dummy for veteran status; $\boldsymbol{occ}$, a vector of dummies for occupation group; $\boldsymbol{ind}$, a vector of dummies for industry sector; $overwork$, a dummy indicating whether the individual worked more than 50 hours a week; and $public$, a dummy variable indicating whether the individual works for a municipal, state, or federal government. Some common variables, such as union status, metropolitan status, and region were excluded. Union and metropolitan status had problems in the sample, particularly for Utah, and region does not make sense to include when a large part of our analysis focuses on comparing Utah to the rest of the nation.

Our selection model is:

$$
\begin{aligned}
&P(E_i = 1|\boldsymbol{X}_i) \\
&= \Phi(\beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i \\
&+ \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} nhhinfant_i \\
&+ \beta_{11} nhhpreschooler_i + \beta_{12} nhholdchild_i + \beta_{13} singlepar_i + \beta_{14} multiadult_i \\
&+ \beta_{15} married_i + \beta_{16} vet_i + \beta_{17} otherhhincome_i + \nu_i)
\end{aligned}
$$

Here, E_i is a binary variable equal to one if an individual is coded to be in the study population. $nhhinfant$, $nhhpreschooler$, and $nhholdchild$ represent the number of infants, preschoolers, and children 6-15 in the household, respectively. $singlepar$ is a dummy variable for single parent status, $multiadult$ is a dummy indicating if there are more than three adults in the household, $otherhhincome_i$ represents other income in the household other than an individual's personal earnings. This could be benefit income, or income from other workers in the household.

One problem with Heckman regression is the choice of specification of selection and wage equations. Sometimes there is no clear distinction between variables that belong to one model and not the other; the actual assignment is somewhat arbitrary. Some have argued that this problem makes the Heckman method worse than the selection bias problem it tries to cure (Bilginsoy, 2013; Freeman & Medoff, 1982). Our preferred specification is not immune to this problem. We did look at more than one choice of division of variables, particularly regarding where variables representing parenthood belong. Clearly parenthood belongs in the selection equation; whether it belongs in the wage equation as well is not as clear.

In the end, our preferred model controls for the effect of parenthood only in the selection model and not the wage equation. Marital status is also included only in the selection model. The relationship between parenthood and the gender gap is complicated, and decisions related to parenthood (such as when to become married, when to have children, how many children to have, and so on) are not independent of economic circumstances, including prevailing wages for women. Thus there are theoretical problems that make simply adding parenthood to the right side of the wage equation too crude an estimate of its effects on the wage gap. Also, while there is considerable collinearity between the Mills ratio and other variables in the wage equation with or without a variable for parenthood being included in the wage equation, these problems appear to become worse when parenthood is included. Thus we feel that our study is not well equipped to quantify the role of parenthood in the gender gap and that different datasets or methodologies might yield more satisfying answers.

Nevertheless, while our preferred model does not include this variable in the wage equation, we decided to present five alternative models for decomposing the wage gap, some of which do include parenthood in the wage equation. The first two alternative models do not control for selection bias. The preferred model and the other three alternative models do, with the third and fourth alternative models using a common selection equation and the last using the same selection equation as the preferred model. The models not using the Heckman method use all variables that would be in the Heckman model save for the variable measuring other household income. The first OLS model and the first two Heckman models use the variable $nhhchild$ (number of children in the household) provided in the CEPR CPS March datasets rather than $nhhinfant$, $nhhpreschooler$, and $nhholdchild$. The other models use $nhhinfant$, $nhhpreschooler$, and $nhholdchild$ in place of $nhhchild$.The last two alternative Heckman models include marital status and binary variables for the presence of children in the household. The children dummy variables are: parent (in the fourth alternative model), which represents whether a child 17 or younger is present; $infparent$ (in the fifth alternative model), for the presence of an infant; $preschoolparent$ (in the fifth model), for the presence of a preschooler (age one to five); and $oldchildparent$ (in the fifth model), for the presence of a child age six to fifteen. We present a summary of the models below:

Table 1: Summary of Specifications Considered

Model	Specifications
Preferred Model	$\log(wage_i) = \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} vet_i + \boldsymbol{\beta_{11}} \cdot \boldsymbol{occ}_i + \boldsymbol{\beta_{12}} \cdot \boldsymbol{ind}_i + \beta_{13} overwork_i + \beta_{14} public_i + \varepsilon_i$ $P(E_i = 1 \mid \boldsymbol{X}_i) = \Phi\big(\beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} nhhinfant_i + \beta_{11} nhhpreschooler_i + \beta_{12} nhholdchild_i + \beta_{13} singlepar_i + \beta_{14} multiadult_i + \beta_{15} married_i + \beta_{16} vet_i + \beta_{17} otherhhincome_i + \nu_i\big)$
Alternative Model 1	$\log(wage_i) = \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} nhhchild_i + \beta_{11} singlepar_i + \beta_{12} multiadult_i + \beta_{13} married_i + \beta_{14} vet_i + \boldsymbol{\beta_{15}} \cdot \boldsymbol{occ}_i + \boldsymbol{\beta_{16}} \cdot \boldsymbol{ind}_i + \beta_{17} overwork_i + \beta_{18} public_i + \varepsilon_i$
Alternative Model 2	$\log(wage_i) = \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} nhhinfant_i + \beta_{11} nhhpreschooler_i + \beta_{12} nhholdchild_i + \beta_{13} singlepar_i + \beta_{14} multiadult_i + \beta_{15} married_i + \beta_{16} vet_i + \boldsymbol{\beta_{17}} \cdot \boldsymbol{occ}_i + \boldsymbol{\beta_{18}} \cdot \boldsymbol{ind}_i + \beta_{19} overwork_i + \beta_{20} public_i + \varepsilon_i$
Alternative Model 3	$\log(wage_i) = \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} vet_i + \boldsymbol{\beta_{11}} \cdot \boldsymbol{occ}_i + \boldsymbol{\beta_{12}} \cdot \boldsymbol{ind}_i + \beta_{13} overwork_i + \beta_{14} public_i + \varepsilon_i$ $P(E_i = 1 \mid \boldsymbol{X}_i) = \Phi\big(\beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} nhhchild_i + \beta_{11} singlepar_i + \beta_{12} multiadult_i + \beta_{13} married_i + \beta_{14} vet_i + \beta_{15} otherhhincome_i + \nu_i\big)$
Alternative Model 4	$\log(wage_i) = \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} parent_i + \beta_{11} married_i + \beta_{12} vet_i + \boldsymbol{\beta_{13}} \cdot \boldsymbol{occ}_i + \boldsymbol{\beta_{14}} \cdot \boldsymbol{ind}_i + \beta_{15} overwork_i + \beta_{16} public_i + \varepsilon_i$ $P(E_i = 1 \mid \boldsymbol{X}_i) = \Phi\big(\beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} nhhchild_i + \beta_{11} singlepar_i + \beta_{12} multiadult_i + \beta_{13} married_i + \beta_{14} vet_i + \beta_{15} otherhhincome_i + \nu_i\big)$
Alternative Model 5	$\log(wage_i) = \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} infantparent_i + \beta_{11} preschoolparent_i + \beta_{12} oldchildparent_i + \beta_{13} married_i + \beta_{14} vet_i + \boldsymbol{\beta_{15}} \cdot \boldsymbol{occ}_i + \boldsymbol{\beta_{16}} \cdot \boldsymbol{ind}_i + \beta_{15} overwork_i + \beta_{17} public_i + \varepsilon_i$ $P(E_i = 1 \mid \boldsymbol{X}_i) = \Phi\big(\beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 nohsdeg_i + \beta_4 somecoll_i + \beta_5 assoc_i + \beta_6 bachelor_i + \beta_7 graduate_i + \beta_8 notwhite_i + \beta_9 notcitizen_i + \beta_{10} nhhinfant_i + \beta_{11} nhhpreschooler_i + \beta_{12} nhholdchild_i + \beta_{13} singlepar_i + \beta_{14} multiadult_i + \beta_{15} married_i + \beta_{16} vet_i + \beta_{17} otherhhincome_i + \nu_i\big)$

Table 1

As mentioned above, the preferred model is more comparable to models used by others while producing results that are plausible in the context of existing literature. However, we present results for other models as well to demonstrate the robustness of some of our findings which hold across specifications.

After performing these procedures, one final question remains: can we call the returns effect labor market discrimination? Remember that this effect captures the effects of men and women being rewarded differently for equal endowments, which could be discrimination but also could be due to biased coefficient estimates due to omitted variables. Thus we need to ask what variables we have left out. We believe that the variables we have included in our wage equation along with the Heckman correction would render any omitted variable bias insignificant, if not nonexistent. Take for example actual work experience, which is a variable we cannot control for in this dataset. Education and age will capture some of this effect in the form of potential work experience, and the effect of women being more likely to drop out of the labor force would be captured by the Heckman correction, so the differences of men and women in work experience is largely controlled for here. Thus, we believe that we have captured most variables and effects that could result in men and women earning different incomes.

THE DATA

In this report, we use the Center for Economic and Policy Research's (CEPR) extracts of the Current Population Survey (CPS) Annual Social and Economic (ASEC) Supplement, more commonly known as CPS March samples (Center for Economic and Policy Research, 2015). CPS is a large nationwide survey conducted monthly in a joint effort by both the Bureau of Labor Statistics and the U.S. Census Bureau, and it collects information on numerous economic and social variables (United States Census Bureau, 2012). The CPS is large enough to allow for analysis at the state level while at the same time providing the variables necessary for our analysis. The ASEC supplement has the information about both income and family structure needed to address the complex issues involved in analyzing the gender gap.

We collected data from 1992 to 2014 and pooled the data into four samples representing four periods of time. The most recent sample is the data from 2009 to 2014. The other periods are 1992 to 1997, 1998 to 2002, and 2003 to 2007. We pooled the samples to improve sample sizes at the state and regional level, and we chose our four periods to allow for a temporal analysis of the changing gender gap. One may label these periods as follows: the 1992 to 1997 period represents the Clinton years; 1998 to 2002 is the dot-com boom and bust; 2003 to 2008 is the housing boom; and 2009 to 2014 is the recovery period from the 2008 Financial Crisis. (This was *not* the motivation for choosing these periods, though; instead, we tried to ensure each period had five to six years.)

The CEPR data files contained most of the variables we needed for the study. In addition to the variables natively present in the files, we generated additional variables from the data for our analysis. We divided education into six groups: less than high-school degree; high-school degree or equivalent; some college but no degree; associate degree or equivalent; bachelor’s degree; and graduate degree.

We created variables to represent the number of children in the household within three age groups: infants (less than one year old), preschool-age children (ages one to five years), and school-age children not old enough to work (ages six to fifteen years). We created these variables by counting the number of children in the data files within a certain age group assigned to individual households. We also created dummy variables to indicate the presence of children within certain age groups in an observation's household, which we use in some of the alternative specifications (but not the preferred specification). These variables should closely approximate whether individuals are parents or guardians of children.

We grouped occupations into eleven major occupation groups (MOGs) and industries into 14 major industry groups (MIGs), based on the MOGs and MIGs defined in the CPS ASEC 2013 documentation (United States Census Bureau, 2013). These definitions changed over time, particularly in 2003, when the MOGs and MIGs classification scheme was changed completely. The MOG and MIG classification schemes from 2003 forward were identical, and we generated our variables according to the definitions provided in the documentation. For the period prior to 2003, we examined the MOG and MIG classification scheme and did our best to translate that scheme into the modern one, basing it off of similar crosswalks developed by the Minnesota Population Center (n.d.) and the U.S. Census Bureau (2014). The scheme we used is presented in the Appendix.

There were sample size issues with some MOGs and MIGs, particularly at the state level for women; individuals representing a particular occupation or industry group simply were not represented. We thus had to group some MOGs together. Farming, forestry and fishing occupations were grouped with transportation and material moving occupations because in the 2009 to 2014 period they had similar mean wages and both were the smallest occupations in Utah.

We generated a variable representing income in the household other than an individual's earned income. This was created by subtracting an individual's earned annual income from the household total income. A variable for the number of adults in a household was generated by subtracting the number of children in the household from the number of people in the household. A dummy variable representing single parents was generated, where someone is classified as a "single parent" if there were children in the household but only one adult. We also created a dummy variable for whether an individual lives in a household with more than two adults. A dummy for overtime work was created, and an individual is classified as an "overtime worker" if the individual works more than 50 hours a week. Finally, we created a dummy variable representing whether an individual is a public sector worker at either the local, state, or federal level.

All non-dummy variables (namely, the age variables, number of children in a household, and other household income) were centered around their respective means, in order to facilitate easier interpretation.

In our study, we are interested in three geographic levels: the national level, the regional level, and the state level. The entire sample is considered to represent the national level. As for the region, we consider Utah to be a member of the Intermountain West region, which consists of the states of Montana, Idaho, Wyoming, Colorado, New Mexico, Arizona, Utah, and Nevada.

We restricted our sample to individuals between the ages of 16 and 65, the working age population. We considered an individual to be in the study population if the individual was employed, worked at least 50 weeks a year and 35 hours a week, was not in the armed forces, and not self-employed or self-incorporated. Throughout our study, we use the variable `rhrearn` as the variable representing real hourly earnings. We required individuals in our study population to have real hourly earnings between $2.13[8] and $100 an hour and not be in the armed forces. The sample also had to be reduced when observations had missing information.

In order to apply the Heckman two-step method, we needed to have a sample that represents the entire working age population. This is for estimating the probability that an individual is in the study population. Most individuals in the CPS March dataset were kept in this sample. We only dropped individuals with other household incomes over $1 million a year and households with more than five preschool-age children. These observations were preventing estimation of probit models. Their share of the sample was near zero, so our sample is nearly as representative of the population without them.

The ASEC supplement provides weights for individuals intended to account for survey design. In the CEPR files, this is the `wgt` variable. We used this variable for weights in all our estimates. This is the extent of accounting for survey design in standard errors, which may result in bias (they will tend to be too small [9] (Center for Economic and Policy Research, n.d.)). We do not believe this to be of major consequence, though. While we did produce standard errors with our estimates, we typically do not report them (with the exception of the regression equations). We used STATA for estimating most results.

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[8] This is the federal minimum wage for tipped workers.
[9] For more information, see: http://ceprdata.org/cps-uniform-data-extracts/cps-outgoing-rotation-group/cps-org-faq/

Below we present summary statistics for the study population:

Table 2: Summary statistics of study population, 2009-2014

	Nation			**Region**			**Utah**		
	Total	**Male**	**Female**	**Total**	**Male**	**Female**	**Total**	**Male**	**Female**
Means									
Real hourly earnings	$23.63	$25.66	$21.15	$23.48	$25.57	$20.68	$23.69	$26.00	$19.77
Natural logarithm of real hourly earnings	2.9859	3.0652	2.8891	2.9828	3.0682	2.8686	3.0035	3.1012	2.8383
Age	41.8994	41.5946	42.2713	41.4841	41.2931	41.7394	39.7247	39.3162	40.4151
Number of children in household	0.7806	0.8259	0.7254	0.8444	0.9128	0.7529	1.1574	1.2973	0.9209
Number of infants in household	0.0370	0.0432	0.0294	0.0421	0.0487	0.0333	0.0690	0.0879	0.0370
Number of children ages 1-5 in household	0.2124	0.2357	0.1839	0.2330	0.2680	0.1861	0.3492	0.4241	0.2228
Number of children ages 6-15 in household	0.4368	0.4552	0.4142	0.4714	0.5015	0.4311	0.6326	0.6858	0.5429
Number of adults in household	2.3269	2.3864	2.2543	2.2783	2.3207	2.2216	2.5098	2.5499	2.4421
Real annual household income other than personal earned income	$37,234.69	$32,395.03	$43,139.79	$34,118.44	$28,593.48	$41,505.83	$36,836.97	$30,741.16	$47,137.32
Proportions									
Female	45.04%			42.79%			37.18%		
Less than high school degree	7.21%	8.90%	5.14%	7.69%	9.12%	5.77%	6.47%	7.22%	5.20%
High school degree or equivalent	27.87%	30.02%	25.25%	26.45%	27.21%	25.44%	26.40%	25.58%	27.80%
Some college, but no degree	17.67%	17.13%	18.33%	20.57%	19.88%	21.50%	24.48%	23.85%	25.55%
Associate degree or equivalent	10.98%	9.74%	12.49%	10.53%	9.88%	11.39%	10.74%	10.28%	11.52%
Bachelor's degree	23.87%	22.67%	25.32%	23.55%	23.49%	23.63%	20.95%	20.62%	21.51%
Graduate degree	12.40%	11.53%	13.47%	11.21%	10.42%	12.26%	10.96%	12.46%	8.42%
Child present	42.92%	43.86%	41.78%	43.10%	44.75%	40.90%	52.93%	56.23%	47.34%
Infant present	3.62%	4.23%	2.89%	4.13%	4.78%	3.25%	6.69%	8.46%	3.70%
Child age 1-5 present	16.75%	18.19%	15.00%	17.71%	19.87%	14.83%	24.39%	28.84%	16.87%
Child age 6-10 present	28.15%	28.60%	27.60%	28.67%	29.64%	27.37%	35.00%	36.63%	32.25%
Not white	33.51%	33.11%	34.00%	31.00%	31.41%	30.44%	16.14%	15.94%	16.48%
Married	59.01%	62.32%	54.96%	60.49%	63.75%	56.13%	66.80%	72.16%	57.75%
Single parent	3.10%	1.03%	5.63%	2.77%	1.07%	5.04%	2.36%	0.61%	5.32%
More than two adults in household	29.26%	30.67%	27.54%	26.73%	27.91%	25.16%	32.78%	32.79%	32.75%
Not a citizen	8.66%	10.55%	6.35%	7.79%	9.08%	6.06%	7.09%	7.49%	6.40%
Veteran	6.78%	11.09%	1.52%	8.13%	12.92%	1.73%	4.92%	7.05%	1.31%
Management, business or financial occupation	16.83%	16.23%	17.55%	16.76%	15.85%	17.98%	16.91%	16.21%	18.11%
Professional or related occupation	23.41%	19.02%	28.77%	22.28%	19.26%	26.32%	21.23%	20.21%	22.94%
Service occupation	14.25%	13.05%	15.72%	15.00%	13.76%	16.67%	10.03%	8.34%	12.89%
Sales or related occupation	9.35%	9.56%	9.10%	10.46%	10.60%	10.28%	10.20%	10.06%	10.45%
Office or administrative support occupation	13.90%	6.86%	22.49%	14.01%	7.26%	23.03%	14.75%	7.59%	26.85%
Farming, forestry, or fishing occupation	0.60%	0.88%	0.25%	0.71%	1.04%	0.26%	0.40%	0.47%	0.28%
Construction or extraction occupation	4.65%	8.28%	0.22%	5.61%	9.64%	0.23%	6.26%	9.92%	0.08%
Installation, maintenance, or repair occupation	4.23%	7.41%	0.35%	4.62%	7.78%	0.40%	5.29%	8.10%	0.55%
Production occupation	6.75%	9.19%	3.78%	4.90%	6.39%	2.92%	8.33%	10.10%	5.33%
Transportation or material moving occupation	6.03%	9.52%	1.77%	5.63%	8.41%	1.91%	6.59%	9.01%	2.52%
Agriculture, forestry, fishing, and hunting sector	0.80%	1.21%	0.30%	1.06%	1.51%	0.47%	0.73%	0.79%	0.64%
Mining sector	0.79%	1.26%	0.21%	2.04%	3.15%	0.56%	2.92%	4.19%	0.77%
Construction sector	5.59%	9.21%	1.16%	6.33%	10.13%	1.24%	7.23%	10.40%	1.87%
Manufacturing sector	12.94%	17.08%	7.88%	9.70%	12.45%	6.02%	14.57%	17.74%	9.22%
Wholesale and retail trade sector	13.22%	14.39%	11.80%	14.05%	14.99%	12.78%	14.23%	14.08%	14.47%
Transportation and utilities sector	5.90%	8.31%	2.97%	5.90%	7.79%	3.37%	6.34%	7.90%	3.70%
Information sector	2.58%	2.90%	2.19%	2.49%	2.88%	1.98%	2.09%	2.43%	1.50%
Financial activities sector	7.66%	6.18%	9.46%	7.57%	5.70%	10.08%	6.76%	5.19%	9.43%
Professional and business services sector	10.25%	11.03%	9.30%	10.50%	11.30%	9.44%	10.23%	10.62%	9.59%
Education and health services sector	23.07%	10.97%	37.84%	20.32%	10.45%	33.52%	18.63%	10.63%	32.15%
Leisure and hospitality sector	6.63%	6.60%	6.68%	9.00%	8.61%	9.52%	4.97%	4.75%	5.35%
Other service sectors	3.83%	3.96%	3.66%	3.76%	3.92%	3.54%	3.95%	3.73%	4.31%
Public administration sector	6.74%	6.90%	6.53%	7.28%	7.12%	7.49%	7.34%	7.54%	7.01%
Overtime work	17.60%	22.06%	12.16%	17.99%	21.80%	12.91%	18.16%	21.95%	11.74%
Public sector worker	17.61%	14.85%	20.97%	18.23%	15.64%	21.69%	17.62%	15.03%	22.00%
Utah resident	0.87%	1.00%	0.72%	12.49%	13.72%	10.85%			
Intermountain region resident	6.97%	7.26%	6.62%						
Sample Size	327,834	178,861	148,973	33,434	19,204	14,230	3,999	2,518	1,481

Table 2 (Data source: CPS March from ceprdata.org)

Table 3: Summary statistics of study population, 2003-2008

	Nation			Region			Utah		
	Total	Male	Female	Total	Male	Female	Total	Male	Female
Means									
Real hourly earnings	$23.34	$25.36	$20.73	$22.64	$24.62	$19.79	$22.49	$25.14	$18.23
Natural logarithm of real hourly earnings	2.9791	3.0592	2.8761	2.9512	3.0319	2.8355	2.9457	3.0614	2.7593
Age	40.8256	40.4669	41.2868	40.0895	39.6889	40.6642	38.8696	38.7449	39.0705
Number of children in household	0.8181	0.8678	0.7543	0.8914	0.9581	0.7956	1.0627	1.1845	0.8665
Number of infants in household	0.0399	0.0483	0.0292	0.0474	0.0567	0.0341	0.0631	0.0761	0.0422
Number of children ages 1-5 in household	0.2192	0.2478	0.1824	0.2490	0.2893	0.1913	0.3281	0.3949	0.2204
Number of children ages 6-15 in household	0.4597	0.4753	0.4398	0.4910	0.5103	0.4633	0.5405	0.5796	0.4775
Number of adults in household	2.3241	2.4017	2.2242	2.2928	2.3417	2.2225	2.5384	2.5599	2.5039
Real annual household income other than personal earned income	$38,264.16	$32,750.66	$45,352.63	$34,003.49	$27,973.92	$42,655.07	$36,788.17	$29,915.96	$47,855.76
Proportions									
Female	43.75%			41.07%			38.30%		
Less than high school degree	9.38%	11.44%	6.74%	10.10%	12.20%	7.07%	7.54%	8.79%	5.52%
High school degree or equivalent	30.69%	31.82%	29.23%	29.25%	29.41%	29.01%	29.62%	28.48%	31.46%
Some college, but no degree	18.51%	17.61%	19.68%	22.06%	21.20%	23.29%	24.14%	23.89%	24.55%
Associate degree or equivalent	9.97%	8.85%	11.41%	9.34%	8.59%	10.41%	9.94%	8.48%	12.29%
Bachelor's degree	21.11%	20.25%	22.22%	19.67%	19.10%	20.49%	19.92%	20.47%	19.05%
Graduate degree	10.33%	10.03%	10.73%	9.59%	9.49%	9.72%	8.84%	9.89%	7.13%
Child present	44.83%	46.01%	43.31%	46.04%	47.54%	43.89%	50.24%	53.43%	45.11%
Infant present	5.45%	6.23%	4.44%	6.35%	7.22%	5.11%	9.15%	10.53%	6.93%
Child age 1-5 present	23.35%	25.02%	21.21%	24.62%	27.09%	21.08%	32.48%	35.73%	27.24%
Child age 6-10 present	38.76%	39.10%	38.33%	39.23%	39.81%	38.41%	43.51%	45.08%	40.98%
Not white	32.01%	31.84%	32.23%	30.74%	32.22%	28.62%	17.06%	16.75%	17.57%
Married	59.85%	63.61%	55.02%	58.98%	62.25%	54.30%	65.57%	71.42%	56.16%
Single parent	3.37%	1.03%	6.38%	3.21%	1.33%	5.91%	2.60%	0.98%	5.20%
More than two adults in household	28.71%	30.60%	26.28%	27.09%	28.09%	25.66%	34.75%	34.42%	35.29%
Not a citizen	9.44%	11.56%	6.73%	10.03%	12.24%	6.85%	7.76%	8.73%	6.18%
Veteran	8.59%	14.15%	1.44%	9.94%	15.76%	1.58%	7.40%	11.47%	0.84%
Management, business or financial occupation	15.35%	14.72%	16.16%	15.54%	14.65%	16.82%	16.46%	15.99%	17.22%
Professional or related occupation	21.00%	17.31%	25.75%	19.50%	16.60%	23.67%	19.18%	17.09%	22.55%
Service occupation	13.39%	12.07%	15.08%	14.54%	13.36%	16.23%	10.24%	7.97%	13.90%
Sales or related occupation	9.86%	9.98%	9.72%	10.80%	10.51%	11.21%	10.74%	11.22%	9.97%
Office or administrative support occupation	14.90%	6.81%	25.29%	14.46%	6.43%	26.00%	15.21%	6.79%	28.79%
Farming, forestry, or fishing occupation	0.60%	0.89%	0.23%	0.83%	1.28%	0.18%	0.50%	0.74%	0.10%
Construction or extraction occupation	5.95%	10.36%	0.27%	8.00%	13.24%	0.49%	8.00%	12.79%	0.29%
Installation, maintenance, or repair occupation	4.43%	7.55%	0.41%	4.41%	7.24%	0.35%	5.05%	8.06%	0.21%
Production occupation	8.25%	10.53%	5.32%	6.03%	7.76%	3.55%	8.14%	9.98%	5.17%
Transportation or material moving occupation	6.27%	9.78%	1.75%	5.88%	8.94%	1.50%	6.48%	9.38%	1.80%
Agriculture, forestry, fishing, and hunting sector	0.80%	1.17%	0.32%	1.13%	1.56%	0.51%	0.73%	0.95%	0.38%
Mining sector	0.57%	0.89%	0.15%	1.42%	2.20%	0.30%	2.12%	3.18%	0.41%
Construction sector	6.93%	11.26%	1.36%	9.29%	14.34%	2.03%	8.75%	13.06%	1.82%
Manufacturing sector	14.90%	18.80%	9.88%	10.13%	12.55%	6.66%	13.65%	16.80%	8.57%
Wholesale and retail trade sector	14.05%	15.26%	12.49%	14.09%	14.69%	13.23%	14.76%	15.01%	14.35%
Transportation and utilities sector	5.97%	8.19%	3.11%	5.88%	7.81%	3.11%	6.28%	8.26%	3.07%
Information sector	2.82%	2.93%	2.68%	2.83%	2.78%	2.89%	2.53%	2.52%	2.56%
Financial activities sector	7.68%	5.78%	10.11%	7.52%	5.51%	10.41%	7.80%	6.45%	9.96%
Professional and business services sector	9.39%	9.63%	9.08%	9.98%	10.57%	9.15%	9.26%	8.77%	10.04%
Education and health services sector	20.32%	9.64%	34.06%	17.81%	8.94%	30.53%	17.41%	9.47%	30.19%
Leisure and hospitality sector	6.37%	6.23%	6.54%	9.20%	8.59%	10.08%	5.71%	5.05%	6.78%
Other service sectors	3.84%	3.88%	3.80%	3.72%	3.78%	3.64%	3.62%	3.63%	3.60%
Public administration sector	6.36%	6.33%	6.41%	6.99%	6.68%	7.45%	7.40%	6.86%	8.28%
Overtime work	18.19%	23.07%	11.90%	18.17%	22.45%	12.02%	19.01%	24.10%	10.80%
Public sector worker	17.02%	14.36%	20.44%	17.67%	15.17%	21.25%	18.28%	15.68%	22.46%
Utah resident	0.78%	0.86%	0.68%	11.49%	12.03%	10.72%			
Intermountain region resident	6.81%	7.13%	6.39%						
Sample Size	374,182	208,578	165,604	41,294	24,141	17,153	4,915	3,039	1,876

Table 3 (Data source: CPS March from ceprdata.org)

Table 4: Summary statistics of study population, 1998-2002

	Nation			Region			Utah		
	Total	Male	Female	Total	Male	Female	Total	Male	Female
Means									
Real hourly earnings	$21.44	$23.56	$18.66	$20.72	$22.64	$17.96	$21.29	$23.70	$17.23
Natural logarithm of real hourly earnings	2.9020	2.9962	2.7791	2.8657	2.9525	2.7414	2.9048	3.0102	2.7278
Age	39.8530	39.6665	40.0962	39.1263	38.8602	39.5068	38.4529	38.4274	38.4957
Number of children in household	0.8478	0.8939	0.7878	0.9192	0.9916	0.8156	1.1574	1.3149	0.8928
Number of infants in household	0.0540	0.0632	0.0419	0.0599	0.0713	0.0436	0.0755	0.0947	0.0432
Number of children ages 1-5 in household	0.3172	0.3474	0.2778	0.3407	0.3730	0.2944	0.3962	0.4762	0.2618
Number of children ages 6-15 in household	0.6919	0.7023	0.6783	0.7589	0.7806	0.7279	0.8054	0.8813	0.6779
Number of adults in household	2.3341	2.4085	2.2370	2.3836	2.4378	2.3061	2.4721	2.5131	2.4031
Real annual household income other than personal earned income	$36,529.06	$31,061.94	$43,663.64	$32,997.91	$27,170.87	$41,332.40	$36,560.71	$30,761.07	$46,306.84
Proportions									
Female	43.38%			41.15%			37.31%		
Less than high school degree	10.00%	11.78%	7.68%	10.80%	12.62%	8.21%	7.03%	8.51%	4.54%
High school degree or equivalent	32.01%	32.35%	31.57%	30.27%	29.94%	30.75%	31.32%	29.19%	34.90%
Some college, but no degree	19.38%	18.51%	20.50%	23.24%	22.02%	24.98%	25.19%	25.22%	25.12%
Associate degree or equivalent	9.69%	8.83%	10.80%	9.37%	8.38%	10.78%	8.56%	8.77%	8.20%
Bachelor's degree	19.97%	19.55%	20.52%	18.85%	19.48%	17.95%	18.82%	18.42%	19.51%
Graduate degree	8.96%	8.98%	8.93%	7.46%	7.56%	7.33%	9.07%	9.88%	7.72%
Child present	46.05%	47.20%	44.56%	46.64%	48.49%	44.00%	53.21%	58.24%	44.77%
Infant present	5.20%	6.08%	4.05%	5.75%	6.82%	4.22%	6.89%	8.58%	4.04%
Child age 1-5 present	24.03%	25.90%	21.59%	25.25%	26.94%	22.83%	26.66%	30.76%	19.76%
Child age 6-10 present	40.49%	40.64%	40.31%	42.33%	42.54%	42.02%	43.05%	45.29%	39.28%
Not white	29.62%	28.95%	30.49%	27.14%	27.17%	27.10%	12.29%	13.06%	11.01%
Married	60.24%	64.46%	54.74%	59.71%	63.11%	54.86%	67.07%	72.28%	58.31%
Single parent	3.33%	0.94%	6.45%	3.47%	1.50%	6.28%	2.94%	1.25%	5.77%
More than two adults in household	28.45%	30.02%	26.41%	28.09%	29.30%	26.35%	33.46%	34.37%	31.92%
Not a citizen	8.84%	10.77%	6.32%	8.38%	9.55%	6.71%	5.88%	6.93%	4.12%
Veteran	10.19%	16.94%	1.38%	12.28%	19.53%	1.92%	8.61%	13.00%	1.22%
Management, business or financial occupation	17.76%	16.02%	20.02%	17.80%	15.55%	21.04%	17.57%	15.44%	21.15%
Professional or related occupation	19.15%	16.60%	22.49%	18.29%	16.99%	20.15%	20.38%	18.67%	23.25%
Service occupation	12.25%	11.58%	13.13%	14.06%	13.44%	14.94%	8.44%	7.77%	9.57%
Sales or related occupation	9.94%	9.74%	10.20%	10.70%	10.49%	11.00%	10.64%	11.10%	9.86%
Office or administrative support occupation	13.61%	5.49%	24.19%	12.81%	4.57%	24.58%	13.80%	5.54%	27.68%
Farming, forestry, or fishing occupation	0.12%	0.17%	0.07%	0.16%	0.18%	0.14%	0.20%	0.00%	0.52%
Construction or extraction occupation	6.81%	11.49%	0.70%	8.44%	13.91%	0.62%	8.34%	13.29%	0.03%
Installation, maintenance, or repair occupation	6.63%	11.24%	0.62%	6.61%	10.89%	0.49%	8.34%	13.15%	0.26%
Production occupation	10.09%	12.47%	6.99%	7.65%	8.95%	5.79%	8.88%	10.61%	5.96%
Transportation or material moving occupation	3.63%	5.21%	1.58%	3.48%	5.03%	1.26%	3.42%	4.43%	1.72%
Agriculture, forestry, fishing, and hunting sector	0.85%	1.24%	0.35%	1.39%	2.10%	0.39%	1.42%	1.34%	1.56%
Mining sector	0.51%	0.77%	0.16%	1.40%	2.17%	0.30%	1.69%	2.67%	0.03%
Construction sector	6.32%	10.14%	1.34%	8.18%	12.80%	1.57%	7.33%	11.08%	1.04%
Manufacturing sector	18.37%	22.42%	13.07%	12.36%	14.81%	8.86%	14.72%	17.10%	10.73%
Wholesale and retail trade sector	14.11%	15.37%	12.47%	15.33%	16.96%	12.99%	15.53%	17.05%	12.96%
Transportation and utilities sector	6.57%	8.96%	3.45%	6.26%	8.39%	3.20%	8.65%	11.54%	3.80%
Information sector	4.72%	5.15%	4.15%	5.48%	5.55%	5.39%	5.69%	6.30%	4.68%
Financial activities sector	7.25%	4.99%	10.20%	6.45%	3.88%	10.13%	6.32%	3.94%	10.32%
Professional and business services sector	6.91%	6.61%	7.32%	6.97%	6.70%	7.36%	6.67%	5.54%	8.56%
Education and health services sector	18.78%	9.02%	31.52%	16.55%	8.18%	28.52%	17.08%	10.68%	27.82%
Leisure and hospitality sector	5.90%	5.65%	6.23%	9.23%	8.13%	10.80%	3.34%	2.20%	5.26%
Other service sectors	3.52%	3.46%	3.60%	3.40%	3.44%	3.36%	3.50%	3.21%	3.98%
Public administration sector	6.18%	6.22%	6.12%	6.99%	6.88%	7.14%	8.07%	7.36%	9.26%
Overtime work	18.99%	24.18%	12.22%	19.92%	24.82%	12.90%	21.23%	26.76%	11.94%
Public sector worker	16.25%	14.00%	19.17%	17.11%	14.91%	20.25%	19.55%	16.15%	25.24%
Utah resident	0.71%	0.78%	0.61%	11.10%	11.82%	10.06%			
Intermountain region resident	6.37%	6.62%	6.04%						
Sample Size	290,053	163,319	126,734	33,285	19,554	13,731	3,777	2,344	1,433

Table 4 (Data source: CPS March from ceprdata.org)

Table 5: Summary statistics of study population, 1992-1997

	Nation			Region			Utah		
	Total	**Male**	**Female**	**Total**	**Male**	**Female**	**Total**	**Male**	**Female**
Means									
Real hourly earnings	$21.39	$23.61	$18.38	$20.30	$22.26	$17.35	$19.84	$21.83	$16.52
Natural logarithm of real hourly earnings	2.9036	3.0019	2.7702	2.8575	2.9485	2.7211	2.8518	2.9505	2.6878
Age	39.0313	38.9145	39.1899	38.3926	38.1568	38.7462	37.0876	37.2952	36.7424
Number of children in household	0.8557	0.9143	0.7763	0.9609	1.0387	0.8441	1.2965	1.4120	1.1046
Number of infants in household	0.0426	0.0511	0.0312	0.0464	0.0570	0.0304	0.0707	0.0805	0.0546
Number of children ages 1-5 in household	0.2366	0.2683	0.1935	0.2627	0.3046	0.2000	0.3575	0.4116	0.2676
Number of children ages 6-15 in household	0.4779	0.4990	0.4493	0.5440	0.5711	0.5032	0.7099	0.7589	0.6285
Number of adults in household	2.2989	2.3608	2.2150	2.2495	2.3025	2.1700	2.3904	2.4532	2.2861
Real annual household income other than personal earned income	$34,854.24	$29,681.64	$41,873.01	$30,646.40	$25,536.69	$38,311.95	$33,516.03	$28,067.16	$42,576.31
Proportions									
Female	42.43%	0.00%	100.00%	40.00%	0.00%	100.00%	37.55%	0.00%	100.00%
Less than high school degree	9.80%	11.53%	7.46%	8.34%	9.79%	6.16%	5.13%	6.11%	3.50%
High school degree or equivalent	33.76%	33.41%	34.23%	31.03%	30.77%	31.43%	33.42%	32.07%	35.65%
Some college, but no degree	19.72%	19.00%	20.71%	25.82%	25.10%	26.90%	29.36%	28.67%	30.51%
Associate degree or equivalent	8.89%	7.98%	10.13%	9.29%	8.95%	9.81%	8.34%	9.19%	6.93%
Bachelor's degree	18.97%	18.78%	19.23%	18.17%	17.65%	18.94%	16.37%	16.50%	16.16%
Graduate degree	8.85%	9.30%	8.24%	7.35%	7.75%	6.76%	7.38%	7.46%	7.24%
Child present	46.89%	48.41%	44.83%	49.36%	51.30%	46.46%	57.01%	59.29%	53.21%
Infant present	4.17%	4.99%	3.06%	4.54%	5.56%	3.00%	6.92%	7.89%	5.32%
Child age 1-5 present	18.83%	20.84%	16.10%	20.73%	23.40%	16.72%	26.57%	29.74%	21.30%
Child age 6-10 present	30.96%	31.60%	30.09%	33.27%	33.97%	32.21%	37.29%	38.39%	35.47%
Not white	24.48%	23.64%	25.63%	20.97%	21.83%	19.67%	9.87%	10.04%	9.59%
Married	62.07%	66.34%	56.29%	62.87%	65.86%	58.39%	70.98%	73.94%	66.07%
Single parent	3.23%	0.91%	6.36%	3.15%	1.02%	6.35%	2.40%	0.91%	4.88%
More than two adults in household	27.39%	28.76%	25.54%	24.68%	26.08%	22.60%	27.86%	29.61%	24.96%
Not a citizen	6.70%	7.69%	5.36%	5.52%	6.37%	4.24%	3.58%	3.89%	3.07%
Veteran	12.88%	21.42%	1.31%	15.63%	24.82%	1.84%	11.97%	18.27%	1.50%
Management, business or financial occupation	16.83%	15.75%	18.29%	17.53%	15.66%	20.33%	18.52%	16.43%	21.99%
Professional or related occupation	18.66%	16.39%	21.73%	18.85%	17.14%	21.41%	18.32%	16.07%	22.07%
Service occupation	11.68%	11.16%	12.39%	12.95%	12.83%	13.13%	8.70%	9.91%	6.67%
Sales or related occupation	9.96%	10.03%	9.86%	11.21%	11.17%	11.29%	9.95%	9.80%	10.19%
Office or administrative support occupation	14.93%	6.10%	26.92%	13.44%	5.21%	25.78%	14.21%	6.50%	27.04%
Farming, forestry, or fishing occupation	0.12%	0.16%	0.06%	0.05%	0.07%	0.02%	0.00%	0.00%	0.00%
Construction or extraction occupation	5.91%	9.77%	0.68%	7.71%	12.44%	0.62%	8.54%	13.42%	0.43%
Installation, maintenance, or repair occupation	6.75%	11.28%	0.61%	7.21%	11.45%	0.85%	8.24%	12.55%	1.07%
Production occupation	11.64%	14.23%	8.11%	7.92%	9.75%	5.17%	10.63%	11.52%	9.14%
Transportation or material moving occupation	3.53%	5.14%	1.34%	3.14%	4.29%	1.40%	2.89%	3.79%	1.41%
Agriculture, forestry, fishing, and hunting sector	0.92%	1.36%	0.31%	1.12%	1.54%	0.49%	0.86%	0.99%	0.65%
Mining sector	0.64%	0.96%	0.21%	1.86%	2.74%	0.53%	1.90%	2.89%	0.26%
Construction sector	4.94%	7.83%	1.02%	6.84%	10.30%	1.65%	5.98%	8.96%	1.02%
Manufacturing sector	21.00%	25.55%	14.82%	14.43%	17.46%	9.88%	17.87%	20.32%	13.81%
Wholesale and retail trade sector	14.16%	15.26%	12.67%	14.80%	15.81%	13.29%	14.18%	14.76%	13.22%
Transportation and utilities sector	6.85%	9.27%	3.57%	7.06%	8.97%	4.20%	7.62%	8.88%	5.53%
Information sector	3.63%	3.84%	3.34%	3.36%	3.41%	3.28%	3.77%	3.78%	3.75%
Financial activities sector	7.55%	5.30%	10.61%	6.88%	4.59%	10.33%	6.82%	4.85%	10.10%
Professional and business services sector	6.16%	5.89%	6.53%	6.69%	6.61%	6.80%	5.41%	4.30%	7.25%
Education and health services sector	18.73%	9.32%	31.51%	17.13%	9.10%	29.18%	16.42%	11.24%	25.02%
Leisure and hospitality sector	5.38%	5.15%	5.70%	8.29%	7.74%	9.12%	5.29%	4.66%	6.32%
Other service sectors	3.40%	3.53%	3.22%	3.63%	3.96%	3.13%	3.33%	4.25%	1.80%
Public administration sector	6.64%	6.74%	6.49%	7.91%	7.77%	8.12%	10.55%	10.11%	11.28%
Overtime work	19.60%	25.18%	12.02%	20.42%	25.39%	12.96%	18.32%	22.94%	10.64%
Public sector worker	17.75%	15.70%	20.54%	20.14%	17.63%	23.90%	22.65%	20.58%	26.10%
Utah resident	0.70%	0.76%	0.62%	12.18%	12.67%	11.44%			
Intermountain region resident	5.73%	5.97%	5.40%						
Sample Size	157,270	89,315	67,955	15,686	9,307	6,379	2,008	1,245	763

Table 5 (Data source: CPS March from ceprdata.org)

RESULTS

Regression Results

We first present regression results for the contemporary period (results for other periods are omitted). We start with the probit models used for estimating the inverse Mills ratio used in the Heckman regressions. These probit models were estimated on most of the sample provided in the CPS data, although some observations had to be removed in order to estimate the model's coefficients. The most we can do with the coefficients of a probit model is comment on their signs and compare their magnitudes. We can use these to comment on the probability an individual is in the labor force. Note that the dependent variable in our probit model is inclusion in the study population, which was described in the Data section.

Table 6: Probit Model Estimates for Women 16-65 For Estimating Probability of Being Employed Full-Time Year Round, 2009-2014 Period

	(1) National	(2) Intermountain	(3) Utah
age	0.162***	0.166***	0.148***
	(0.00142)	(0.00467)	(0.0119)
age^2	-0.00192***	-0.00199***	-0.00173***
	(1.71×10^{-5})	(5.67×10^{-5})	(0.000146)
$nohsdeg$	-0.523***	-0.505***	-0.566***
	(0.00964)	(0.0319)	(0.0862)
$somecoll$	0.0328***	-0.0118	-0.00639
	(0.00768)	(0.0249)	(0.0615)
$assoc$	0.223***	0.0748**	-0.121
	(0.00923)	(0.0310)	(0.0741)
$bachelor$	0.355***	0.196***	0.147**
	(0.00774)	(0.0263)	(0.0662)
$graduate$	0.456***	0.331***	0.378***
	(0.00975)	(0.0342)	(0.104)
$notwhite$	0.0623***	0.0676***	0.126**
	(0.00566)	(0.0195)	(0.0606)
$nhhinfant$	-0.263***	-0.237***	-0.410***
	(0.0132)	(0.0396)	(0.0891)
$nhhpreschooler$	-0.161***	-0.205***	-0.269***
	(0.00486)	(0.0152)	(0.0348)
$nhholdchild$	-0.148***	-0.155***	-0.168***
	(0.00320)	(0.0100)	(0.0223)
$singlepar$	0.0526***	0.0506	0.150
	(0.0116)	(0.0394)	(0.107)
$multiadult$	-0.00170	-0.0323	0.0182
	(0.00594)	(0.0199)	(0.0493)
$married$	0.0232***	-0.0412*	-0.249***
	(0.00661)	(0.0221)	(0.0574)
$notcitizen$	-0.247***	-0.262***	0.01000
	(0.00986)	(0.0334)	(0.0951)
vet	-0.000166	-0.0801	0.0295
	(0.0228)	(0.0692)	(0.222)
$otherhhincome$	-2.87×10^{-6}***	-2.75×10^{-6}***	-2.72×10^{-6}***
	(5.99×10^{-8})	(1.94×10^{-7})	(4.37×10^{-7})
$constant$	-0.423***	-0.349***	-0.217***
	(0.00718)	(0.0243)	(0.0641)
Observations	389,762	40,088	4,742

Heteroskedasticity-robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$[10]

Table 6 (Data source: CPS March from ceprdata.org)

According to the results of our probit model, older women are more likely to be in the labor force than younger women, along with more educated women. The more

[10] Recall that a p-value indicates the maximum level of significance a number can be considered statistically significant from (in this case) zero. The smaller the p-value, the more significant a number is considered. An estimate with a p-value of 0.03 would be considered statistically significant at the 90% and 95% confidence levels, but not the 99% confidence level.

children women have, the less likely they are to be working or looking for work, with younger children inhibiting work more than older children. Women who are not citizens are also less likely to work at the national and regional levels, but not at the state level. The more income the household sees from other sources, the less likely a woman is to be employed.

None of these facts are surprising, but there are interesting patterns when one compares these regressions. Notice that while education does increase the likelihood of employment across all geographic regions, it has less of an impact on Utah women. Also, being married has a much stronger negative effect in Utah than at the national or regional levels (in fact, at the national level, marital status has a positive effect, although it is small). Individuals who are not white or identify as Hispanic are also more likely to be working, especially in Utah. Children also inhibit employment for Utah women more than women at the national or regional levels.

Next, we present log regression results corrected for selection bias for all geographic regions. We present the estimated wage functions for men and women, along with a wage function that represents the wage function if discrimination were to disappear overnight (*not* the wage equation that would prevail if discrimination never existed!). Here, we can interpret the coefficients of the variables *other* than the inverse Mills ratio as being the percentage increase in hourly earnings per unit change in that variable; in the case of binary variables (such as level of education), this is the percentage difference In wages of individuals belonging to a particular group over the baseline group. For education, we designated individuals with only a high school degree as the baseline. The baseline occupation group is management, business, and financial occupations, and the baseline industry group is the agricultural, forestry, fishing, and hunting sectors (chosen for no reason other than they were the first listed occupation or industry groups).

We do not interpret the coefficient of the inverse Mills ratio like the other variables. There is an interpretation of the value of the coefficient that we are not particularly interested in here[11]. However, we are interested in the sign of this coefficient. If the sign of the coefficient is positive, female workers exhibit positive selection; if negative, we observe negative selection. In the former case, naïve measures such as OLS will overestimate women's mean wages, while in the latter case they would underestimate their mean wages if selection bias were not a factor. This results in an underestimated wage gap in the case of positive selection, or an overestimated wage gap in the case of negative selection.

We present our wage equation regression results below:

[11] The coefficient is the ratio between the covariance of the error terms of the wage equation and individuals' reservation wage equation (the function that determines the minimum wage an individual must be offered in order to work) and the standard deviation of the error term of the reservation wage equation. For more information, see Heckman (1979).

Table 7: National Wage Equation Model Estimates for Full-Time Year-Round Workers, 2009-2014 Period

	(1) Male	(2) Female	(3) Pooled
age	0.0619***	0.0609***	0.0585***
	(0.000887)	(0.00130)	(0.000702)
age^2	-0.000617***	-0.000622***	-0.000585***
	(1.05×10^{-5})	(1.52×10^{-5})	(8.28×10^{-6})
$nohsdeg$	-0.171***	-0.246***	-0.191***
	(0.00551)	(0.00730)	(0.00434)
$somecoll$	0.103***	0.0924***	0.0993***
	(0.00417)	(0.00429)	(0.00301)
$assoc$	0.145***	0.198***	0.167***
	(0.00506)	(0.00520)	(0.00359)
$bachelor$	0.313***	0.395***	0.345***
	(0.00454)	(0.00520)	(0.00332)
$graduate$	0.498***	0.621***	0.543***
	(0.00590)	(0.00647)	(0.00425)
$notwhite$	-0.0917***	-0.0292***	-0.0671***
	(0.00318)	(0.00307)	(0.00221)
$notcitizen$	-0.0988***	-0.110***	-0.104***
	(0.00517)	(0.00645)	(0.00399)
vet	0.0103**	0.0299***	0.0208***
	(0.00444)	(0.0115)	(0.00411)
Professional or related occupation	-0.0671***	-0.0981***	-0.0826***
	(0.00480)	(0.00477)	(0.00338)
Service occupations	-0.396***	-0.418***	-0.400***
	(0.00613)	(0.00580)	(0.00416)
Sales or related occupation	-0.196***	-0.292***	-0.235***
	(0.00679)	(0.00735)	(0.00499)
Office or administrative support occupation	-0.373***	-0.268***	-0.297***
	(0.00655)	(0.00465)	(0.00369)
Farming, forestry, fishing, transportation or material moving occupation	-0.406***	-0.444***	-0.402***
	(0.00636)	(0.0110)	(0.00528)
Construction or extraction occupation	-0.259***	-0.274***	-0.253***
	(0.00757)	(0.0366)	(0.00690)
Installation, maintenance, or repair occupation	-0.199***	-0.169***	-0.193***
	(0.00624)	(0.0241)	(0.00552)
Production occupation	-0.333***	-0.443***	-0.354***
	(0.00630)	(0.00897)	(0.00507)
Mining sector	0.479***	0.265***	0.452***
	(0.0177)	(0.0502)	(0.0167)
Construction sector	0.221***	0.163***	0.212***
	(0.0145)	(0.0301)	(0.0131)
Manufacturing sector	0.281***	0.204***	0.263***
	(0.0136)	(0.0277)	(0.0122)
Wholesale and retail trade sector	0.124***	0.0281	0.0966***
	(0.0137)	(0.0276)	(0.0122)
Transportation and utilities sector	0.340***	0.238***	0.317***
	(0.0138)	(0.0283)	(0.0124)
Information sector	0.261***	0.173***	0.239***
	(0.0156)	(0.0292)	(0.0136)
Financial activities sector	0.243***	0.165***	0.226***
	(0.0145)	(0.0276)	(0.0125)
Professional and business services sector	0.249***	0.166***	0.232***
	(0.0139)	(0.0276)	(0.0124)
Education and health services sector	0.0556***	0.0504*	0.0942***
	(0.0141)	(0.0274)	(0.0123)
Leisure and hospitality sector	-0.00438	-0.0583**	-0.0129
	(0.0146)	(0.0279)	(0.0127)
Other services sector	0.00575	-0.0317	0.00612
	(0.0152)	(0.0283)	(0.0131)
Public administration sector	0.388***	0.301***	0.381***
	(0.0151)	(0.0280)	(0.0129)
$overwork$	-0.0693***	-0.0919***	-0.0756***
	(0.00353)	(0.00496)	(0.00287)
$public$	-0.00477	-0.0808***	-0.0511***
	(0.00538)	(0.00438)	(0.00338)
$mills$		-0.223***	-0.127***
		(0.0116)	(0.00760)
$female$			-0.106***
			(0.00620)

Table 7: National Wage Equation Model Estimates for Full-Time Year-Round Workers, 2009-2014 Period

	(1) Male	(2) Female	(3) Pooled
$constant$	2.932***	2.940***	2.936***
	(0.0140)	(0.0285)	(0.0124)
Observations	178,861	148,973	327,834
$\bar{R}^2$	0.404	0.390	0.406

Heteroskedasticity-robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: (Data source: CPS March from ceprdata.org)

Table 8: Intermountain Region Wage Equation Model Estimates for Full-Time Year-Round Workers, 2009-2014 Period

	(1) Male	(2) Female	(3) Pooled
age	0.0622*** (0.00293)	0.0532*** (0.00427)	0.0578*** (0.00236)
age^2	-0.000629*** (3.42×10^{-5})	-0.000528*** (4.98×10^{-5})	-0.000580*** (2.76×10^{-5})
$nohsdeg$	-0.162*** (0.0185)	-0.244*** (0.0222)	-0.193*** (0.0143)
$somecoll$	0.0717*** (0.0128)	0.0708*** (0.0138)	0.0726*** (0.00945)
$assoc$	0.110*** (0.0163)	0.155*** (0.0172)	0.132*** (0.0119)
$bachelor$	0.269*** (0.0140)	0.335*** (0.0174)	0.298*** (0.0108)
$graduate$	0.444*** (0.0194)	0.531*** (0.0239)	0.478*** (0.0151)
$notwhite$	-0.121*** (0.0102)	-0.0583*** (0.0107)	-0.0961*** (0.00740)
$notcitizen$	-0.0795*** (0.0184)	-0.0913*** (0.0212)	-0.0886*** (0.0140)
vet	0.0248* (0.0130)	-0.0525 (0.0388)	0.0201 (0.0123)
Professional or related occupation	-0.0482*** (0.0155)	-0.0725*** (0.0179)	-0.0614*** (0.0117)
Service occupations	-0.398*** (0.0194)	-0.385*** (0.0212)	-0.386*** (0.0139)
Sales or related occupation	-0.207*** (0.0222)	-0.269*** (0.0246)	-0.232*** (0.0165)
Office or administrative support occupation	-0.356*** (0.0198)	-0.262*** (0.0158)	-0.293*** (0.0119)
Farming, forestry, fishing, transportation or material moving occupation	-0.404*** (0.0201)	-0.391*** (0.0361)	-0.392*** (0.0171)
Construction or extraction occupation	-0.222*** (0.0210)	-0.110 (0.0865)	-0.206*** (0.0189)
Installation, maintenance, or repair occupation	-0.160*** (0.0191)	-0.140** (0.0674)	-0.148*** (0.0170)
Production occupation	-0.350*** (0.0213)	-0.427*** (0.0375)	-0.362*** (0.0182)
Mining sector	0.627*** (0.0471)	0.258*** (0.0872)	0.565*** (0.0414)
Construction sector	0.272*** (0.0450)	0.0549 (0.0756)	0.228*** (0.0393)
Manufacturing sector	0.374*** (0.0440)	0.146** (0.0725)	0.320*** (0.0380)
Wholesale and retail trade sector	0.210*** (0.0442)	-0.0419 (0.0718)	0.142*** (0.0380)
Transportation and utilities sector	0.393*** (0.0446)	0.180** (0.0751)	0.345*** (0.0388)
Information sector	0.289*** (0.0493)	0.0517 (0.0766)	0.229*** (0.0416)
Financial activities sector	0.287*** (0.0477)	0.113 (0.0715)	0.255*** (0.0390)
Professional and business services sector	0.288*** (0.0444)	0.107 (0.0714)	0.252*** (0.0381)
Education and health services sector	0.103** (0.0452)	-0.00230 (0.0700)	0.125*** (0.0377)
Leisure and hospitality sector	0.0958** (0.0458)	-0.0796 (0.0728)	0.0586 (0.0390)
Other services sector	0.0488 (0.0485)	-0.132* (0.0757)	0.0125 (0.0410)
Public administration sector	0.418*** (0.0466)	0.259*** (0.0712)	0.404*** (0.0390)
$overwork$	-0.0561*** (0.0121)	-0.103*** (0.0180)	-0.0695*** (0.00999)
$public$	-0.0227 (0.0166)	-0.122*** (0.0159)	-0.0815*** (0.0113)
$mills$		-0.154*** (0.0351)	-0.129*** (0.0255)
$female$			-0.103*** (0.0195)

Table 8: Intermountain Region Wage Equation Model Estimates for Full-Time Year-Round Workers, 2009-2014 Period

	(1) Male	(2) Female	(3) Pooled
$constant$	2.896*** (0.0446)	2.984*** (0.0745)	2.929*** (0.0383)
Observations	19,204	14,230	33,434
$\bar{R}^2$	0.401	0.377	0.404

Heteroskedasticity-robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8 (Data source: CPS March from ceprdata.org)

Table 9: Utah Wage Equation Model Estimates for Full-Time Year-Round Workers, 2009-2014 Period

	(1) Male	(2) Female	(3) Pooled
age	0.0803*** (0.00638)	0.0489*** (0.00791)	0.0673*** (0.00486)
age^2	-0.000823*** (7.57×10^{-5})	-0.000463*** (9.34×10^{-5})	-0.000674*** (5.77×10^{-5})
$nohsdeg$	-0.137*** (0.0412)	-0.278*** (0.0623)	-0.194*** (0.0345)
$somecoll$	0.0457 (0.0283)	0.0237 (0.0321)	0.0425** (0.0214)
$assoc$	0.0805** (0.0323)	0.0704* (0.0398)	0.0893*** (0.0253)
$bachelor$	0.241*** (0.0332)	0.243*** (0.0424)	0.247*** (0.0256)
$graduate$	0.411*** (0.0435)	0.576*** (0.0630)	0.459*** (0.0353)
$notwhite$	-0.0863** (0.0336)	-0.0268 (0.0343)	-0.0664*** (0.0242)
$notcitizen$	-0.157*** (0.0466)	-0.0640 (0.0556)	-0.130*** (0.0358)
vet	-0.0286 (0.0349)	-0.123 (0.104)	-0.0435 (0.0336)
Professional or related occupation	-0.0616* (0.0348)	-0.0454 (0.0438)	-0.0651** (0.0271)
Service occupations	-0.289*** (0.0494)	-0.314*** (0.0472)	-0.310*** (0.0334)
Sales or related occupation	-0.157*** (0.0528)	-0.173*** (0.0620)	-0.163*** (0.0406)
Office or administrative support occupation	-0.317*** (0.0431)	-0.218*** (0.0369)	-0.269*** (0.0276)
Farming, forestry, fishing, transportation or material moving occupation	-0.355*** (0.0436)	-0.303*** (0.0906)	-0.335*** (0.0378)
Construction or extraction occupation	-0.207*** (0.0505)	-0.118 (0.188)	-0.183*** (0.0460)
Installation, maintenance, or repair occupation	-0.102** (0.0403)	0.154 (0.0963)	-0.0724** (0.0357)
Production occupation	-0.269*** (0.0448)	-0.330*** (0.0649)	-0.286*** (0.0369)
Mining sector	0.775*** (0.126)	-0.0512 (0.153)	0.562*** (0.111)
Construction sector	0.434*** (0.118)	-0.135 (0.135)	0.237** (0.103)
Manufacturing sector	0.470*** (0.115)	-0.134 (0.116)	0.275*** (0.0992)
Wholesale and retail trade sector	0.357*** (0.119)	-0.257** (0.118)	0.139 (0.101)
Transportation and utilities sector	0.567*** (0.118)	-0.117 (0.124)	0.349*** (0.101)
Information sector	0.348*** (0.134)	-0.0747 (0.146)	0.199* (0.114)
Financial activities sector	0.390*** (0.122)	-0.0910 (0.117)	0.232** (0.102)
Professional and business services sector	0.417*** (0.119)	-0.0437 (0.113)	0.264*** (0.101)
Education and health services sector	0.288** (0.121)	-0.206* (0.108)	0.131 (0.100)
Leisure and hospitality sector	0.115 (0.125)	-0.305*** (0.117)	-0.0135 (0.104)
Other services sector	0.285** (0.126)	-0.305** (0.123)	0.0770 (0.106)
Public administration sector	0.482*** (0.123)	0.0129 (0.112)	0.319*** (0.103)
$overwork$	-0.0522* (0.0270)	-0.129*** (0.0415)	-0.0640*** (0.0227)
$public$	0.000451 (0.0415)	-0.0458 (0.0425)	-0.00901 (0.0286)
$mills$		-0.101 (0.0640)	-0.103* (0.0526)
$female$			-0.141*** (0.0400)

Table 9: Utah Wage Equation Model Estimates for Full-Time Year-Round Workers, 2009-2014 Period

	(1) Male	(2) Female	(3) Pooled
$constant$	2.743*** (0.120)	3.133*** (0.122)	2.925*** (0.102)
Observations	2,518	1,481	3,999
$\bar{R}^2$	0.393	0.347	0.400

Heteroskedasticity-robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9 (Data source: CPS March from ceprdata.org)

Many of the patterns we see in the wage functions are not surprising. Pay increases with age, which is a proxy for experience; however, it increases at a decreasing rate. More education also increases individuals' pay. Individuals who are not white or identify as Hispanic make less, along with individuals who are not U.S. citizens. The highest-paying occupations are management, business, and financial occupations (the designated baseline occupation), while farming, forestry, fishing, transportation and material moving occupations tend to be the lowest-paying occupations. At the national and regional levels, the highest paying sector is associated with natural resource extraction, what we refer to as the mining sector (it includes oil and gas extraction, coal mining, metallic and nonmetallic mineral mining, and mining support activities). The lowest-paying sector is the leisure and hospitality sector.

Some results did surprise us. In all wage functions, overwork is associated with lower hourly earnings. This appears to contradict the findings of Cha and Weeden (2014), which suggested that recently overwork has been associated with *higher* pay and a growing importance in earnings (and the persistence of the gender gap in wages). Cha and Weeden employed a different methodology than what was used here. First, their dependent variable is hourly *wages*, while our dependent variable is hourly *earnings*. Second, they use CPS Merged Outgoing Rotation Group (MORG) data, while we are using ASEC data. Third, they do not use the Heckman method to correct for selection bias. *A priori*, the coefficient of overwork could be either positive or negative; one could observe overtime workers being rewarded with higher wages, or individuals with low wages choosing to overwork more in order to compensate for their low hourly wages. Regardless, we do not have an explanation for why our results contradict Cha and Weeden's findings, but overwork is not central to our study.

Other interesting patterns appear when inspecting the wage functions. At the national level, women experience greater returns to education than men. This is true in the Intermountain region as well, but the benefits to education are not as great for Utah women. At the national level, the mining sector is the highest-paying sector for both men and women, and the lowest-paying sector leisure and hospitality. In Utah this is still true for men, but for women, mining does not nearly pay as well as it would at the national level. In fact, mining pays women the same as, if not less than, the agriculture, forestry, fishing, and hunting sectors pay, which tend to be low-paying sectors in general. And at all geographic levels, women in the public sector earn less than men in the public sector.

When we examine the coefficient of the Mills ratio, we find that, at the national and regional levels, there is statistically significant evidence for negative selection. In Utah, the evidence for negative selection is not statistically significant at conventional levels. This means that at the national and regional levels, the raw wage gap will be larger than the wage gap corrected for selection bias, while in Utah, there is no statistically significant difference between the observed wage gap and the wage gap corrected for selection bias.

Decomposition Results

We now move on to presenting the results of our Oaxaca-Blinder decompositions of the gender gap in wages at the national, regional, and state levels. The gender gap we compute is the difference in log wages between men and women, which we can interpret as the male wage premium, or the percentage by which male hourly wages exceed female hourly wages. We therefore report our results as percentage points (though they are truly log points multiplied by 100).

In our tables, we first report the raw (uncorrected) wage gap. This is the difference between men's and women's mean log wages, and the closest analogue in this paper to commonly reported gender gap numbers[12]. We then report the wage gap corrected for selection bias (which, for the sake of brevity, we refer to as the corrected wage gap). This is the wage gap corrected by the Heckman method to account for women's selection bias, and is the more useful measure of the wage gap when trying to quantify wage discrimination. Since we observe negative selection in the contemporary period, this number will always be smaller than the uncorrected wage gap. We follow this with a breakdown of the wage gap into a part attributable to women being paid differently than what they would be paid if discrimination ceased to exist (called the "returns effect"), and a part attributable to differing characteristics between men and women (the "endowment effect"). The endowment effect we further break down so we can examine how exactly the variables we controlled for in our wage equation impact the wage gap.

[12] See the report by Voices for Utah Children (2015).

We present our results below, along with various figures presenting the same information visually:

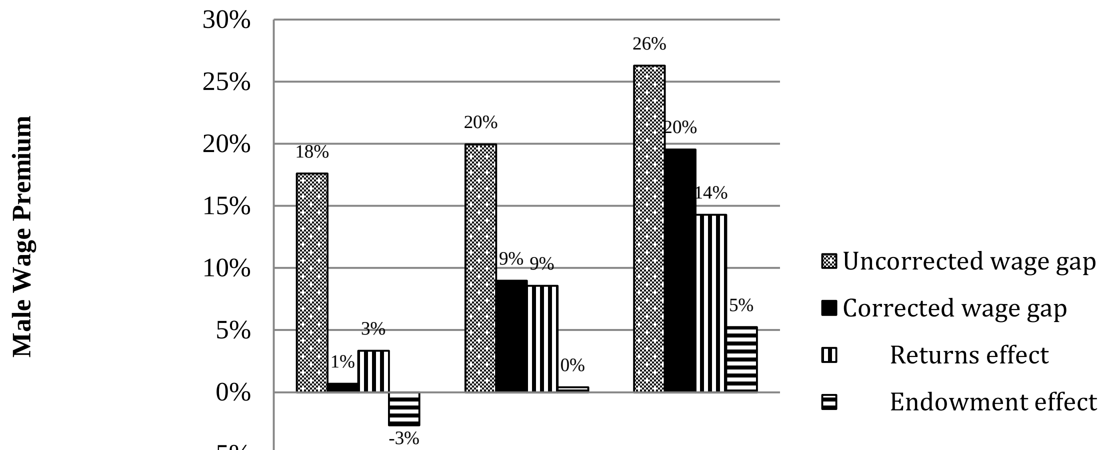
Table 10 Decomposition of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers, 2009-2014 Period

	Nation	Intermountain Region	Utah
Uncorrected wage gap	17.60%	19.96%	26.29%
Corrected[13] wage gap	0.68%	8.97%	19.55%
Returns effect	3.34%	8.57%	14.30%
Endowment effect	-2.66%	0.40%	5.25%
Age[14]	-0.49%	-0.28%	-0.25%
Education	-3.26%	-1.89%	1.06%
Less than high school degree	-1.32%	-1.08%	-0.61%
High school degree or equivalent	-0.77%	-0.23%	0.24%
Some college, but no degree	0.07%	0.09%	0.11%
Associate degree or equivalent	-0.02%	0.00%	0.02%
Bachelor's degree	-0.49%	-0.02%	-0.13%
Graduate degree	-0.74%	-0.64%	1.42%
Not white	0.03%	-0.05%	0.02%
White	0.03%	-0.05%	0.02%
Not citizen	-0.44%	-0.27%	-0.14%
Veteran	0.20%	0.22%	-0.25%
Occupation	-2.28%	-1.04%	0.88%
Management, business or financial occupation	-0.33%	-0.49%	-0.36%
Professional or related occupation	-1.60%	-1.20%	-0.33%
Service occupation	0.41%	0.45%	0.56%
Sales or related occupation	0.01%	0.00%	-0.01%
Office or administrative support occupation	0.79%	0.98%	1.58%
Farming, forestry, fishing, transportation, or material moving occupation	-1.31%	-1.17%	-0.99%
Construction or extraction occupations	-0.06%	0.24%	0.04%
Installation, maintenance, or repair occupation	0.38%	0.61%	0.86%
Production occupation	-0.58%	-0.45%	-0.47%
Industry	3.99%	3.86%	4.50%
Agriculture, forestry, fishing, and hunting sector	-0.18%	-0.24%	-0.03%
Mining sector	0.27%	0.88%	1.20%
Construction sector	0.16%	0.02%	0.20%
Manufacturing sector	0.65%	0.60%	0.53%
Wholesale and retail trade sector	-0.25%	-0.19%	0.03%
Transportation and utilities sector	0.66%	0.53%	0.57%
Information sector	0.03%	0.00%	-0.01%
Financial activities sector	-0.11%	-0.13%	-0.08%
Professional and business services sector	0.07%	0.05%	0.05%
Education and health services sector	2.65%	2.32%	1.77%
Leisure and hospitality sector	0.02%	0.15%	0.14%
Other service sectors	-0.06%	-0.08%	0.08%
Public administration sector	0.07%	-0.06%	0.06%
Overtime work	-0.75%	-0.62%	-0.65%
Public sector worker	0.31%	0.49%	0.06%

Table 10 (Data source: CPS March from ceprdata.org)

[13] Here and henceforth, “corrected” means corrected for selection bias.
[14] Age is the sum of the effects of the age and age^2 variables.

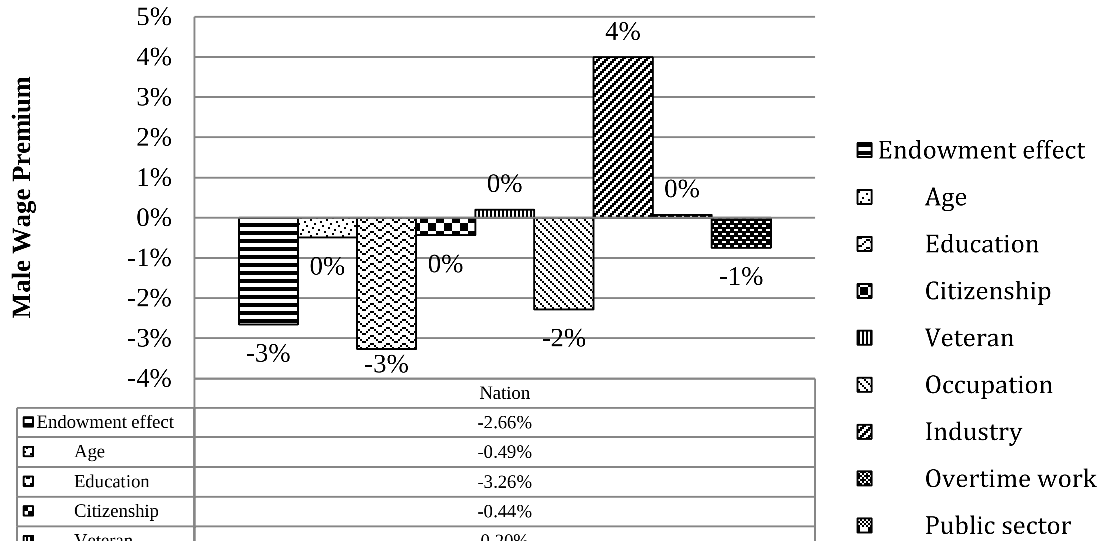
Figure 1: Decomposition of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers, 2009-2014 Period



	Nation	Intermountai n Region	Utah
Uncorrected wage gap	17.60%	19.96%	26.29%
Corrected wage gap	0.68%	8.97%	19.55%
Returns effect	3.34%	8.57%	14.30%
Endowment effect	-2.66%	0.40%	5.25%

Figure 1 (Data source: Table 10)

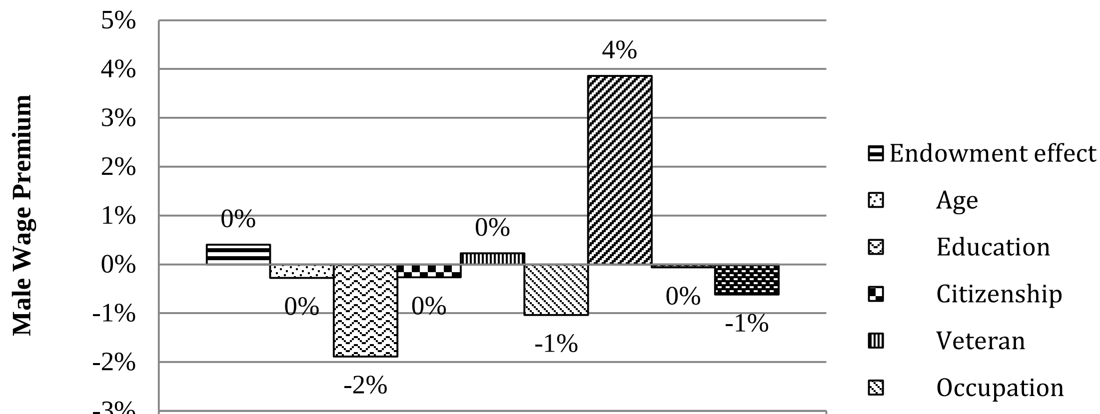
Figure 2: Detailed Decomposition of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers Nationally, 2009-2014 Period



	Nation
Endowment effect	-2.66%
Age	-0.49%
Education	-3.26%
Citizenship	-0.44%
Veteran	0.20%
Occupation	-2.28%
Industry	3.99%
Overtime work	0.07%
Public sector	-0.75%

Figure 2 (Data source: Table 10)

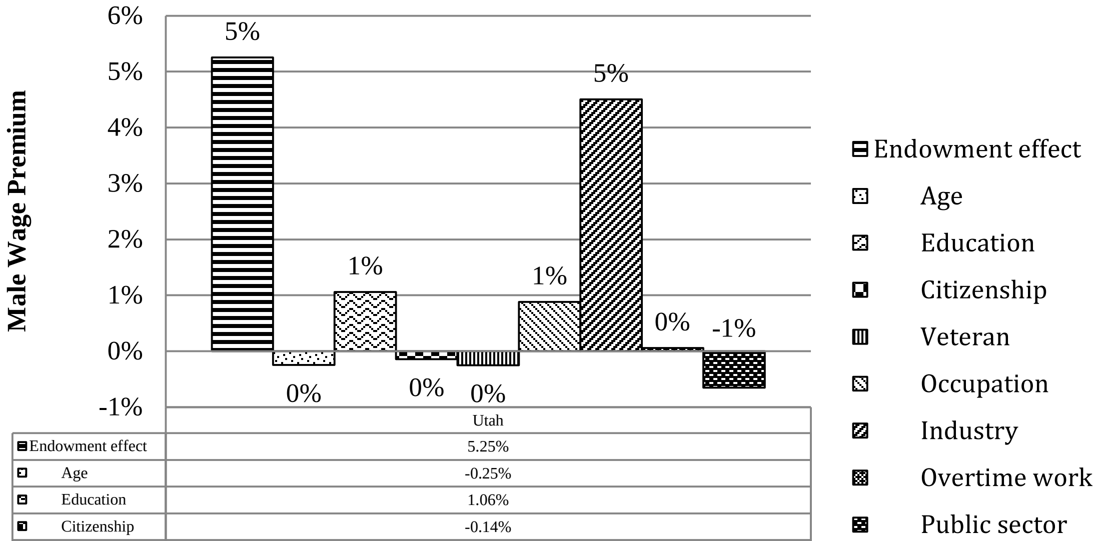
Figure 3: Detailed Decomposition of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers in the Intermountain Region, 2009-2014 Period



	Intermountain Region
Endowment effect	0.40%
Age	-0.28%
Education	-1.89%
Citizenship	-0.27%
Veteran	0.22%
Occupation	-1.04%
Industry	3.86%
Overwork	-0.06%
Public sector	-0.62%

Figure 3 (Data source: Table 10)

Figure 4: Detailed Decomposition of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers in Utah, 2009-2014 Period



	Utah
Endowment effect	5.25%
Age	-0.25%
Education	1.06%
Citizenship	-0.14%
Veteran	-0.25%
Occupation	0.88%
Industry	4.50%
Overtime work	0.06%
Public sector	-0.65%

Figure 4 (Data source: Table 10)

While the uncorrected wage gap is a $0.18 male wage premium at the national level, the wage gap corrected for selection bias is not statistically different from zero. This alone is an interesting finding and we discuss it later. However, there is still evidence for some discrimination at the national level. Even though the returns effect is not necessarily wage discrimination exclusively, we believe that, in light of the variables we have controlled for while correcting for selection bias, the returns effect is representative of wage discrimination (we will discuss this notion further later). In Figure 1 we see evidence for a small yet statistically significant amount of discrimination in wages at the national level; women earn $0.97 for every dollar earned by men with similar attributes. The negative endowment effect seen in both Figure 1 and Figure 2 means that, in the absence of discrimination, women should be earning 3% *more* per hour than men. When we look at the detailed decomposition of the endowment effect portion of the wage gap (as shown in Figure 2), women have advantages over men in educational attainment and occupational distribution, although they have a disadvantage in industrial distribution. Despite these advantages, wage discrimination results in a near-wash at the national level and there is no statistically significant wage gap.

In the Intermountain region, the difference between the corrected and uncorrected wage gaps is not as big as at the national level (see Figure 1). Most of the wage gap in the intermountain region is due to discrimination against women and results in women earning \$0.91 for every dollar earned by men with similar attributes. The endowment effect in the Intermountain region is near zero. Examining the endowment effect in detail, while women's educational attainment and occupational distribution collectively decrease the wage gap by four percentage points, women's industrial composition increases it by four percentage points (see Figure 3), thus resulting in a wash.

Utah has the worst gap of all three geographic regions by any measure one selects (see Figure 1). The difference between the corrected and uncorrected wage gaps is the smallest of the geographic levels examined. In fact, there is no statistically significant difference[15] between the corrected and uncorrected wage gaps in Utah at any conventional level of significance. Utah has the largest uncorrected wage gap (\$0.74 per men's dollar), the largest gap after correcting for selection bias (\$0.81 per men's dollar), the largest gap attributable to discrimination (\$0.86 per dollar earned by similar men), and the largest gap attributable to women's endowments (\$0.95 per men's dollar if

[15] See the regression results in Table 9; because the coefficient of the mills variable is not statistically significant, there is no statistically significant difference between the wage gap and the wage gap corrected for selection bias via the Heckman method.

discrimination disappeared). We also see a positive endowment effect, which means that the wage gap is larger because female workers' attributes tend to result in lower pay when compared to men (in addition to discrimination). Women's attributes relative to men result in men earning 5% more per hour than women.

While discrimination accounts for a smaller share of the corrected wage gap than at the national or regional levels, in Utah, it has a larger share of the uncorrected wage gap and is the largest discrimination effect overall, with similarly qualified Utah women earnings $0.86 for every dollar earned by similarly qualified men (see Figure 1). Furthermore, the endowment effect is positive, and this appears to be due to women being *less* educated than men and having an unfavorable occupation distribution in addition to an unfavorable industrial distribution (see Figure 4). This is the opposite of the tendency at the national level. In other words, the factors that serve to decrease the wage gap at the national and regional levels, educational attainment in particular, serve to *increase* the gap in Utah.

Geographic Region Comparison Results

Now we decompose the difference between the wage gaps of Utah and other geographic regions. We are effectively subtracting Utah's wage gap from the wage gap of the nation or the Intermountain region. Thus, a negative number suggests that Utah is worse in some characteristic (for example, a negative difference between wage gaps means Utah's wage gap is larger), while a positive number means Utah is better. We present our results below:

Table 11: Decomposition of the Difference in Male Wage Premiums Among Full-Time Year-Round Workers between Utah and Other Geographic Regions, 2009-2014 period

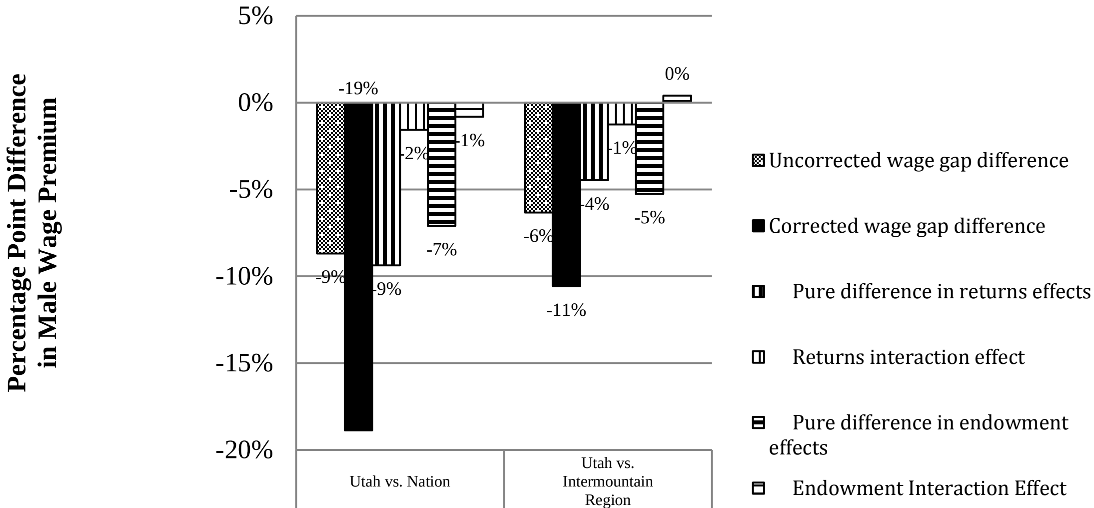
	Utah vs. Nation	Utah vs. Intermountain Region
Uncorrected wage gap difference	-8.68%	-6.33%
Corrected[16] wage gap difference	-18.87%	-10.58%
Pure difference in returns effects	-9.38%	-4.47%
Returns interaction effect	-1.58%	-1.26%
Endowment interaction effect	-0.81%	0.40%
Pure difference in endowment effects	-7.10%	-5.26%
Age[17]	-0.30%	-0.08%
Education	-4.00%	-2.83%
Less than high school degree	-0.57%	-0.42%
High school degree or equivalent	-0.94%	-0.48%
Some college, but no degree	-0.03%	-0.01%
Associate degree or equivalent	0.01%	0.00%
Bachelor's degree	-0.28%	0.11%
Graduate degree	-2.19%	-2.05%
Not white	0.01%	-0.06%
White	0.01%	-0.06%
Not citizen	-0.36%	-0.21%
Veteran	-0.04%	-0.06%
Occupation	-1.72%	-1.11%
Management, business or financial occupation	0.13%	-0.05%
Professional or related occupation	-1.00%	-0.63%
Service occupation	-0.26%	-0.23%
Sales or related occupation	0.01%	0.01%
Office or administrative support occupation	-0.24%	-0.25%
Farming, forestry, fishing, transportation, or material moving occupation	-0.26%	-0.09%
Construction or extraction occupations	0.00%	-0.01%
Installation, maintenance, or repair occupation	-0.04%	-0.02%
Production occupation	-0.07%	0.15%
Industry	-0.69%	-0.88%
Agriculture, forestry, fishing, and hunting sector	-0.15%	-0.20%
Mining sector	-0.72%	-0.29%
Construction sector	-0.01%	0.00%
Manufacturing sector	0.05%	-0.16%
Wholesale and retail trade sector	-0.25%	-0.21%
Transportation and utilities sector	0.15%	0.03%
Information sector	0.00%	0.00%
Financial activities sector	0.02%	0.00%
Professional and business services sector	0.03%	0.03%
Education and health services sector	0.49%	0.14%
Leisure and hospitality sector	-0.11%	0.06%
Other service sectors	-0.14%	-0.17%
Public administration sector	-0.02%	-0.13%
Overtime work	0.02%	0.09%
Public sector worker	-0.03%	-0.04%

Table 11 (Data source: CPS March from ceprdata.org)

16 Here and henceforth, "corrected" means corrected for selection bias.

17 Age is the sum of the effects of the age and age^2 variables.

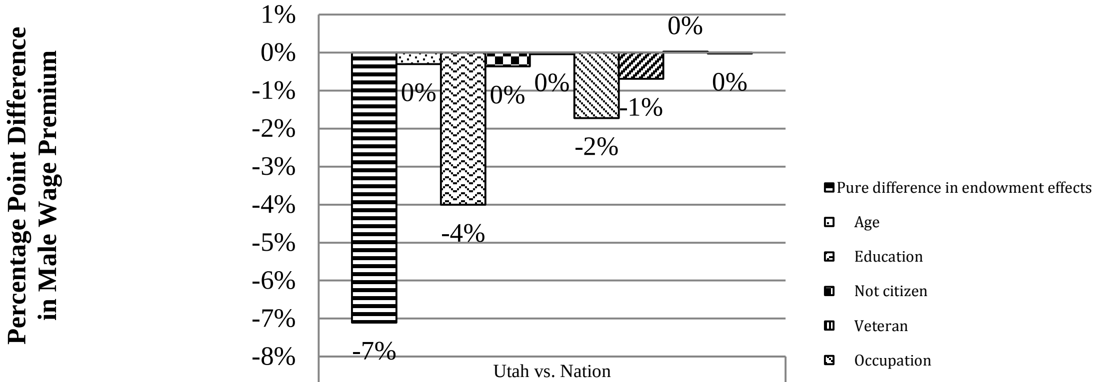
Figure 5: Decomposition of Difference of Male Wage Premiums Between Utah and Other Geographic Regions Among Full-Time Year-Round Workers, 2009-2014 Period



	Utah vs. Nation	Utah vs. Intermountain Region
Uncorrected wage gap difference	-8.68%	-6.33%
Corrected wage gap difference	-18.87%	-10.58%
Pure difference in returns effects	-9.38%	-4.47%
Returns interaction effect	-1.58%	-1.26%
Pure difference in endowment effects	-7.10%	-5.26%
Endowment Interaction Effect	-0.81%	0.40%

Figure 5 (Data source: Table 11)

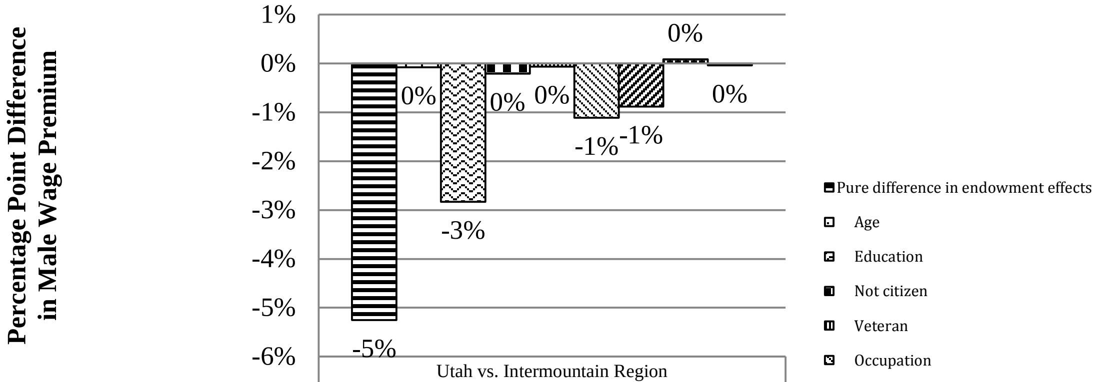
Figure 6: Decomposition of Difference of Male Wage Premiums Between Utah and the Nation Among Full-Time Year-Round Workers, 2009-2014



	Utah vs. Nation
Pure difference in endowment effects	-7.10%
Age	-0.30%
Education	-4.00%
Not citizen	-0.36%
Veteran	-0.04%
Occupation	-1.72%
Industry	-0.69%
Overtime work	0.02%
Public sector	-0.03%

Figure 6 (Data source: Table 11)

Figure 7: Decomposition of Difference of Male Wage Premiums Between Utah and the Intermountain Region Among Full-Time Year-Round Workers, 2009-2014



	Utah vs. Intermountain Region
Pure difference in endowment effects	-5.26%
Age	-0.08%
Education	-2.83%
Not citizen	-0.21%
Veteran	-0.06%
Occupation	-1.11%
Industry	-0.88%
Overtime work	0.09%
Public sector	-0.04%

Figure 7 (Data source: Table 11)

Utah's corrected wage gap is worse than the corrected wage gaps at either the national or regional level (see Figure 5). When compared to the nation, discrimination is the worst offender (see Figure 5). Nine percentage points of the difference between the Utah and national wage gaps can be attributed to differences in the returns effects, which suggest there is more discrimination in Utah than at the national level. This is greater than the seven percentage points of the difference that can be attributed to differences in the endowment effects in the nation and Utah. Meanwhile, differing endowments is the worst offender at the regional level (see Figure 5). Four percentage points of the difference between the Utah and regional wage gaps can be attributed to differences in the returns effects, which suggest there is more discrimination in Utah than in the Intermountain region. However, this is smaller than the five percentage points of the difference that can be attributed to differences in the endowment effects in the Intermountain region and Utah.

In either case, no matter what metric is selected, Utah is worse. Women's educational attainment relative to men, along with their occupational and industrial distribution, serves to make Utah's wage gap larger than the nation's by four percentage points. This is also true in the Intermountain region (although the difference is three percentage points). When we peer deeper, we see that a lack of women with graduate degrees, women with professional or management occupations, and the low number of women working in the high-paying mining sector help explain why Utah has a larger gender wage gap than the nation or region (see Table 11).

Temporal Analysis Results

We now present a temporal analysis of the gender gap in wages. We compare the current period (2009 to 2014) to prior periods, namely: the 1992 to 1997 period; the 1998 to 2002 period; and the 2003 to 2008 period. Notice that the current period can also be identified as the recovery period from the 2008 Financial Crisis, and the 2003 to 2008 period represents the period during which the housing bubble that fueled that crisis developed. The 1992 to 1997 period is the furthest back we look and the only period for which we do a detailed comparison of the change in the wage gap. We subtract the wage gap of the past from the wage gap of the present, so a negative number would indicate an improvement in the wage gap. We present results for all three geographic regions below:

Table 12: Decomposition of Male Wage Premium Among Full-Time Year-Round Workers, 1992-2014

		Nation	Intermountain Region	Utah
2009-2014	**Uncorrected wage gap**	17.60%	19.96%	26.29%
	Corrected[18] wage gap	0.68%	8.97%	19.55%
	Endowment effect	-2.66%	0.40%	5.25%
	Returns effect	3.34%	8.57%	14.30%
2003-2008	**Uncorrected wage gap**	18.32%	19.64%	30.21%
	Corrected wage gap	8.16%	5.93%	23.54%
	Endowment effect	-2.46%	-0.88%	6.01%
	Returns effect	10.62%	6.81%	17.53%
1998-2002	**Uncorrected wage gap**	21.71%	21.11%	28.25%
	Corrected wage gap	12.30%	11.73%	30.90%
	Endowment effect	-1.60%	-1.04%	2.30%
	Returns effect	13.90%	12.77%	28.61%
1992-1997	**Uncorrected wage gap**	23.17%	22.74%	26.28%
	Corrected wage gap	19.22%	23.16%	37.45%
	Endowment effect	-0.40%	-0.01%	1.45%
	Returns effect	19.62%	23.17%	36.00%

Table 12 (Data source: CPS March from ceprdata.org)

[18] Here and henceforth, “corrected” means corrected for selection bias.

Table 13: Decomposition of the Change of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers

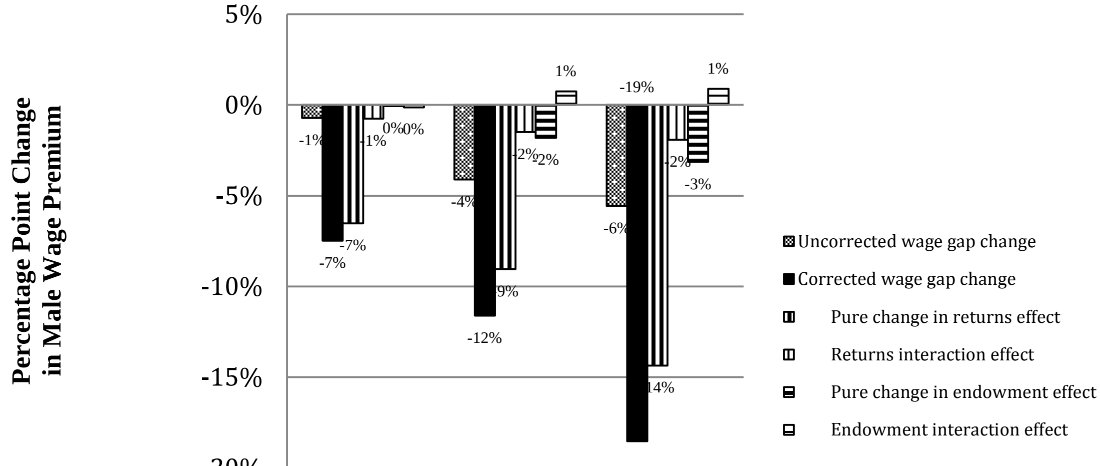
	2003-2008 vs. 2009-2014			1998-2002 vs. 2009-2014			1992-1997 vs. 2009-2014		
	Nation	Intermountain Region	Utah	Nation	Intermountain Region	Utah	Nation	Intermountain Region	Utah
Uncorrected wage gap change	-0.71%	0.32%	-3.92%	-4.10%	-1.15%	-1.96%	-5.57%	-2.78%	0.01%
Corrected[19] wage gap change	-7.48%	3.04%	-3.99%	-11.62%	-2.76%	-11.35%	-18.54%	-14.19%	-17.90%
Pure change in returns effect	-6.53%	2.27%	-3.51%	-9.06%	-2.93%	-14.75%	-14.36%	-12.87%	-21.52%
Returns interaction effect	-0.75%	-0.51%	0.27%	-1.50%	-1.26%	0.44%	-1.92%	-1.73%	-0.18%
Endowment interaction effect	-0.13%	-0.21%	-1.24%	0.75%	1.96%	1.57%	0.88%	0.90%	0.20%
Pure change in endowment effect	-0.07%	1.49%	0.49%	-1.81%	-0.52%	1.39%	-3.14%	-0.49%	3.60%
Age[20]	0.31%	0.62%	-0.58%	-0.07%	0.35%	-1.48%	-0.19%	0.35%	-0.91%
Education	-0.64%	-0.01%	-0.23%	-1.52%	-1.05%	0.89%	-2.14%	-0.97%	1.15%
Less than high school degree	0.33%	0.56%	-0.06%	0.12%	0.32%	0.53%	0.11%	0.09%	0.16%
High school degree or equivalent	-0.34%	-0.19%	-0.13%	-0.59%	-0.32%	-0.42%	-0.81%	-0.30%	-0.13%
Some college, but no degree	-0.05%	-0.03%	-0.01%	-0.04%	-0.07%	0.05%	-0.03%	-0.01%	-0.01%
Associate degree or equivalent	0.00%	0.00%	0.03%	-0.01%	-0.02%	0.09%	-0.01%	0.00%	0.03%
Bachelor's degree	-0.12%	0.21%	0.00%	-0.30%	-0.27%	0.03%	-0.37%	0.17%	-0.13%
Graduate degree	-0.45%	-0.55%	-0.06%	-0.70%	-0.68%	0.62%	-1.04%	-0.92%	1.23%
Not white	0.02%	0.12%	-0.01%	-0.02%	-0.04%	0.05%	-0.04%	0.05%	0.03%
White	0.02%	0.12%	-0.01%	-0.02%	-0.04%	0.05%	-0.04%	0.05%	0.03%
Not citizen	0.06%	0.23%	0.19%	0.02%	-0.02%	0.30%	-0.17%	-0.08%	-0.03%
Veteran	-0.07%	-0.03%	-0.11%	-0.08%	0.06%	0.30%	-0.19%	-0.08%	0.22%
Occupation	-0.31%	0.07%	0.00%	-0.78%	-0.60%	0.76%	-1.13%	-0.51%	0.90%
Management, business or financial occupation	0.03%	0.01%	-0.13%	0.63%	0.72%	0.73%	0.28%	0.52%	0.63%
Professional or related occupation	-0.20%	0.00%	0.34%	-0.66%	-0.67%	0.26%	-0.74%	-0.46%	0.41%
Service occupation	-0.05%	0.00%	-0.19%	0.17%	0.21%	0.50%	0.21%	0.35%	1.09%
Sales or related occupation	0.00%	0.02%	-0.02%	0.03%	0.02%	0.00%	0.01%	0.01%	0.00%
Office or administrative support occupation	-0.14%	-0.22%	-0.18%	-0.14%	-0.21%	-0.18%	-0.21%	-0.25%	-0.09%
Farming, forestry, fishing, transportation, or material moving occupation	0.05%	0.18%	0.24%	-0.74%	-0.55%	-0.29%	-0.67%	-0.63%	-0.49%
Construction or extraction occupations	0.02%	-0.03%	-0.04%	0.07%	0.07%	0.16%	0.03%	0.00%	-0.05%
Installation, maintenance, or repair occupation	0.00%	0.03%	-0.03%	-0.13%	-0.15%	-0.41%	-0.11%	-0.17%	-0.29%
Production occupation	-0.02%	0.09%	0.00%	0.01%	-0.02%	-0.01%	0.07%	0.13%	-0.31%
Industry	0.44%	0.26%	0.36%	0.45%	0.54%	0.26%	0.47%	0.40%	2.02%
Agriculture, forestry, fishing, and hunting sector	-0.01%	0.00%	0.07%	-0.01%	0.17%	-0.06%	0.04%	0.00%	0.05%
Mining sector	0.07%	0.20%	0.19%	0.09%	0.21%	0.22%	0.08%	0.12%	0.25%
Construction sector	-0.04%	-0.04%	-0.02%	-0.02%	-0.04%	0.00%	0.05%	0.01%	0.00%
Manufacturing sector	0.02%	0.05%	0.02%	-0.01%	0.05%	0.12%	-0.14%	-0.12%	0.17%
Wholesale and retail trade sector	0.02%	-0.06%	0.08%	0.03%	0.13%	0.22%	0.00%	0.03%	0.16%
Transportation and utilities sector	0.03%	-0.04%	-0.16%	-0.02%	-0.08%	-0.38%	-0.05%	-0.05%	0.12%
Information sector	0.03%	0.02%	-0.01%	-0.03%	0.09%	-0.03%	0.02%	0.05%	0.10%
Financial activities sector	0.05%	0.01%	-0.03%	0.09%	0.04%	-0.04%	0.09%	0.02%	0.00%
Professional and business services sector	0.05%	0.02%	0.11%	0.05%	0.02%	-0.02%	0.05%	0.00%	0.05%
Education and health services sector	0.23%	0.17%	0.09%	0.42%	0.30%	0.40%	0.41%	0.33%	0.68%
Leisure and hospitality sector	-0.04%	-0.10%	-0.25%	-0.10%	-0.27%	-0.43%	-0.10%	-0.07%	-0.22%
Other service sectors	-0.04%	-0.05%	0.08%	-0.09%	-0.06%	-0.02%	0.00%	0.09%	0.44%
Public administration sector	0.08%	0.07%	0.21%	0.04%	-0.02%	0.26%	0.02%	0.00%	0.21%
Overtime work	0.10%	0.11%	0.21%	0.18%	0.23%	0.33%	0.27%	0.29%	0.17%
Public sector worker	0.00%	0.00%	0.01%	0.03%	0.04%	-0.08%	0.03%	-0.01%	0.01%

Table 13 (Data source: CPS March from ceprdata.org)

19 Here and henceforth, "corrected" means corrected for selection bias.

20 Age is the sum of the effects of the age and age^2 variables.

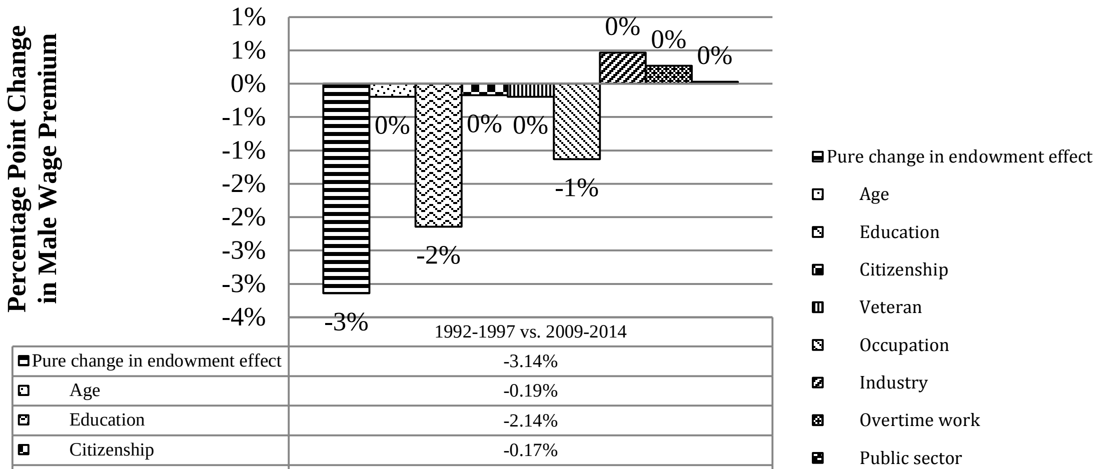
Figure 8: Decomposition of the Change of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers in the Nation



	2009-2014 vs. 2003-2008	2009-2014 vs. 1998-2002	2009-2014 vs. 1992-1997
Uncorrected wage gap change	-0.71%	-4.10%	-5.57%
Corrected wage gap change	-7.48%	-11.62%	-18.54%
Pure change in returns effect	-6.53%	-9.06%	-14.36%
Returns interaction effect	-0.75%	-1.50%	-1.92%
Pure change in endowment effect	-0.07%	-1.81%	-3.14%
Endowment interaction effect	-0.13%	0.75%	0.88%

Figure 8 (Data source: Table 13)

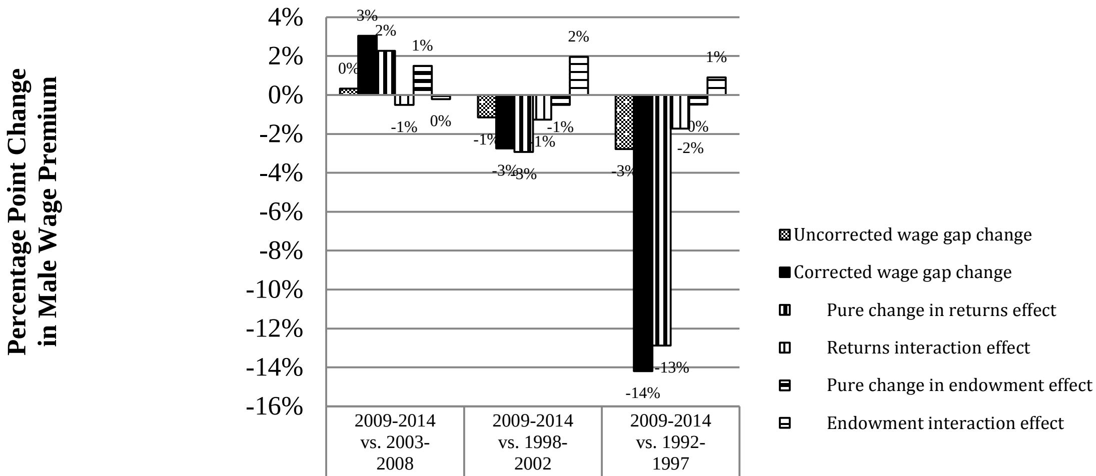
Figure 9: Detailed Decomposition of the Change of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers in the Nation, 2009-2014 vs. 1992-1997



	1992-1997 vs. 2009-2014
Pure change in endowment effect	-3.14%
Age	-0.19%
Education	-2.14%
Citizenship	-0.17%
Veteran	-0.19%
Occupation	-1.13%
Industry	0.47%
Overtime work	0.27%
Public sector	0.03%

Figure 9 (Data source: Table 13)

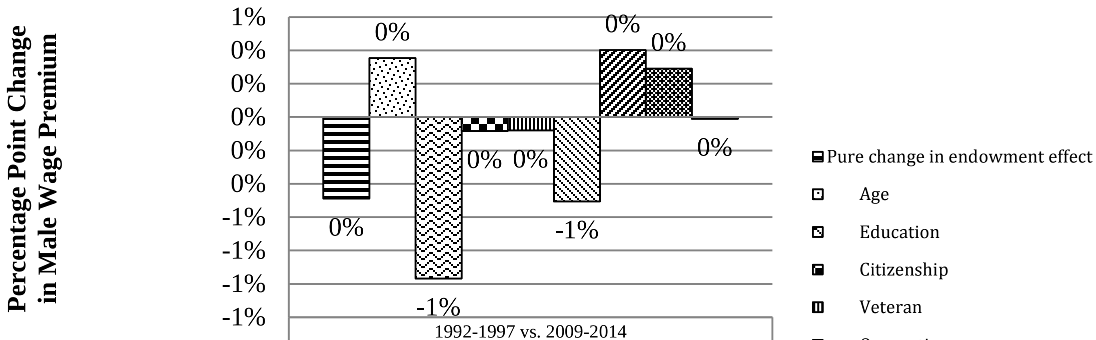
Figure 10: Decomposition of the Change of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers in the Intermountain Region



	2009-2014 vs. 2003-2008	2009-2014 vs. 1998-2002	2009-2014 vs. 1992-1997
Uncorrected wage gap change	0.32%	-1.15%	-2.78%
Corrected wage gap change	3.04%	-2.76%	-14.19%
Pure change in returns effect	2.27%	-2.93%	-12.87%
Returns interaction effect	-0.51%	-1.26%	-1.73%
Pure change in endowment effect	1.49%	-0.52%	-0.49%
Endowment interaction effect	-0.21%	1.96%	0.90%

Figure 10 (Data source: Table 13)

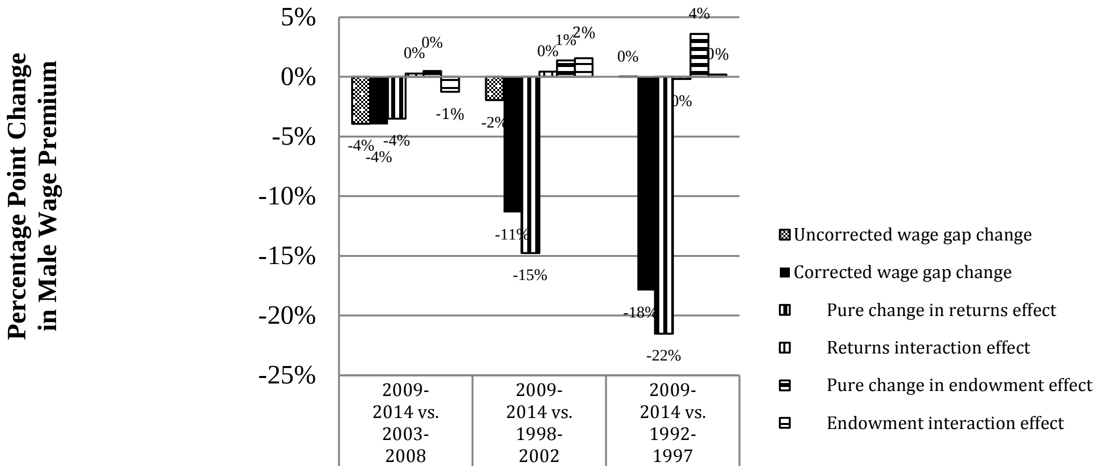
Figure 11: Detailed Decomposition of the Change of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers in the Intermountain Region, 2009-2014 vs. 1992-1997



	1992-1997 vs. 2009-2014
Pure change in endowment effect	-0.49%
Age	0.35%
Education	-0.97%
Citizenship	-0.08%
Veteran	-0.08%
Occupation	-0.51%
Industry	0.40%
Overtime work	0.29%
Public sector	-0.01%

Figure 11 (Data source: Table 13)

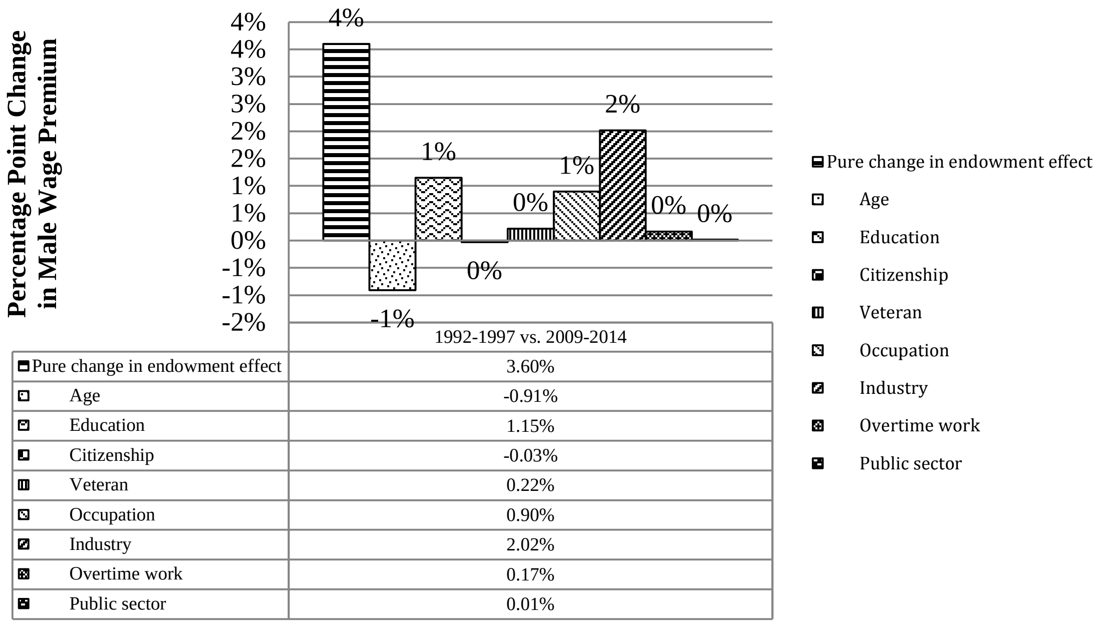
Figure 12: Decomposition of the Change of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers in Utah



	2009-2014 vs. 2003-2008	2009-2014 vs. 1998-2002	2009-2014 vs. 1992-1997
Uncorrected wage gap change	-3.92%	-1.96%	0.01%
Corrected wage gap change	-3.99%	-11.35%	-17.90%
Pure change in returns effect	-3.51%	-14.75%	-21.52%
Returns interaction effect	0.27%	0.44%	-0.18%
Pure change in endowment effect	0.49%	1.39%	3.60%
Endowment interaction effect	-1.24%	1.57%	0.20%

Figure 12 (Data source: Table 13)

Figure 13: Detailed Decomposition of the Change of the Male Wage Premium in Hourly Earnings Among Full-Time Year-Round Workers in Utah, 2009-2014 vs. 1992-1997



	1992-1997 vs. 2009-2014
Pure change in endowment effect	3.60%
Age	-0.91%
Education	1.15%
Citizenship	-0.03%
Veteran	0.22%
Occupation	0.90%
Industry	2.02%
Overtime work	0.17%
Public sector	0.01%

Figure 13 (Data source: Table 13)

At all geographic levels, the reduction in the corrected wage gap appears to be associated mostly with a drop in discrimination (see Figure 8, Figure 10 and Figure 12). At the national level, there has been considerable progress in closing the wage gap over the past two decades, and we also see the endowment effect dropping almost entirely due to increasing education among women relative to men (see Figure 9). In fact, women today tend to be *more* educated than men at the national level (Voices for Utah Children, 2015). Of the three geographic levels, the nation is seeing the most rapid progress in closing the earnings gap currently. The corrected wage gap in the contemporary period is seven percentage points less than what it was in the prior period, almost exclusively due to a fall in the returns effect, which is more than any other period's gap has fallen in the same time frame.

The Intermountain region actually performs the worst of our three geographic levels in improving its wage gap. In fact, the corrected wage gap is three percentage points *worse* in the contemporary period than what it was during the housing bubble (see Figure 10). Both discrimination and the endowment effect can be blamed for the deterioration of the wage gap. The returns effect increased by three percentage points and the endowment effect two percentage points. Nevertheless, the Intermountain region is better than it was twenty years ago, mostly due to less discrimination but also due to improving education levels among women (see Figure 11).

With the poor performance of the Intermountain region in mind, Utah is performing well relative to its neighbors, but poorly relative to the rest of the nation. While the uncorrected wage gap shows little improvement, Utah's corrected wage gap is eighteen percentage points than it was twenty years ago, and this is due completely to less labor market discrimination (see Figure 12). Women's endowments, however, worsened relative to men over this period. Women's educational attainment relative to men along with their occupational and industrial distribution is to blame (see Figure 13). Regarding education, this does not mean that Utah women are not as educated as they were in the past. Both Utah men and Utah women tend to be well educated compared to the rest of the nation. What's more likely is Utah men have become much more educated, while Utah women have not changed as much since the mid-1990s.

Decomposition aside, there is another interesting phenomenon we observe here. Negative selection bias prevails in all regions as early as the 2003 to 2007 period, but this does not always hold. In the Intermountain region, there is actually *positive* selection in the 1992 to 1997 period, and there is some evidence for positive selection in Utah as late as the 1998 to 2002 period (the national wage gap always sees negative selection). Thus we have some evidence for a switch from positive to negative selection at least in Utah over the past twenty years. This switch is interesting to consider. We can think of positive selection as indicating that those women who are working tend to be more motivated or more attached to the labor force. It is also evidence that women are less willing to accept lower wages; given a low wage offer, they would rather choose not to work. We cannot say for certain why this switch occurred. If we believe that in the past women preferred not to work, it could reflect changing attitudes toward work among women, or a response to stagnant male wages which leads women entering the labor force in order to improve a household's standard of living. On the other hand, it could reflect changing employer attitudes about women and an increased willingness to hire women. Our study cannot distinguish between these possibilities, but they are worth investigating.

Alternative Model Results

We conclude this section by discussing the results found in alternative models. While we have reasons for selecting the model we chose for the preferred model, examining the results of other models may illustrate the robustness of some of our findings, or the reasons why we chose our preferred model over others. Below we present the decomposition results of other models:

Table 14: Decomposition Results for Different Model Specifications Among Full-Time Year-Round Workers, 2009-2014 Period

		Nation	Intermountain Region	Utah
Preferred Model	**Uncorrected wage gap**	17.60%	19.96%	26.29%
	Corrected[21] wage gap	0.68%	8.97%	19.55%
	Endowment effect	-2.66%	0.40%	5.25%
	Returns effect	3.34%	8.57%	14.30%
Alternative Model 1 (uses nhhchild; no Heckman)	**Uncorrected wage gap**	17.60%	19.96%	26.29%
	-	-	-	-
	Endowment effect	-2.08%	1.02%	7.25%
	Returns effect	19.68%	18.94%	19.04%
Alternative Model 2 (no Heckman)	**Uncorrected wage gap**	17.60%	19.96%	26.29%
	-	-	-	-
	Endowment effect	-2.05%	1.07%	7.23%
	Returns effect	19.65%	18.89%	19.05%
Alternative Model 3 (uses nhhchild)	**Uncorrected wage gap**	17.60%	19.96%	26.29%
	Corrected wage gap	2.56%	10.97%	22.52%
	Endowment effect	-2.66%	0.40%	5.21%
	Returns effect	5.21%	10.57%	17.31%
Alternative Model 4 (uses nhhchild; controls for parenthood in wage equation)	**Uncorrected wage gap**	17.60%	19.96%	26.29%
	Corrected wage gap	-2.62%	9.69%	14.60%
	Endowment effect	-1.98%	1.17%	6.85%
	Returns effect	-0.64%	8.51%	7.75%
Alternative Model 5 (controls for parenthood in wage equation)	**Uncorrected wage gap**	17.60%	19.96%	26.29%
	Corrected wage gap	-5.80%	6.75%	13.96%
	Endowment effect	-1.93%	1.22%	6.98%
	Returns effect	-3.86%	5.53%	6.98%

Table 14 (Data source: CPS March from ceprdata.org)

As we can see, the endowment effect does not change dramatically between models. The estimate of the gap, along with the returns effect, differs considerably. Alternative models 1 and 2 have the largest returns effects, which are also very similar between geographic regions, but recall that these models do not control for selection bias, and rely on OLS estimates of wage functions. Thus their estimates of discrimination are overstated since there are numerous possible factors which differ between men and women that will not be controlled for. Another interesting note is that adding detail to specification used in alternative model 1 (namely, by

[21] Here and henceforth, "corrected" means corrected for selection bias.

differentiating children by age) does not change the results (shown in alternative model 2) dramatically. This is a good sign if one is concerned about omitted variable bias.

Alternative models 4 and 5 actually present evidence for *reverse* discrimination at the national level, where women are actually the beneficiaries of discrimination. We even looked at the estimates of discrimination by alternative model 4 in states with the smallest observed wage gaps (such as California and Massachusetts), and found reverse discrimination on the order of 10% in favor of women! These two models include variables for parenthood in the wage equation along with variables for marital status. Strangely, these models suggest that there is wage discrimination associated with motherhood, but on the whole wage discrimination is in favor of women. These are highly surprising results and most likely a result of collinearity between the inverse Mills ratio and the other variables, which appear in both the wage and selection equations in these models. The constant and the coefficient of the inverse Mills ratio change dramatically when these variables are included, and while there is collinearity even without these variables (the variables measuring age are the biggest source of collinearity), these variables make the problem worse. Thus we believe these results to be dubious, likely a result of poor choice of variables to include in the wage equation. These dubious findings support the argument that parenthood variables belong in the selection equation more than the wage equation. Alternative model 3 does not exhibit this behavior, and it uses the same wage equation as the preferred model.

There is a common theme among the models that use the Heckman correction, though: the nation has the smallest wage gap, while Utah has the largest. Furthermore, all of these models show evidence for the presence of discrimination against women in Utah. Also, Utah women are disadvantaged by their endowments relative to men. Of these facts all our models agree.

Below we present the results produced by multiple models of the comparison between Utah and other geographic regions:

Table 15: Decompositions by Multiple Models of the Difference in Male Wage Premiums Among Full-Time Year-Round Workers between Utah and Other Geographic Regions, 2009-2014 Period

		Utah vs. Nation	Utah vs. Intermountain Region
Preferred Model	**Uncorrected difference**	-8.68%	-6.33%
	Corrected difference	-18.87%	-10.58%
	Pure difference in returns effects	-9.38%	-4.47%
	Wage structure interaction effect	-1.58%	-1.26%
	Pure difference in endowment effects	-7.10%	-5.26%
	Endowment interaction effect	-0.81%	0.40%
Alternative Model 1 (uses nhhchild; no Heckman)	**Uncorrected difference**	-8.68%	-6.33%
	-	-	-
	Pure difference in returns effects	3.00%	2.10%
	Wage structure interaction effect	-2.35%	-2.20%
	Pure difference in endowment effects	-7.83%	-5.98%
	Endowment interaction effect	-1.50%	-0.25%
Alternative Model 2 (no Heckman)	**Uncorrected difference**	-8.68%	-6.33%
	-	-	-
	Pure difference in returns effects	2.76%	1.89%
	Wage structure interaction effect	-2.17%	-2.05%
	Pure difference in endowment effects	-7.87%	-5.98%
	Endowment interaction effect	-1.41%	-0.18%
Alternative Model 3 (uses nhhchild)	**Uncorrected difference**	-8.68%	-6.33%
	Corrected difference	-19.97%	-11.55%
	Pure difference in returns effects	-10.66%	-5.58%
	Wage structure interaction effect	-1.44%	-1.16%
	Pure difference in endowment effects	-7.08%	-5.24%
	Endowment interaction effect	-0.79%	0.43%
Alternative Model 4 (uses nhhchild; controls for parenthood in wage equation)	**Uncorrected difference**	-8.68%	-6.33%
	Corrected difference	-17.22%	-4.91%
	Pure difference in returns effects	-4.81%	3.40%
	Wage structure interaction effect	-3.58%	-2.64%
	Pure difference in endowment effects	-7.61%	-5.81%
	Endowment interaction effect	-1.22%	0.13%
Alternative Model 5 (controls for parenthood in wage equation)	**Uncorrected difference**	-8.68%	-6.33%
	Corrected difference	-19.76%	-7.21%
	Pure difference in returns effects	-7.24%	1.13%
	Wage structure interaction effect	-3.61%	-2.58%
	Pure difference in endowment effects	-7.76%	-5.87%
	Endowment interaction effect	-1.15%	0.11%

Table 15 (Data source: CPS March from ceprdata.org)

Alternative models 1 and 2 find that Utah's wage gap is worse than the national or Intermountain region wage gaps. This is due exclusively to differing endowment effects; according to these models, Utah is actually better regarding wage discrimination than either the nation or the region. Again, these models likely suffer from selection bias, which makes their results untrustworthy.

Alternative models 3, 4, and 5 agree that Utah has more wage discrimination than the nation, but only alternative model 3 agrees with the preferred model that discrimination is worse in Utah than the Intermountain region (and, again, these two models share a common wage equation). Alternative models 4 and 5 argue that discrimination is better in Utah than the Intermountain region. All our models agree, though, that Utah's wage gap is made larger by the endowment effect.

Finally, we present the results of different models in the change of the wage gap over time

Table 16: Decompositions by Multiple Models of the Difference in Male Wage Premiums Among Full-Time Year-Round Workers between Utah and Other Geographic Regions, 2009-2014 Period

		2003-2008 vs. 2009-2014			1998-2002 vs. 2009-2014			1992-1997 vs. 2009-2014		
		Nation	Intermountain Region	Utah	Nation	Intermountain Region	Utah	Nation	Intermountain Region	Utah
Preferred Model	**Uncorrected difference**	-10.45%	0.32%	-3.92%	-4.10%	-1.15%	-1.96%	-5.57%	-2.78%	0.01%
	Corrected difference	-7.48%	3.04%	-3.99%	-11.62%	-2.76%	-11.35%	-18.54%	-14.19%	-17.90%
	Pure difference in returns effects	-6.53%	2.27%	-3.51%	-9.06%	-2.93%	-14.75%	-14.36%	-12.87%	-21.52%
	Wage structure interaction effect	-0.75%	-0.51%	0.27%	-1.50%	-1.26%	0.44%	-1.92%	-1.73%	-0.18%
	Pure difference in endowment effects	-0.07%	1.49%	0.49%	-1.81%	-0.52%	1.39%	-3.14%	-0.49%	3.60%
	Endowment interaction effect	-0.13%	-0.21%	-1.24%	0.75%	1.96%	1.57%	0.88%	0.90%	0.20%
Alternative Model 1 (uses nhhchild; no Heckman)	**Uncorrected difference**	-10.45%	0.32%	-3.92%	-4.10%	-1.15%	-1.96%	-5.57%	-2.78%	0.01%
	-	-	-	-	-	-	-	-	-	-
	Pure difference in returns effects	0.11%	-0.65%	-4.20%	-1.99%	-1.89%	-6.46%	-1.64%	-1.59%	-5.78%
	Wage structure interaction effect	-0.57%	-0.22%	0.51%	-1.11%	-0.96%	0.20%	-1.68%	-1.83%	-0.84%
	Pure difference in endowment effects	-0.11%	1.40%	0.43%	-1.86%	-0.51%	1.55%	-3.23%	-0.42%	4.24%
	Endowment interaction effect	-0.13%	-0.21%	-0.67%	0.86%	2.21%	2.75%	0.98%	1.06%	2.39%
Alternative Model 2 (no Heckman)	**Uncorrected difference**	-0.71%	0.32%	-3.92%	-4.10%	-1.15%	-1.96%	-5.57%	-2.78%	0.01%
	-	-	-	-	-	-	-	-	-	-
	Pure difference in returns effects	0.15%	-0.63%	-4.12%	-1.93%	-1.78%	-6.52%	-1.56%	-1.46%	-5.59%
	Wage structure interaction effect	-0.60%	-0.24%	0.51%	-1.16%	-1.15%	0.27%	-1.72%	-1.91%	-0.76%
	Pure difference in endowment effects	-0.13%	1.40%	0.43%	-1.88%	-0.49%	1.51%	-3.26%	-0.44%	4.23%
	Endowment interaction effect	-0.14%	-0.21%	-0.75%	0.87%	2.27%	2.78%	0.97%	1.02%	2.13%
Alternative Model 3 (uses nhhchild)	**Uncorrected difference**	-10.45%	0.32%	-3.92%	-4.10%	-1.15%	-1.96%	-5.57%	-2.78%	0.01%
	Corrected difference	-7.76%	2.76%	-1.55%	-13.85%	-3.30%	-3.09%	-18.97%	-14.25%	-15.11%
	Pure difference in returns effects	-6.86%	1.93%	-1.07%	-11.40%	-3.57%	-6.40%	-14.89%	-12.98%	-18.71%
	Wage structure interaction effect	-0.70%	-0.45%	0.31%	-1.39%	-1.18%	0.46%	-1.83%	-1.69%	-0.17%
	Pure difference in endowment effects	-0.07%	1.49%	0.49%	-1.80%	-0.51%	1.39%	-3.14%	-0.49%	3.59%
	Endowment interaction effect	-0.13%	-0.20%	-1.28%	0.75%	1.96%	1.45%	0.88%	0.91%	0.19%
Alternative Model 4 (uses nhhchild; controls for parenthood in wage equation)	**Uncorrected difference**	-10.45%	0.32%	-3.92%	-4.10%	-1.15%	-1.96%	-5.57%	-2.78%	0.01%
	Corrected difference	-3.63%	5.58%	-16.61%	-10.54%	7.91%	3.85%	-14.01%	-14.23%	-17.43%
	Pure difference in returns effects	-2.13%	5.00%	-16.14%	-7.38%	8.09%	0.61%	-9.00%	-12.66%	-21.23%
	Wage structure interaction effect	-1.15%	-0.60%	0.30%	-1.97%	-1.59%	0.03%	-2.66%	-2.22%	-1.39%
	Pure difference in endowment effects	-0.18%	1.43%	0.42%	-1.93%	-0.57%	1.48%	-3.28%	-0.48%	4.13%
	Endowment interaction effect	-0.17%	-0.25%	-1.18%	0.74%	1.97%	1.74%	0.92%	1.12%	1.06%
Alternative Model 5 (controls for parenthood in wage equation)	**Uncorrected difference**	-10.45%	0.32%	-3.92%	-4.10%	-1.15%	-1.96%	-5.57%	-2.78%	0.01%
	Corrected difference	-2.29%	7.77%	7.83%	-8.14%	14.61%	12.75%	-13.58%	-16.00%	-16.13%
	Pure difference in returns effects	-0.68%	7.28%	7.35%	-3.97%	15.52%	14.13%	-8.38%	-14.92%	-14.42%
	Wage structure interaction effect	-1.25%	-0.68%	-0.69%	-2.99%	-3.35%	-2.88%	-2.79%	-2.42%	-2.26%
	Pure difference in endowment effects	-0.19%	1.41%	1.42%	-1.94%	0.46%	-0.53%	-3.32%	0.59%	-0.51%
	Endowment interaction effect	-0.17%	-0.23%	-0.26%	0.76%	1.98%	2.03%	0.91%	0.75%	1.06%

Table 16 (Data source: CPS March from ceprdata.org)

Alternative models 1 and 2 show much smaller changes in the wage gap than the models utilizing the Heckman method. When selection bias is controlled for, the wage gap can change considerably, and this shows up in the preferred model along with alternative models 3, 4, and 5. Alternative models 4 and 5 show a modest drops in wage discrimination, along with a modest change in the wage gap in general. All models agree that the wage gap grew in the Intermountain region between the housing boom and 2008 financial crisis recovery periods, but disagree in cause and magnitude. Alternative models 1 and 2 suggest that wage discrimination decreased while the endowment effect grew. The other models suggest both increasing discrimination and a strengthening endowment effect are responsible. Alternative models 4 and 5 suggest major increases in these effects, and even suggest that the wage gap in the Intermountain region now is *worse* than it was in the 1998 to 2002 period, yet *better* than in the earliest period examined. The preferred model and alternative model 3 don't have these wild fluctuations in the change of the wage gap of the Intermountain region, and suggest a more tempered and consistent improvement since the earliest period, though an increase since the 2008 financial crisis. Finally, alternative models 3 and 4 suggest the biggest improvement for Utah's wage gap since the 1992 to 1997 period, and the biggest improvement since the housing boom period.

With this in mind, the results of alternative models 4 and 5 appear to be unstable and exhibiting strange patterns. Nevertheless, all models can agree that there appears to be improvement in the wage gap in all periods over the past twenty years.

DISCUSSION OF FINDINGS' INTERPRETATION

Let's recap the results presented in the previous section. Our methodology suggests that there is no wage gap at the national level. After correcting for selection bias, women earn as much per hour as men. There may still be discrimination, but because women tend to have favorable endowments compared to men, the returns effect is cancelled out and there is no wage gap. This is not true for either the Intermountain region or Utah, though. In fact, Utah's wage gap is larger than either the national or regional wage gaps. This is due to both the endowment effect and the returns effect being larger. Utah has been seeing more improvement in its wage gap than its neighbors in the most recent decade and saw remarkable improvement since the 1990s, but has not been keeping up with the nation. Utah women's endowments have not been keeping pace with men's endowments, unlike the rest of the nation.

So after this econometric exercise, is there evidence for discrimination against women? Before we can answer that question, we first need to define discrimination. There are multiple forms that discrimination could take in the working world. Coworkers may harass female employees. Women may be largely excluded from certain occupations by employers, discouraged from pursuing careers not traditionally considered suitable careers for women, or encouraged to pursue traditionally female (and low-paying) careers simply because of their gender. The workplace may have policies in place that put women at a disadvantage compared to men. These forms of discrimination may (and likely do) exist and represent an injustice against women, yet we do not address them in this paper. Here, we are interested in only one type of discrimination: wage discrimination, or when an employer undervalues female workers by paying them less (or overvalues male workers by paying them more).

This study does not address why people would discriminate against women, or the form discrimination takes. Discrimination may not reflect any malice on the part of employers but rather results from subconscious beliefs and biases against women or deeply engrained habits among both employers and female workers that affect their pay. For example, Correll et. al. (2007) found that *both* men *and* women exhibited beliefs and expectations that could be considered discriminatory against mothers. If this is the case, additional legislation to crack down on wage discrimination may have no effect. Furthermore, the onus for solving the problem of wage discrimination falls not just on employers but on the larger society to try to reverse the expectations and social norms that work against women.

In our study, we analyze the gender wage gap corrected for selection bias, which is a different measure of the wage gap than the uncorrected difference in wages between men and women. This new wage gap is then divided into a returns effect and an endowment effect. We would like to address a number of questions that arise after performing this procedure. First, can we associate this difference, or the wage gaps associated with the wage structure or endowment effects, with discrimination against women? Second, why is the corrected wage gap different from the uncorrected wage gap, sometimes substantially so?

First, let’s discuss the wage structure and endowment effects, and how they should be interpreted. There are two primary issues with the depiction of discrimination that the OB method produces. One is that interpreting the returns effect as discriminatory may be overstating discrimination in wages. The other is implicitly justifying the disparity of wages due to the endowment effect (Polachek, 2007).

Researchers are often reluctant to call the returns effect discrimination. The reason is that while discrimination will be captured here, so will other unmeasured variables that, if we had included them, would decrease the returns effect and increase the endowment effect. This is an omitted variable bias problem, so the question that must be answered is whether we have omitted variables and how big an impact they would have. There are variables that are missing, the most noticeable one being *actual* work experience versus *potential* work experience (which we proxy with an individual's age). However, our use of the Heckman correction should help with this problem. James Heckman's key insight into selection bias is that it is an omitted variable problem, and all that is needed is adding that missing variable (the inverse Mills ratio) to an OLS regression (Heckman, 1979). Omitted variables such as actual work experience will not only be associated with earnings but also with women's selection behavior, so by including the inverse Mills ratio we help remove this variable's effect from the other variables' coefficients. So while there could be omitted variables that contribute to the returns effect, we believe that the majority of this effect represents wage discrimination.

What about the endowment effect? Does it represent the part of the wage gap that is *not* due to discrimination? Not necessarily. In fact, you cannot even say it is the part of the wage gap that is not due to wage discrimination. Women's investment in their individual human capital is not independent of the earnings they make in the labor force. If they do not expect to earn as much because of discrimination, they may make different decisions than they would have if wage discrimination did not exist. Wage discrimination may encourage division of labor in the household that more often than not results in the woman being the homemaker and the man being the breadwinner. Even with wage discrimination aside, the endowment effect could measure the impact of other barriers women face that we may call discriminatory, even though it is not wage discrimination. For example, if we find a wage gap associated with working women's industrial composition, that gap may be attributed to differing industrial preference (which may be socialized by, say, career guidance counselors exhibiting bias) or differing employer preferences for male and female workers across sectors that also could be discriminatory. The key is to remember that OB decomposition makes no comment on causal factors, and divides the wage gap in an accounting sense. The gap associated with the endowment effect is best thought of as the wage gap if wage discrimination were to disappear overnight, not what the gap would be if wage discrimination never existed to begin with.

We next discuss the correction for selection bias. Most researchers correct for selection bias and do little else, and a meta-analysis of wage gap studies suggests that correcting for selection bias isn't as important as it once used to be (Jarrell & Stanley, 2004), but in our study the wage gap corrected for selection bias is nearly zero and is very different from the uncorrected wage gap. It is possible to determine why the correction for selection bias is as large as it is by examining the relationship between the coefficients of the probit model and the coefficients of the log wage regression. However, while this may be an interesting topic for future research, this paper is focused on trying to identify discrimination, so we will not perform such an analysis here. We will simply say that making the correction for selection bias is necessary if we want to identify discrimination. Failing to do so may result in unmeasured variables that differ between men and women and affect both wages and entrance into the labor force (such as individual motivation, attachment to the labor force, actual work experience, etc.) biasing the coefficients of our wage regressions and, with them, our estimate of discrimination.

Interestingly, we see a shift from positive to negative selection in Utah, a pattern that we did not see in the period studied at the national level but may have happened before 1992. We cannot give a reason why this happened, though one hypothesis is a shift in women's preferences. Perhaps Utah women in the early and mid-1990s preferred not to work and would accept work only if they were exceptionally good workers offered good wages. Perhaps when male wages began to stagnate, though, women began to enter the labor force in greater numbers to help maintain the household standard of living, even though those women might have otherwise not entered. This trend may also have happened later in Utah than it had in the rest of the nation.

Admittedly, the methods we applied in this paper are imperfect, particularly the correction for selection bias. As observed by Freeman and Medoff (1982), multiple equation methods (including the Heckman two-step method) attempt to pull more information from data than the data may actually possess, which harms the robustness of these methods' findings. They are not a substitute for better data and research methods. Longitudinal data, for example, allows for methods such as fixed effects regression that correct for selection bias and omitted variable bias.

Unfortunately, such a dataset with a sufficient sample size for Utah is not publicly available. We believe that we are using the best dataset available for answering the questions posed in this paper, and that the methods we apply, while imperfect, are necessary and the best available. We are encouraged by the fact that our findings at the national level do not disagree significantly with results from other studies, even those using superior datasets (see O'Neill and O'Neill (2005) and Fortin et. al. (2010)). In fact, our estimates are roughly in line with the projection for closure of the gap made by Jarrell and Stanley (2004).

As for criticisms directed at the practice of decomposition, we feel that while both the endowment and returns effects could both represent discrimination, they represent different forms of discrimination or the effects of discrimination. Differentiating the returns effect (then calling it wage discrimination) and the endowment effect are useful for trying to see more of the underlying structure of the gender gap and could lead to policy insights that may help close that gap. For example, identifying lack of education in Utah women as a contributor to the wage gap could certainly lead to solutions to encourage women to pursue more education.

With these issues in mind, is there evidence for wage discrimination against women in the nation in general and Utah in particular? We believe our results suggest there may be a little discrimination at the national level, more at the regional level, and even more in Utah. While the discrimination problem is getting better, it still exists. It may not be long before wage discrimination disappears in the nation, but it will take longer for it to disappear in Utah. Furthermore, other forms of discrimination that affects earnings, which were not the focus of this paper, may continue to exist.

Some of course may still doubt that we controlled for attributes and selection bias correctly or whether we can call the returns effect discrimination, and thus doubt our findings. We note that our depiction of the endowment effect does not differ much between models. This suggests that we have quantified well the effects of education, occupation, industrial distribution and other variables on the wage gap. So those who do not believe that we have identified discrimination would then be tasked with finding variables in which men and women differ other than the ones we control for to explain the remaining returns effect, since the endowment effect (using the variables we control for in this study) is rather robust.

So what can Utah do to close its gender wage gap? This paper does not focus on policy recommendations: for that, see the paper published by Voices for Utah Children (2015). We will comment that Utah needs to consider how it can encourage women, especially mothers, to continue to develop their human capital. For example, programs such as paid maternity leave that allow women to more easily resume work and training after giving birth have been found to help close the pay gap associated with motherhood (Waldfogel, 1998). Utah should examine workplace policies and determine if they have a disparate impact on women. We also encourage a cultural conversation about the role of women in society. While Utah culture encourages both women and men to be industrious and productive members of the community (and we see this in Utah women's participation rate in the workforce, which tends to be higher than average (Voices for Utah Children, 2015)), women are expected to assume the responsibility of homemaker. This may translate into biases against women (conscious or unconscious) that result in wage discrimination.

CONCLUSION

Based on the CPS dataset's results, the evidence for earnings discrimination at the national level is tenuous and suggests that if it does exist it's not very large. Utah's wage gap is worse than the nation's due to both Utah women's attributes relative to Utah men and wage discrimination against women being worse than at the national or regional levels. This gap has been improving over time, but recently the improvement has slowed, and Utah women's endowments have actually stagnated compared to the achievements of Utah men over the past two decades.

We do not believe wage discrimination is a problem to gloss over and wait for market forces to fix. The gender gap is tied to poverty issues along with individual and family well-being, aside from the injustice it represents on its own. Closing this gap should be considered a key part of growing Utah's economy into a prosperous and technologically-driven one that promises equal opportunity for all. We hope that this paper will illuminate the problem and generate solutions.

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APPENDIX

As discussed in the Data section, due to changing coding schemes for industry and occupation, we had to create our own crosswalk for industry and occupation classifications in order to make the schemes used in the 1992-1997 and 1998-2002 periods compatible with the contemporary period. We based our crosswalk off crosswalks created by Minnesota Population Center (n.d.) and the U.S. Census Bureau (2014)[22]. Below we show the industry and occupation codes assigned to their respective MIGs and MOGs. In other periods, we used the MOGs and MIGs suggested by the CPS documentation.

[22] For the Minnesota Population Center occupation crosswalk, see:
https://usa.ipums.org/usa/resources/volii/documents/occ1990_xwalk.xls
For the U.S. Census Bureau industry variable crosswalk, see:
http://www.census.gov/people/io/files/IndustryCrosswalk90-00-02-07-12.xls

Table 17: Major Occupation Group Classification used for CPS March Samples from 1992 to 2002

Major Occupation Group	Occupation Codes
Management, business, and financial	003-018, 020-034, 036, 037, 065, 254, 373, 375, 473, 475, 476
Professional and related	043-174, 176-232, 234, 235, 390, 465
Service	019, 175, 405-464, 466-469, 479, 485-487, 773
Sales and related	243-253, 255-290, 318
Office and administrative support	303-317, 319-374, 376-389, 391
Farming, forestry and fishing	480-484, 488-499
Construction and extraction	035, 543, 545-548. 550-576, 578-617, 643, 844, 866, 869, 889, 890
Installation, maintenance, and repair	503-539, 544, 549, 577, 804, 865
Production	233, 628-642, 644-772, 774-799, 874
Transportation and material moving	803-843, 845-864, 867, 868, 870-873, 875-888
Armed forces	905

Table 17

Table 18: Major Industry Group Classification used for CPS March Samples from 1992 to 2002

Major Industry Group	Industry Codes
Agriculture, forestry, fishing, and hunting	010, 011, 013-019, 021-032, 230
Mining	040-050
Construction	060
Manufacturing	100-170, 172-229, 231-392, 610
Wholesale and retail trade	500-609, 611-640, 642-691
Transportation and utilities	400-439, 443-472
Information	171, 440-442, 732, 800, 852
Financial activities	700-712, 742, 801
Professional and business services	012, 020, 721-741, 841, 882-893
Education and health services	812-840, 842-851, 853-871
Leisure and hospitality	641, 762, 770, 800-810, 872
Other services	750-761, 763-769, 771-791
Public administration	900-932
Armed forces	940-960

Table 18

Name of Candidate:	Curtis G. Miller
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