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# DISCUSSION PAPER SERIES

IZA DP No. 10673

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## ABSTRACT

# Is the Gender Pay Gap in the US Just the Result of Gender Segregation at Work?

This study examines the gender wage gap between male and female workers in the US using a cross-section from the Current Population Survey (CPS) It shows that the extent of gender segregation by both industry and occupation is significantly greater than previously supposed. For the wage gap this creates problems of sample selection bias, of non-comparability between male and female employment. To address these problems the study uses a matching approach, which we also extend to a more recent methodological version with a yet stronger statistical foundation – Inverse Probability Weighted Regression Adjustment (IPWRA) - not previously used in related studies. Despite this, doubts remain about even these well founded and appropriate techniques in the presence of such strong gender segregation. To secure even greater precision we repeat the matching analysis for a small number of industries and occupations, each carefully selected for employing similar numbers of men and women. This is an approach that has not previously been explored in the relevant literature. The findings for the full sample are replicated at the level of industry and occupation, where comparability is more reliable. The study supports the view of the existing literature that the gender wage gap varies by factors such as age and parenthood. But it also finds that, even when these and other important "control" variables such as part-time working, industry and occupation are taken into account, a statistically significant gender wage gap remains.

JEL Classification:	C31, J16, J31, K38
Keywords:	gender pay gap, segregation, sample selection bias,
	propensity score matching IPWRA, USA

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# AN EMPIRICAL ANALYSIS OF THE GENDER PAY GAP IN THE UNITED STATES

#### 1. Introduction

This paper looks at determinants of the gender wage gap in the US. The gender wage gap has been extensively researched previously and the US more than many countries. Many studies look for determinants and explanations of the crude gender wage gap – for explanations as to why the mean wage for women is less than for men. This approach is both useful and valid. The relevant literature has been both extensive long established: see the early review by Weichselbaumer and Winter-Ebmer (2005). The findings that wage gaps are related to gender segregation at work (such as the study by Walby and Ohlsen, 2002) or that they increase with age (for example Pastore et al, 2016) are of importance in understanding what creates the gap. This paper is, in part, in keeping with this tradition in that it looks at determinants of the gender gap. It shows that, despite important differences between the employment of men and women, the conclusion that women are paid less than men for essentially the same work is inescapable.

However, there is another theme in the same literature which seeks to identify a "residual" wage gap – the difference in pay between men and women which cannot be explained by age, education or other determinants. In short, this theme within the literature looks for evidence that women do not indeed receive the same pay for the same work as men. This paper is also in that tradition. It takes a Popper type approach. That women do not receive the same pay as men for the same work is a falsifiable proposition. It then focuses on whether or not the evidence allows us to falsify this proposition. The use of a matching approach is a comparatively recent methodological innovation to the study of the gender pay gap and such studies (see Novo 2008) are still few. This study extends the matching methodology to include the recent development of Inverse Probability Weighted Regression Adjustment estimators. The paper shows this approach to be a powerful tool in understanding the gender gap.

There are extensive difficulties in being able to identify accurately the "same work" to assess whether or not women receive less than the same pay. This is one key reason for the extensive research on the subject. In this paper we use a large sample of individuals drawn from the US Current Population Survey to investigate this residual gender wage gap. We find that, after careful construction of control groups at an industry level, we remain unable to reject the proposition that women do indeed receive less pay for the same work despite differences arising from gender segregation, part-time working and other factors. Our approach using matching techniques both for the full sample and for specific industries and occupations represents a stronger attempt to falsify the existence of a gender wage gap in the US than previous research. It provides increased confidence that the findings of previous research are robust. An important contribution of the paper is that it shows gender segregation by both industry and by occupation to have been far more extensive than had been supposed. This, in turn, suggests that problems of sample selection bias in gender wage comparisons are much more acute than previously supposed. Many men and women are simply not in comparable forms of employment.

A second important contribution is methodological. Like a small number of previous studies, a propensity score matching approach is used to address this lack of comparability. This matching approach is extended to the more recent, more statistically robust Inverse Probability Weighted Regression Adjustment (IPWRA) estimator to provide an even more suitable set of controls for non-comparability. As far as can be ascertained this approach has not been previously used in gender wage gap studies.

Despite using a more robust statistical approach there remain residual doubts whether even the best of techniques could provide an adequate degree of comparability in the presence of such extensive gender segregation. To address this the analysis conducted for the full sample is repeated for a small number of selected industries and occupations. These were not chosen at random but because they employ similar proportions of both men and women. The results for these industries and occupations produce essentially the same conclusions as for the full sample: that no matter how far differences in male and female employment are taken into account a gender wage gap persists.

Section 2 provides a review of literature, section 3 summarises the data and its key characteristics and section 4 provides an overview of our methodology. In section 5, we present our Heckman regression analysis and in sections 6 and 7 our matching analysis, firstly for the full sample and then for three selected industries. Our conclusions are presented in section 8.

#### 2. Review of Literature

The issue of a gender pay gap has hardly been neglected in the empirical literature. Weichselbaumer and Winter-Ebmer (2005) found in their meta-analysis a total of 263 papers with empirical estimates (at that time) of a gender wage gap in one form or another. That it continues to be a topic of interest is partly attributable to its importance but also with the extensive problems and complexity in its estimation. The early literature on the subject had few of the modern advantages of micro data or modern estimation techniques. This, too, means that there remains scope for careful and sensible application of both.

A useful way to divide the existing literature is with respect to the particular aspect or determinant of the gender wage gap that they emphasise. Firstly, a number of studies focus upon evidence that the gender pay gap widens as workers age. In a study of Azerbaijan Pastore et al (2016) found the gender wage gap to widen over time. Bertrand et al (2010) in a study of US MBAs attributed a growing gender wage gap which increased with age to differences in training, career interruptions and weekly hours of work. Manning and Swaffield (2008), in a study of the UK, found that the gender wage gap increased with age.

Some research has linked education to the gender wage gap. The study of Italy provided by Mussida and Picchio (2014).found the gender wage gap to be greater at lower levels of education. Balu and Kahn (1997) found increased demand for highly skilled workers to have widened the gender wage gap for high skill workers. Irrespective of a gender wage gap there is a long and well established literature linking education and wages. Mincer (1958) was unquestionably one of the early researchers involved and there exists a considerable volume of subsequent research supporting the view that education increases wages. Of particular note is the paper by Acemoglu and Autor (2011),

Blau and Kahn (2016) find that, with a decline or reversal in some of the determinants (such as education) of earlier wage gaps in the US that segregation by both occupation and industry remains and important cause of the remaining gender wage gap. The link between gender segregation and the wage gap has long since been made. Polachek (1981) constructs a model in which female earnings potential depreciates during temporary exits from the labour force at the same time that males remaining in the labour force see their earnings potential appreciate from continued skill development. This affects investment in skills and, hence, occupational choice. Polachek (1985) further extends this link between gender wages and a life-cycle view of occupational choice. Polachek (2014) finds the gender pay gap to be smaller between single men and women and larger between married men and women. This is attributable to his life-cycle model of human capital and the resulting different occupational structure between the genders. Cohen et al (2009), in another study of the US, found growing gender segregation but that it coincided with a decreasing gender wage gap. Barón and Cobb-Clark (2010) examined the effects of occupational segregation on the gender wage gap in Australia. They found the gender wage gap to be fully explained by productivity characteristics but not fully explained for high wage workers. Ohlsen and Walby (2004) found evidence from the UK that labour market rigidities - including the segregation of women into certain occupations and into smaller, non-unionised firms - were responsible for about 36% of the gender wage gap. Walby and Ohlsen (2002) also found both occupational and industrial segregation to have been prevalent in the UK. Livanos and Pouliakas (2012), in a study of Greece, found that gender segregation with respect to educational subject explained part of the gender wage gap. Pastore and Verashchagina (2011) found that the gender wage gap more than doubled during the transition from plan to market in Belarus, particularly because women have experienced increasing segregation in low-wage industries.

That women are much more likely than men to work part-time, which attracts lower rates of pay, has often been identified as an important contributor to the gender wage gap. Blau and Kahn (2013) found that US policies encouraged women to undertaken part-time work in lower level jobs. Ermisch and Wright (1993) provide evidence that women in the UK received lower wages in part-time than in full-time work.

In a study of wages in India, Menon (2009) found the gender wage gap to increase with respect to openness to international trade. Oostendorp (2009) found evidence that the occupational gender wage gap tends to decrease with respect to trade and foreign direct investment in richer countries but little evidence of any effect in poorer countries.

#### 3. Data - Key Characteristics of the Sample

Our sample comprised a total of 82,887 employed individuals interviewed between October 2011 and March 2012 (6 sets of monthly interviews). These were drawn from a larger sample of 638,062 individuals (employed and not) aged 15 years or older. The data were taken from the US Current Population Survey (CPS). Details of the sampling and methodology used to conduct the survey can be found on the CPS website - <u>https://www.census.gov/programs-surveys/cps.html</u>. Only those individual returns which reported an hourly wage or sufficient information for one to be calculated were included in the sample of employed individuals. The remainder of the sample were used to adjust for possible sample selection bias.

The purpose of this section is to identify the most important characteristics of our sample for further analysis - to identify what is commonly referred to as the "stylized facts". The sample comprises a total of 41,677 males (50.3% of the total) and 41,210 females (49.7% of the total). The mean hourly wage for women was \$20.02 against a mean of \$24.15 for men. This implies a (crude) gender pay gap of \$4.13 per hour or about 21%. There are, of course, many other factors to consider.

In our sample a much higher proportion of female workers (11.3%) were single parents than were male workers (4.0%). This, almost certainly, relates to the finding that the proportion of female workers who are part-time employees (25.6%) is close to being double the proportion of male workers who are employed on a part-time basis (12.7%). The prevalence of part-time working amongst women is one possible explanation of lower mean wages for females. The sample mean hourly wage for part-time workers was about \$15 compared to around \$24 for full-time workers. The first, combined key characteristic of our sample is that a much higher proportion of women than men work part-time and working part-time typically results in a lower hourly rate of pay than does working full-time.

As discussed previously there is an extensive literature which supports the proposition that more education results in higher wages. Table 1 provides summary details of the sample mean hourly wage for different levels of education and reports the proportion of females in each educational category. As with previous studies mean wages increase at every level of education, such that the highest level (post-graduate degree) attracts a mean wage more than three times the lowest level (no high school diploma). However, women represent slightly under 50% of the total sample but more than 50% of the sample at each of the four higher education levels. They are also under-represented at the lowest educational level, comprising only 42% of the relevant sub-sample. This initial examination suggests that, as so often noted before, education is an important determinant of wages but low educational attainment does not seem to be a plausible explanation for the gender pay gap.

Table 1: Mean Hourly Wages and Proportion of Females by Educational Level						
Mea						
Education level	Observations	% female	wage (\$)			
Post-graduate degree	10028	51.94%	37.28			
Bachelor's degree	18354	52.06%	28.93			
Associate degree	8952	56.22%	20.78			
Some college but no degree	15801	50.91%	17.94			
High school diploma	22699	45.86%	16.69			
No high school diploma	7053	41.94%	11.63			
Source: US Current Population Surv						

Other studies, such as Pastore et al (2016), have found that the gender pay gap increases with age. Table 2 provides details of the gap between mean male and female wages by age group. The results show the wage gap to increase with age, at least between the ages of 21 and 60.

Thus, our sample of US workers exhibits similar properties with respect to a gender pay gap that widens with age.

Table 2: the Q							
Age group	Mean wa	ge	gender pa	ay gap			
	Male	Male Female		wages)			
	\$	\$	\$	%			
15-20	10.09	8.68	1.40	16.2%			
21-30	16.85	15.36	1.49	9.7%			
31-40	24.32	21.28	3.03	14.3%			
41-50	28.26	21.48	6.78	31.6%			
51-60	31.20	22.44	8.76	39.1%			
over 60	26.88	22.15	4.73	21.3%			
Source: US C	Source: US Current Population Survey						

A number of previous studies have found a wage premium associated with union membership. Our later analysis considers this more fully but a relevant feature of our sample is that union membership rates are only slightly different between men and women. In our sample 12.7% of male workers and 11.2% of females were union members. This makes it unlikely that union membership is the dominant cause of the gender pay gap.

A very striking feature of the US Current Population Census (CPS) data is the high degree of gender segregation in employment. Appendix 1 reports the share of females in total employment for each of 262 detailed categories of industry, along with the mean hourly wage for each. At total of 34,064 workers (41% of the sample) are employed in an industry where one gender accounts for 75% or more of the total workforce. A majority of the sample – 44,016 workers or 53.1% of the total – are employed in industries where one gender accounts for 2/3 or more of total employment. There are also non-trivial differences in wages which

employ a high proportion of women and those which employ a high proportion of men. Those industries for which employment was at least two thirds men exhibited a mean hourly wage of \$22.63. In contrast those industries which employed at least two thirds women a mean hourly wage of \$19.09.

Appendix 2 provides a similar analysis but by occupation. It reports the share of women in each of 525 detailed occupations together with the mean hourly wage for each occupation. If men and women are to a substantial extent in different industries they are even more likely to be engaged in different occupations. More than one half of the sample - 51.659 workers or 50.3% of the sample – were engaged in an occupation for which one gender accounted for 75% or more of total employment. A total of 59,527 workers (71.8% of the sample) were in occupations where one gender accounted for two thirds or more of overall employment. As with industries, those occupations in which men are concentrated exhibited a higher mean wage than those in which women are concentrated. Those occupations for which men represented 75% or more of employment exhibited a mean hourly wage of \$23.39, those for which women represented 75% or more of employment a mean hourly wage of \$21.05.

What these findings emphasise is that, to a large extent, men and women work in different industries and different occupations. This gender segregation complicates our understanding of the nature of a gender pay gap. That is, underlying the issue of the gender pay gap is one of equity. The same pay for undertaking the same work is a clear principle. But very often women and men are segregated into different industries and different occupations which make a clear comparison more complex. For this reason our later analysis focuses on trying to control for differences in industry and occupation between men and women.

#### 4. Methodology

#### 4.1 Regression

Our starting point, as with many previous studies, is with a regression model – the Heckman selection model in this case. We used a Mincer (1958) type equation, with the dependent variable being the log of hourly wages (lhwage). Our specification was:

In hwage =  $X\beta + Z\gamma + W\theta + u$ 

(1)

where Z is a matrix of observations of occupational and sector dummy variables (13 sectors), W a matrix of observations of 4 ethnic dummy variables and 4 regional dummy variables (one of each omitted in estimation). The matrix X is a matrix of observations of the following variables:

- gender -(0,1), 1 if female
- age age (in years)
- sparent single parent (0,1), 1 if a single parent
- educyears number of years of education, starting from first grade
- hours number of hours worked per week
- migrant -(0,1), 1 if born outside the US

- union -(0,1), I if a union member
- parttime -(0,1), 1 if a part-time worker.

We estimated two different versions of the model. Model 1 used dummy variables for 22 aggregate categories of occupation and model 2 for 525 disaggregated categories of occupation. In both models we used a redundant variables test for the exclusion of all sector and occupation dummy variables.

#### 4.2 **Propensity Score Matching with a Single Treatment Variable**

As we have seen in the preceding review of literature a key issue in empirical studies of the gender pay gap is the need to try to compare like with like when comparing pay for men and women. Some authors - Nopo (2008) and Frölich (2007) in particular - have advocated and used matching estimators of gender pay gaps. Both authors propose the technique as an alternative to the de-compositions of the type proposed by Blinder (1973) and Oaxaca (1973), arguing that it provides a more solid basis for comparing male and female wages when important differences in observable characteristics exist between the two groups. Nopo (2008) also makes the point that matching estimators are not dependent upon measuring the distributions of male and female earnings at a specific point – usually at the mean. Certainly the basis of the matching approach in the selection of a carefully matched control sample has considerable appeal in addressing the issue of a gender pay gap. For conciseness we do not attempt to provide an exposition are referred to the original authors.

A matching approach starts by defining an outcome variable (log of hourly earnings) and a (0,1) treatment variable (female). It seeks to establish whether a statistically significant difference exists in the log of hourly earnings between the *treated* (female) group and the *untreated* (male) group. The procedure selects a control group from *untreated* (male) which is selected to be, as far as possible, identical in all other key characteristics to the *treated* (female) group. This process of creating a "matched" control group is done by the creation of a propensity score, normally (as in this study) by developing a probit model to identify the key characteristics of the treated group.

There are three main parameters within the matching approach::

ATE – the average treatment effect in the population (all indviduals). ATT – the average treatment effect for "treated" individuals (female workers) ATNT – the average treatment for "untreated" individuals (male workers).

These parameters are defined as follows:

$$ATE = E(Y1i - Y0i) \equiv E(\beta i)$$
<sup>(1)</sup>

 $ATT = E(Y1i - Y0i | Di = 1) \equiv E(\beta i | Di = 1)$ (2)

$$ATNT = E(Y1i - Y0i| Di = 0) \equiv E(\beta i|Di = 0)$$
(3)

Where Y is the outcome and where subscript 1 denotes individuals who are "treated" (female) and subscript 0 denotes those that are not. D indicates whether or not "treatment" was received (1 for treated and 0 for untreated).

In this paper we use kernel density matching (with bootstrapped standard errors) to test for a statistically significant gender pay gap between men and women within our sample. Although propensity score matching is an effective technique for reducing bias on observables (mismatches between male and female workers) it does not follow that it always produces an adequate control group. A further advantage of the technique is that is possible to check how well the control group is matched with the group of interest. The existing literature finds that the gender wage gap varies according to key population characteristics. To test for similar effects in our sample we divide the sample into two and conduct the matching analysis separately for each sub-sample. This is conducted for (i) parents and non-parents (ii) married and unmarried and (iii) young and older workers.

For the full sample our earlier summary of the sample characteristics suggests that there must be real concerns with matching when there is a substantial degree of gender segregation by both industry and occupation. To avoid the risk that such gender segregation makes the creation of an adequate control group difficult we conduct a matching analysis not only for the full sample but for several identifiable sub-samples. The study also repeats the matching analysis for three individual industries – banking, grocery stores and restaurants. We also repeat this analysis for five different occupations – accountants, assemblers, customer service representatives, janitors and lawyers. These were not selected at random but because they (a) have comparable numbers of male and female employees and (b) each offer a sufficiently large sample size (each industry excess of 1200 observations and each occupation in excess of 600).

A standard concern within the literature is with bias on observables (common support) – in essence how well does the control group of male (untreated) match with the female (treated) group according to observable characteristics. This study presents evidence for the extent to which the matching process reduced bias on observables in Appendix 3. A further, more intractable problem is the risk of bias on unobservables – that an excluded variable may have biased the results. This type of problem is not unique to matching estimators. Problems with confounding variables and omitted variable bias are well known in relation to other estimators. To reduce the risk of bias on observables the probit model (used to create the propensity score) was first estimated in a general form, including as many potentially relevant variables as the available data would allow. However, as King and Nielsen (2016) have pointed out, this creates a further risk of bias from matching on irrelevant variables. To limit this risk a "specific" form of the probit model (in which all variables jointly insignificant were removed from the general specification) was used to create the propensity score employed.

#### 4.3 Matching with Two Treatment Variables

A further possible limitation with the single treatment approach to matching is that other variables interact with gender in a way that makes more like a second treatment than a control. For example, the wages of part-time workers are lower than those of full-time workers but more women work part-time than men. Having two treatment variables – for example gender and part-time working – provides an opportunity to assess how both interact rather than thinking of part-time working as being independent of gender. Likewise, the interaction between gender and parenthood in determining pay is of more interest when both are treatment variables than parenthood is simply, in effect, a control.

Cattaneo (2010) and Cattaneo et al (2013) propose an estimator – inverse probability weighting regression analysis (IPWRA) – which allows for two or more (0,1) treatment effects on the same outcome variable. IPWRA estimators have desirable properties beyond the ability to include more than one treatment effect. As King and Nielsen (2016) point out they are less prone to mis-matching on irrelevant observables. The IPWRA approach estimates both a treatment model and an outcome model. Unlike the basic matching approach this means that the treatment is modelled as an endogenous variable. More importantly IPWRA is a "doubly robust" estimator, which offers some protection against possible incorrect assumptions. Hirano et al (2003) show that doubly robust estimator exhibit a lower bias than estimators without the doubly robust property. A Monte Carlo study by Busso et al (2013) shows that bias corrected matching performs well when the match between treated and untreated is poor but, since the performance of the estimator is sensitive to the underlying data generating process, recommend the use of more than one estimator of treatment effects. That is the approach adopted by this study in using both propensity score and IPWRA estimators.

Readers requiring a more detailed exposition of these issues are referred to the original papers. Note: for computational reasons it was not possible to include occupation and sector dummies in the IPWRA analysis. The appropriate comparison with propensity score matching estimates is with those estimated without these dummies.

#### 5. Regression Results

Table 3 presents regression results for a Heckman selection model. Regression analysis was by means of the Heckman model (maximum likelihood option) in *STATA14*. The results are reported in Table 3.

Variable         Coefficient/ standard error           gender         -0.1608***           (0.0044)         age           union         0.0068***           (0.0002)         0.0705***           union         0.1705***           (0.0049)         0.0728***           (0.0049)         0.0788***           (0.0049)         0.0788***           (0.0048)         0.0728***           (0.0048)         0.0728***           (0.0048)         0.0728***           (0.0048)         0.0728***           (0.0048)         0.0427***           (0.0041)         -0.0424***           (0.0007)         constant           2.3675***         (0.0007)           constant         2.3675***           (0.0007)         constant           sector dummies         yes           regional dummies         yes           race dummies         yes           sector dummies         yes           gender         -0.0411***           (0.0041)         age           -0.0023***         (0.0041)           age         -0.0023***           (0.0041)         -2.6711***           (0.005)	Table 3: Heckman Model Estimates (maximum likelihood)			
standard error           gender         -0.1608***           (0.0044)         (0.0068***           age         0.0068***           (0.0002)         0.1705***           (0.0062)         0.0728***           married         0.0728***           (0.0048)         0.0728***           (0.0048)         -0.225***           (0.0048)         -0.225***           (0.0048)         -0.225***           (0.0061)         -0.0424***           (0.0061)         -0.042***           (0.0061)         -0.042***           (0.0061)         -0.042***           (0.0061)         -0.042***           (0.0007)         -0.0225**           occupation dummies         yes           regional dummies         yes           regional dummies         yes           regional dummies         yes           gender         -0.0411***           (0.0001)         -0.0023***           (0.0001)         -0.0023***           (0.0001)         -0.022***           (0.0001)         -0.022***           (0.0003)         -0.022***           (0.0004)         -0.022***           (0.005)         <	Variable	Coefficient/		
gender         -0.1608***           age         (0.0044)           age         (0.0063)           union         0.1705***           married         0.0728***           married         (0.0049)           parent         (0.0048)           parttime         -0.2225***           (0.0048)         -0.0424***           (0.0061)         -0.0424***           (0.0061)         -0.0424***           (0.0061)         -0.0425***           (0.0061)         -0.0425***           (0.0061)         -0.0425***           (0.0077)         constant           2.3675***         (0.0007)           constant         2.3675***           (0.0078)         -9.042***           (0.0077)         constant           2.3675***         (0.0077)           constant         2.3675***           (0.0077)         -9.0225***           occupation dummies         yes           sector dummies		standard error		
(0.0044)           age         (0.0002)           union         (0.0002)           married         (0.002)           married         (0.0049)           parent         (0.0048)           parttime         (0.0048)           parttime         (0.00414)           migrant         (0.00414)           migrant         (0.00414)           educyears         (0.0061)           educyears         (0.0061)           educyears         (0.0061)           coccupation dummies         yes           regional dummies         yes           race dummies         yes           sector dummies         yes           gender         -0.0023***           (0.0001)         (0.0001)           married         0.1064***           (0.0001)         (0.0001)           married         -0.0023***           (0.0005)         (0.0061)           retired         -2.6711***           (0.0005)         (0.0061)           school         0.3509***           (0.0061)         0.3509***           (0.0061)         0.3509***           (0.0061)         0.5050	gender	-0.1608***		
age         0.0068***           (0.0002)         0.1705***           (0.0062)         0.0728***           (0.0042)         0.0728***           (0.0049)         0.0728***           (0.0048)         0.0788***           (0.0048)         0.0788***           (0.0048)         0.0728***           (0.0041)         -0.2225***           (0.0061)         -0.0424***           migrant         -0.0424***           (0.0061)         -0.0424***           (0.0061)         -0.0427***           (0.0007)         constant           constant         2.3675***           (0.007)         constant           cocupation dummies         yes           sector dummies         yes           regional dummies         yes           gender         -0.0411***           (0.0041)         age           -0.0023***         (0.0041)           age         -0.0411***           (0.0041)         -2.6711***           (0.0041)         -2.6711***           (0.005)         -2.6711***           migrant         -0.0222***           (0.0061)         0.3509***           (0.0065)	5	(0.0044)		
(0.0002)           union         (0.1705***           married         (0.0062)           married         (0.0049)           parent         (0.0048)           parttime         -0.2225***           (0.0061)         (0.0061)           educyears         (0.0067)           constant         (0.0077)           constant         (0.2225)           occupation dummies         yes           regional dummies         yes           sector dummies         yes           regional dummies         yes           sector dummies         yes           sector dummies         yes           gender         -0.0411***           (0.0004)         -0.0023***           (0.0004)         -0.0023***           (0.0004)         -0.0023***           (0.0004)         -0.0023***           (0.0048)         -0.0023***           (0.0048)         -0.0023***           (0.005)         -0.0022***           (0.0061)         -0.0022***           (0.0061)         -0.0022***           (0.0061)         -0.0022***           (0.0061)         -0.0022***           (0.0065)         -0	age	0.0068***		
union         0.1705***           married         (0.0062)           married         0.0728***           (0.0049)           parent         (0.0048)           parttime         -0.2225***           (0.0144)           migrant         -0.0424***           (0.0061)         0.0457***           (0.007)         constant           educyears         (0.007)           constant         2.3675***           (0.0007)         constant           sector dummies         yes           regional dummies         yes           sector dummies         yes           sector dummies         yes           gender         -0.0411****           (0.0001)         married           married         0.0481***           (0.0001)         married           migrant         -0.022***           (0.0013)         0.3509***           (0.0061)         0.3509***           (0.0061)         0.3509***           (0.0067)         (0.0061)           school         0.3509***           (0.0077)         (0.0061)           school         0.3509***           (0.00767)<		(0.0002)		
Interview       (0.0062)         married       (0.0049)         parent       (0.0048)         parent       (0.0048)         parttime       -0.2225***         (0.0061)       (0.0061)         educyears       (0.0077)         constant       (0.0077)         constant       (0.0077)         constant       (0.0077)         constant       (0.0077)         constant       (0.0077)         constant       (0.0007)         constant       (0.0077)         constant       (0.0077)         constant       (0.0077)         constant       (0.0007)         gender       (0.0041)         age       -0.0023***         (0.0001)       (0.0041)         age       -0.0023***         (0.0001)       (0.0043)         parent       (0.0043)         parent       (0.0043)         migrant       -0.0222****         (0.0061)       (0.0061)         school       (0.0077)         constant       -1.0268***         (0.0065)       (0.0065)         observations       638,062         censored obse	union	0 1705***		
married $0.0728^{***}$ married $0.0728^{***}$ married $0.0788^{***}$ married $0.0788^{***}$ migrant $0.0488$ migrant $-0.2225^{***}$ migrant $-0.0424^{***}$ migrant $0.0457^{***}$ migrant $0.0457^{***}$ migrant $0.0457^{***}$ migrant $0.0457^{***}$ migrant $0.0457^{***}$ migrant $0.0457^{***}$ migrant $0.0007$ constant $2.3675^{***}$ married         yes           sector dummies         yes           sector dummies         yes           selection component         (0.0041)           gender $-0.0023^{***}$ married $0.0063^{***}$ migrant $0.0087^{***}$ migrant $-0.0222^{***}$ migrant $-0.0222^{***}$ migrant $0.0063^{***}$ migrant $0.00063^{***}$ migrant $0.0026^{****}$		(0,0062)		
Image: Second	married	0.0728***		
parent $0.0788^{***}$ parttime $0.0788^{***}$ (0.0048) $-0.2225^{***}$ migrant $0.0457^{***}$ (0.0061) $0.0457^{***}$ (0.0007) $0.0457^{***}$ (0.0007) $0.0457^{***}$ (0.0007) $0.0457^{***}$ (0.0007) $0.0457^{***}$ (0.0007) $0.0457^{***}$ (0.0007) $0.0457^{***}$ (0.0007) $0.0457^{***}$ (0.0007) $0.0457^{***}$ (0.0007) $0.0457^{***}$ (0.0025) $9^{es}$ sector dummies $yes$ sector dummies $yes$ race dummies $yes$ sector domponent $9^{es}$ gender $-0.023^{***}$ (0.0041) $0.0023^{***}$ (0.0041) $0.0003^{***}$ parent $0.0987^{***}$ (0.0041) $0.0023^{***}$ (0.005) $0.0587^{***}$ retired $-2.6711^{***}$ (0.0041) $-0.0222^{***}$ (0.005) $0.3509^{***}$		(0.0049)		
parttime       (0.0048)         migrant       -0.2225***         (0.0043)       (0.0043)         migrant       -0.0424***         (0.0061)       (0.0061)         educyears       0.0457***         (0.0007)       (0.0007)         constant       2.3675***         (0.2225)       (0.0007)         occupation dummies       yes         sector dummies       yes         regional dummies       yes         sector dummies       yes         sector dummies       yes         gender       -0.0411***         (0.0001)       (0.001)         married       0.1064***         (0.0001)       (0.001)         married       0.0987***         (0.0005)       (0.005)         retired       -2.6711***         (0.0061)       0.3509***         (0.0061)       0.3509***         (0.0061)       0.3509***         (0.0077)       (0.0065)         observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739,43         Probability > chi2	narent	0.0788***		
parttime       -0.2225***         migrant       -0.0424***         (0.0061)         educyears       0.0457***         (0.0007)       (0.0007)         constant       2.3675***         (0.2225)       (0.2225)         occupation dummies       yes         sector dummies       yes         regional dummies       yes         race dummies       yes         gender       -0.0411***         (0.0041)       (0.0041)         age       -0.0411***         (0.001)       married         married       (0.0041)         age       -0.04023***         (0.0041)       (0.0048)         parent       (0.0048)         parent       0.0987***         (0.005)       (0.1088)         migrant       -0.0222***         (0.0061)       0.3509***         (0.0062)       0.3509***         (0.0063)       (0.0065)         observations       638,062         censored observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43	parent	(0.0048)		
partnine       -0.2223         (0.0144)         migrant       -0.0424***         (0.0061)         educyears       0.0457***         (0.0007)         constant       2.3675***         (0.2225)         occupation dummies       yes         regional dummies       yes         regional dummies       yes         race dummies       yes         sector dummies       yes         gender       -0.0411***         (0.0001)       -0.0023***         (0.001)       -0.0023***         (0.0048)       -0.0023***         (0.0048)       -0.0023***         (0.005)       (0.005)         retired       -2.6711***         (0.0048)       -0.0222***         (0.0061)       0.3509***         (0.0061)       0.3509***         (0.0062)       0.3509***         (0.0063)       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         (0.0013)       0.0126	narttime	_0 2225***		
migrant         -0.0424***           (0.0061)         -0.0424***           (0.0061)         -0.0424***           (0.0007)         -0.0457***           (0.0007)         -0.0457***           (0.0007)         -0.0457***           (0.0007)         -0.0457***           (0.2225)         occupation dummies         yes           sector dummies         yes           regional dummies         yes           sector component         -yes           gender         -0.0411***           (0.0041)         -0.0023***           (0.0041)         -0.0023***           (0.0041)         -0.0023***           (0.0043)         -0.0023***           (0.0043)         -0.0023***           (0.0043)         -0.0023***           (0.0043)         -0.0222***           (0.0048)         -0.0222***           (0.005)         -1.0268***           (0.0061)         0.3509***           (0.0065)         -1.0268***           (0.0065)         -1.0268***           (0.0065)         -1.0268***           (0.0065)         -57.110           observations         638,062           censored obs <t< td=""><td>partime</td><td>(0.0144)</td></t<>	partime	(0.0144)		
Initial $-0.0424$ (0.0061)educyears $0.0457^{***}$ (0.0007)constant $2.3675^{***}$ (0.225)occupation dummiesyessector dummiesyesregional dummiesyessector dummiesyessector dummiesyesgender $-0.0411^{***}$ (0.0001) $0.00411^{***}$ age $-0.0411^{***}$ (0.0001) $0.1064^{***}$ (0.0001) $0.1064^{***}$ (0.0001) $0.0087^{***}$ (0.005) $(0.005)$ retired $-2.6711^{***}$ (0.005) $(0.0061)$ school $0.3509^{***}$ (0.0061) $0.3509^{***}$ (0.0065) $0.3509^{***}$ (0.0065) $0.3509^{***}$ (0.0065) $0.3509^{***}$ (0.0065) $0.3509^{***}$ (0.0065) $0.3509^{***}$ (0.0065) $0.3509^{***}$ (0.0065) $0.0065$ observations $557,110$ uncensored obs $80,952$ Wald, chi square (62) $42739.43$ Probability > chi2 $0.0000$ rho $0.0126$ (0.0013) $0.0067$ information $0.0067$ (0.0013) $0.0067$ (0.0013) $0.0067$	migrant	(0.0144)		
(0.0457***           (0.0457***           (0.0007)           constant         2.3675***           (0.2225)           occupation dummies         yes           sector dummies         yes           regional dummies         yes           race dummies         yes           gender         -0.0411***           (0.0001)         (0.0041)           age         -0.0023***           (0.0001)         (0.0041)           married         0.1064***           (0.0001)         (0.0048)           parent         0.0987***           (0.005)         (0.005)           retired         -2.6711***           (0.0061)         (0.0061)           school         0.3509***           (0.0061)         (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739,43           Probability > chi2         0.0000           nb         0.5302           (0.0013)         1           ambda         0.00067	Inigrant	-0.0424		
0.0437**           (0.0007)           constant         (0.0007)           constant         (0.2225)           occupation dummies         yes           sector dummies         yes           regional dummies         yes           sector dummies         yes           selection component         (0.0041)           gender         -0.0411***           (0.0001)         (0.0001)           married         (0.0001)           married         (0.0048)           parent         (0.0048)           parent         (0.005)           retired         -2.6711***           (0.0061)         (0.0061)           school         0.3509***           (0.0065)         (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739,43           Probability > chi2         0.0000           nho         0.5302           (0.0013)         1           ambda         0.0067           (0.0258)         0.0067	a du cua a ra			
(0.007)           constant         2.3675***           (0.2225)         0           occupation dummies         yes           sector dummies         yes           race dummies         yes           Selection component         (0.0041)           gender         -0.0411***           (0.0001)         (0.0001)           married         0.1064***           (0.0001)         (0.0001)           married         0.0987***           (0.005)         (0.005)           retired         -2.6711***           (0.0061)         (0.0061)           migrant         -0.0222***           (0.0061)         0.309***           (0.0065)         (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           (0.0013)         (0.0067)           sigma         0.5302           (0.0067)         (0.0258)	educyears	0.0457		
Constant       (0.2225)         occupation dummies       yes         sector dummies       yes         regional dummies       yes         race dummies       yes         Selection component       (0.0041)         gender       -0.0023***         (0.0001)       (0.0041)         age       -0.0023***         (0.0001)       (0.0048)         parent       0.0087***         (0.005)       (0.005)         retired       -2.6711***         (0.005)       (0.005)         retired       -0.0222***         (0.0061)       (0.0061)         school       0.3509***         (0.0065)       (0.0767)         constant       -1.0268***         (0.0065)       (0.0065)         observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         (0.0013)       (0.0067)         (0.0013)       0.0067				
(0.2225)occupation dummiesyessector dummiesyesregional dummiesyesrace dummiesyesSelection component(0.0041)gender-0.0411*** $(0.0041)$ -0.0023*** $(0.0001)$ (0.0001)married0.1064*** $(0.0048)$ 0.0987*** $(0.005)$ -2.6711*** $(0.005)$ -2.6711*** $(0.0061)$ 0.3509*** $(0.0061)$ 0.3509*** $(0.0061)$ 0.3509*** $(0.0065)$ 0.0065)observations638,062censored observations557,110uncensored obs80,952Wald, chi square (62)42739.43Probability > chi20.0000rho0.0126 $(0.0013)$ 0.0067sigma0.5302 $(0.0013)$ 0.0067Note: *** significant at 99%	constant	2.36/5***		
occupation dummes         yes           sector dummies         yes           regional dummies         yes           scace dummies         yes           Selection component         -0.0411***           gender         -0.0023***           (0.0001)         (0.0001)           married         0.1064**           (0.0001)         (0.0004)           married         0.0987***           (0.005)         (0.005)           retired         -2.6711***           (0.1108)         .00987***           (0.005)         (0.1108)           migrant         -0.0222***           (0.0061)         .3509***           (0.0061)         .3509***           (0.0065)         0.059           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           (0.0043)         .5302           (0.0043)         .5302           (0.0043)         .5302           (0.00258)         .00067		(0.2225)		
sector dummies         yes           regional dummies         yes           race dummies         yes           Selection component         (0.0041)           gender         -0.0023***           (0.0001)         (0.0001)           married         0.1064***           (0.0001)         (0.0048)           parent         0.0987***           (0.005)         (0.005)           retired         -2.6711***           (0.108)         (0.0061)           migrant         -0.0222***           (0.0061)         (0.0061)           school         0.3509***           (0.0061)         (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           (0.00485)         sigma           0.5302         (0.0013)           lambda         0.0067           (0.0258)         0.0067	occupation dummies	yes		
regional dummies         yes           race dummies         yes           Selection component         -0.0411***           gender         -0.0023***           (0.0001)         (0.0001)           married         0.1064***           (0.0041)         (0.0001)           married         0.1064***           (0.0048)         (0.0048)           parent         0.0987***           (0.005)         (0.005)           retired         -2.6711***           (0.1108)         (0.0061)           migrant         -0.0222***           (0.0061)         (0.0061)           school         0.3509***           (0.0077)         (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.5302           sigma         0.5302           sigma         0.5302           Note: *** significant at 99%         0.0067	sector dummies	yes		
race dummies         yes           Selection component         -0.0411****           gender         -0.0411****           age         -0.0023***           (0.0001)         (0.0001)           married         0.1064***           (0.0048)         (0.0048)           parent         0.0987***           (0.005)         (0.005)           retired         -2.6711***           (0.108)         (0.108)           migrant         -0.0222***           (0.0061)         (0.0061)           school         0.3509***           (0.0065)         (0.0067)           constant         -1.0268***           (0.0065)         (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           (0.0013)         0.0302           sigma         0.5302           ilambda         0.0067           (0.0258)         0.0067	regional dummies	yes		
Selection component         -0.0411***           gender         -0.0411***           (0.0041)         -0.0023***           (0.0001)         -0.0023***           married         0.1064***           (0.0001)         0.1064***           parent         0.0987***           (0.005)         (0.005)           retired         -2.6711***           (0.0061)         -2.6701***           (0.0061)         -0.0222***           (0.0061)         0.3509***           (0.0061)         0.3509***           (0.0063)         0.3509***           (0.0065)         0.00065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           (0.0485)         (0.0013)           sigma         0.5302           (0.0067         (0.0067           (0.0067         (0.0258)	race dummies	yes		
gender       -0.0411***         age       (0.0041)         age       -0.0023***         (0.0001)       0.1064***         married       0.1064***         (0.0041)       0.1064***         (0.0048)       0.0987***         (0.005)       (0.005)         retired       -2.6711***         (0.0061)       0.3509***         (0.0061)       0.3509***         (0.0061)       0.3509***         (0.0061)       0.3509***         (0.0061)       0.3509***         (0.0065)       0.050         observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         (0.0485)       (0.0485)         sigma       0.5302         (0.0013)       0.0067         (0.0067       (0.0258)	Selection component			
age         (0.0041)           age         -0.0023***           (0.0001)         (0.0001)           married         0.1064***           (0.0048)         (0.0048)           parent         (0.0048)           parent         (0.0048)           retired         -2.6711***           (0.1108)         -2.6711***           (0.0061)         -0.0222***           (0.0061)         0.3509***           (0.0061)         0.3509***           (0.0061)         0.3509***           (0.00767)         (0.0767)           constant         -1.0268***           (0.0065)         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           (0.0485)         5302           sigma         0.5302           lambda         0.0067           (0.0258)         0.0067	gender	-0.0411***		
age       -0.0023***         married       (0.0001)         married       0.1064***         (0.0048)         parent       (0.0987***         (0.005)         retired       -2.6711***         (0.1108)         migrant       -0.0222***         (0.0061)         school       0.3509***         (0.0061)         school       0.3509***         (0.0767)         constant       -1.0268***         (0.0065)         observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739,43         Probability > chi2       0.0000         rho       0.0126         (0.0485)       5302         sigma       0.5302         lambda       0.0067         (0.0258)       0.0067		(0.0041)		
(0.0001)           married         (0.004***           (0.0048)           parent         (0.0087***           (0.005)           retired         -2.6711***           (0.1108)           migrant         -0.0222***           (0.0061)           school         0.3509***           (0.0767)           constant         -1.0268***           (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.5302           sigma         0.5302           lambda         0.0067           (0.0258)         0.0067	age	-0.0023***		
married       0.1064***         parent       (0.0048)         parent       0.0987***         (0.005)       (0.005)         retired       -2.6711***         (0.1108)       (0.1108)         migrant       -0.0222***         (0.0061)       0.3509***         school       0.3509***         (0.0767)       (0.0767)         constant       -1.0268***         (0.0065)       (0.0065)         observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         (0.0485)       (0.0485)         sigma       0.5302         lambda       0.0067         (0.0258)       0.0258		(0.0001)		
(0.0048)           parent         0.0987***           (0.005)           retired         -2.6711***           (0.1108)           migrant         -0.0222***           (0.0061)           school         0.3509***           (0.0767)           constant         -1.0268***           (0.0065)         0           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           sigma         0.5302           ilambda         0.0067           (0.0258)         0.0067	married	0.1064***		
parent         0.0987***           (0.005)           retired         -2.6711***           (0.1108)           migrant         -0.0222***           (0.0061)           school         0.3509***           (0.0767)           constant         -1.0268***           (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           (0.0485)         sigma           0.5302         (0.0013)           lambda         0.0067           (0.0258)         Note: *** significant at 99%		(0.0048)		
(0.005)         retired       -2.6711***         (0.1108)         migrant       -0.0222***         (0.0061)         school       0.3509***         (0.0767)         constant       -1.0268***         (0.0065)         observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         (0.0485)       (0.0013)         lambda       0.0067         (0.0258)       Note: *** significant at 99%	parent	0.0987***		
retired -2.6711*** (0.1108) migrant 0.0022*** (0.0061) school 0.3509*** (0.0767) constant 1.0268*** (0.0065) observations 638,062 censored observations 557,110 uncensored obs 80,952 Wald, chi square (62) 42739.43 Probability > chi2 0.0000 rho 0.0126 (0.0485) sigma 0.5302 (0.0013) lambda 0.0067 (0.0258)		(0.005)		
migrant       (0.1108)         migrant       -0.0222***         (0.0061)       0.3509***         (0.0767)       (0.0767)         constant       -1.0268***         (0.0065)       (0.0065)         observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         (0.0485)       (0.0485)         sigma       0.5302         lambda       0.0067         (0.0258)       Note: *** significant at 99%	retired	-2.6711***		
migrant       -0.0222***         school       (0.0061)         school       0.3509***         (0.0767)       (0.0767)         constant       (0.0065)         observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         sigma       0.5302         lambda       0.0067         wote: *** significant at 99%       558		(0.1108)		
(0.0061)           school         0.3509***           (0.0767)           constant         -1.0268***           (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           (0.0485)         10           sigma         0.5302           lambda         0.0067           Note: *** significant at 99%	migrant	-0.0222***		
school       0.3509***         constant       (0.0767)         constant       -1.0268***         observations       (0.0065)         observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         (0.0485)       (0.0485)         sigma       0.5302         lambda       0.0067         (0.0258)       0.0258)		(0.0061)		
(0.0767)           constant         -1.0268***           (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           (0.0485)         (0.0485)           sigma         0.5302           lambda         0.0067           Note: *** significant at 99%	school	0.3509***		
constant       -1.0268***         0.00065)       (0.0065)         observations       638,062         censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         sigma       0.5302         lambda       0.0067         Note: *** significant at 99%		(0.0767)		
observations         (0.0065)           observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           intersection         (0.0485)           sigma         0.5302           lambda         0.0067           Note: *** significant at 99%         0.0000	constant	-1.0268***		
observations         638,062           censored observations         557,110           uncensored obs         80,952           Wald, chi square (62)         42739.43           Probability > chi2         0.0000           rho         0.0126           (0.0485)         0.5302           sigma         0.5302           lambda         0.0067           Note: *** significant at 99%         0.0258)		(0.0065)		
censored observations       557,110         uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         sigma       0.5302         lambda       0.0067         (0.0258)	observations	638,062		
uncensored obs       80,952         Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         (0.0485)       (0.0485)         sigma       0.5302         lambda       0.0067         (0.0258)       0.0258)	censored observations	557,110		
Wald, chi square (62)       42739.43         Probability > chi2       0.0000         rho       0.0126         (0.0485)       (0.0485)         sigma       0.5302         (0.0013)       0.0067         (0.0258)       0.0258)	uncensored obs	80,952		
Probability > chi2       0.0000         rho       0.0126         (0.0485)       (0.0485)         sigma       0.5302         (0.0013)       (0.0067         (0.0258)       (0.0258)	Wald, chi square (62)	42739.43		
rho 0.0126 (0.0485) sigma 0.5302 (0.0013) lambda 0.0067 (0.0258)	Probability > chi2	0.0000		
(0.0485) sigma 0.5302 (0.0013) lambda 0.0067 (0.0258)	rho	0.0126		
sigma 0.5302 (0.0013) lambda 0.0067 (0.0258)		(0.0485)		
(0.0013)         lambda       0.0067         (0.0258)	sigma	0.5302		
lambda 0.0067 (0.0258)		(0.0013)		
Note: *** significant at 99%	lambda	0.0067		
Note: *** significant at 99%		(0.0258)		
	Note: *** significant at 99%	(0.0200)		

For the selection component the results show that women are statistically significantly (at 99% confidence) less likely to be employed than men. Unsurprisingly older and retired workers are statistically significantly less likely to have remained in some form of employment. Parents are statistically significantly (at 99%) more likely to be employed. Individuals still in education (note: our sample includes only individuals aged 15 or over) are statistically significantly more likely to be in some form of employment. Presumably, this reflects the need for individuals to work their way through college. Finally, migrants to the US were also statistically significantly less likely to be employed.

For the remainder of the Heckman model there is a statistically significant (at 99% confidence) estimated gender wage gap of 16%. Of the control variables age, union membership, being married, parenthood and education years were found to have positive and statistically significant effects (at 99%) on hourly wages. Part-time working and being a migrant were found to have statistically significant (at 99%) negative effects on hourly earnings.

The regression analysis is, we believe, of use in its own right and provides evidence to the existence of a gender pay gap which persists despite the inclusion of a considerable number of control variables. The limitations of the Heckman procedure in studies of gender pay gaps are well known and have been discussed in the literature. It does, however, give some important insight into the variables that might be needed to identify an appropriate control group in a matching process. That is, it is clear that a proper comparison between males and females would require matching on a large number of variables. These include industry, occupation, education, age, union membership, ethnicity and region.

#### 6. Treatment Effects – Full Sample

The first step in the matching process is to create a propensity score by which a control group is selected, to allow comparison between female and male workers with key common characteristics. This was done, as in most such studies, using a probit model to create the propensity score. The (0,1) dependent variable was gender (1 if female) and the independent variables included:

- age
- education
- hours worked
- part-time
- union membership
- sector
- occupational category
- ethnicity
- region
- married
- parent
- migrant

Note that the data for hourly wages were calculated by dividing usual weekly earnings by usual weekly hours. A large proportion of the sample were not hourly paid and reported only weekly earnings, requiring the calculation of an hourly equivalent. This implies that the "hourly wage" for weekly paid workers varies with respect to hours as well as with respect to weekly wages. For this reason hours worked was added as a control variable.

Estimation was conducted in Stata14 and the results are reported in Table 4. Matching was by means of kernel density and bootstrapped standard errors are reported for ATT. Results are reported for two different models – one that includes sector and occupation dummies in the propensity score and one that does not. Both models show that, even when matched with a carefully selected control group, evidence of a statistically significant (at 99%) gender pay gap persists. However, the two versions produce different estimate values for the gender pay gap. Without industry or occupation variables to capture the effects of gender segregation at work the results suggest a gender pay gap of about 17%. When industry and occupation are included this falls to about 12%. Note, however, the exclusion of these dummy variables switches industry and occupation from observables to unobservables, and simply transfers bias to unobservables.

Standard checks on the bias on observables (how effective the match between the group of interest and the control group) are presented in Appendix 3. These checks show that the model without industry and occupation variables produces an outcome which, whilst not perfect, is much better than that for the model when these are included. That is, excluding industry and occupation produces a better outcome with respect to selection on observables. This needs careful interpretation. It does not suggest that excluding industry and occupation dummies produces more reliable estimates because the relevant effects are simply transferred to bias on unobservables. An alternative, more plausible conclusion is that gender segregation is so extensive that industry and occupation dummies are not sufficient to secure a wholly satisfactory match in the full sample between female workers and a control group of male workers.

Table 4: Propensity Score Matching results (full sample), outcome variable = log of hourly wages							
Kernel density	matching, tre	atment = fema	ale, bootstrappe	ed standard er	rors		
	Treated	Controls	Difference	S.E.	T-stat	Observ	vations
						Untreated	Treated
						(male)	(female)
FULL SAMPLE	:						
(a) with indust	try and occupa	tion dummies					
Unmatched	2.7523	2.9303	-0.1779	0.0045	-39.37	40,752	40,011
ATT	2.7523	2.8698	-0.1175	0.0060	-19.42		
(b) without in	dustry and occ	upation dumm	ies				
Unmatched	2.7523	2.9303	-0.1779	0.0045	-39.37	40,752	40,011
ATT	2.7523	2.9185	-0.1662	0.0048	-34.76		
SAMPLE DIVID	ED BY PARENT	HOOD					
(a) parents							
Unmatched	2.7827	3.0671	-0.2844	0.0075	-37.88	13,795	14,020
ATT	2.7827	2.9620	-0.1792	0.0132	-13.62		
(b) non-parent	ts						
Unmatched	2.7359	2.8603	-0.1244	0.0056	-22.19	26,954	25,989
ATT	2.7359	2.8339	-0.0980	0.0072	-13.67		
SAMPLE DIVID	ED BY MARITA	L STATUS					
(a) married							
Unmatched	2.8653	3.0881	-0.2228	0.0060	-37.21	23,485	20,729
ATT	2.8653	3.0395	-0.1742	0.0091	-19.22		
(b) unmarried							
Unmatched	2.6309	2.7156	-0.0847	0.0065	-13.10	17,265	19,282
ATT	2.6309	2.7343	-0.1034	0.0089	-11.59		
SAMPLE DIVID	ED BY AGE GR	OUP					
(a) Young (24 d	or under)						
Unmatched	2.1934	2.2970	-0.1036	0.0096	-10.80	4,096	4,235
ATT	2.1934	2.2448	-0.0514	0.0116	-4.42		
(b) Older (25 o	or over)						
Unmatched	2.8186	3.0011	-0.1825	0.0047	-39.22	36,654	35,774
ATT	2.8186	2.9564	-0.1379	0.0065	-21.34		
SAMPLE DIVID	ED BY PART-TI	ME AND FULL-	TIME				
(a) Part-time							
Unmatched	2.4470	2.4063	0.0407	0.0103	3.97	5,461	10,962
ATT	2.4470	2.4759	-0.0289	0.0141	2.04		
(b) Full-time							
Unmatched	2.8622	3.0084	-0.1462	0.0048	-30.37	35,451	29,403
ATT	2.8622	3.0299	-0.1677	0.0066	-25.47		

Table 4 also reports matching results for a number of sub-samples, created to reflect effects found to have an influence on the gender wage gap in the existing literature. The estimate of the gender wage gap for parents was about 18% compared to about 10% for non-parents, confirming the importance of having children in understanding the gap. For married workers there are broadly similar estimates – a gender wage gap of about 17% for married workers and about 10% for unmarried. The estimate of the gender wage gap for young (aged 24 or under) workers is very much lower at about 5% but still statistically significant at 99% confidence. By comparison the estimated gender wage gap for older workers was

approximately 18%. Finally, the lowest estimated gender wage gap was for part-time workers at roughly 3%, statistically significant at 95% but not 99% confidence.

Table 5 reports inverse probability weighting regression adjustment (IPWRA) analysis using female as a treatment variables and each of a number of other treatment variables (separately). The other treatment variables were:

- married
- young (24 or under)
- parent, and
- part-time.

The results of the IPWRA analysis consistently suggest a statistically significant gender wage gap. Depending on the second treatment effect estimates of the gap vary from about 13% (when *married* or *parent* are the second treatment) to just under 20% (when *part-time* is the second treatment). With respect to the second treatment variables the results suggest that married workers (male and female) are typically paid about 11% more than unmarried ones, that young workers are typically paid at least 30% less than older ones and that parents (of both genders) are paid about 10% more than non-parents.

Some of the other results of the IPWRA analysis imply estimates of the gender wage gap which are worth noting. These are:

- an estimated statistically significant gender wage gap for married women of around 24-28% (compared to married males)
- no statistically significant gender wage gap for part-time workers
- a statistically significant estimated gender wage gap of about 25% for female compared to male parents.
- a statistically significant estimated wage difference between part-time and full-time workers of about 33-35%
- Since part-time workers are predominantly female there is a substantial overlap between the female and part-time categories. The combined effects of being both female and a part-time worker is in the order of a 35-42% reduction in mean hourly wages. That is, part-time working is an important mechanism by which women are paid less than men

Table 5 : IPWRA Results for the Full Sample						
Outcome variable = log of hourly w	/age					
		Treatme	nt Group			
Control Group	None	Female	Married	Both		
None	_	-0.125144***	0.115671***	-0.0633846***		
None	-	(0.006543)	(0.0107098)	(0.0138961)		
Female	0.1298907***	_	0.283408***	0.0872596***		
Feinale	(0.0057258)	_	(0.0073488)	(0.0067485)		
Married	-0.109139***	-0.2408149***	_			
	(0.0103845)	(0.0099226)	_			
Both	0.0419071***	-0.0876773***	0.2152207***	_		
	(0.0093642)	(0.0070426)	(0.005651)			
		Treatme	nt Group			
Control Group	None	Female	Young	Both		
None	_	-0.1582487***	-0.3050489***	-0.3828652***		
None	_	(0.0048917)	(0.011865)	(0.0133226)		
Female	0.1792499***	-	-0.2470155***	-0.3243379***		
	(0.0042308)		(0.0107038)	(0.0109828)		
Voung	0.4713551***	0.3182097***	_	-0.0903919***		
	(0.0245741)	(0.0226418)		(0.0100671)		
Both	0.5906125***	0.4086961***	0.0995921***	_		
	(0.0237252)	(0.0210996)	(0.0101585)			
		Treatme	nt Group			
Control Group	None	Female	Parent	Both		
None	_	-0.1311908***	0.1028185***	-0.0823592***		
		(0.0052239)	(0.0074061)	(0.0067756)		
Female	0.1457914***	-	0.2798527***	0.0583344***		
	(0.0047408)		(0.0079426)	(0.0060906)		
Parent	-0.1128119***	-0.2552655***	-	-0.2093114***		
	(0.0120452)	(0.019492)		(0.0106078)		
Both	0.0939689***	-0.0467048***	0.2235659***	-		
	(0.0069651)	(0.0076259)	(0.0075187)			
		Treatme	nt Group			
Control Group	None	Female	Part-time	Both		
None	-	-0.1980886***	-0.3359224***	-0.4119995***		
		(0.0049261)	(0.056984)	(0.0567705)		
Female	0.1981587***	-	-0.2665149***	-0.3804477***		
	(0.0044029)		(0.0357973)	(0.029303)		
Part-time	0.3513055***	0.0966296	-	-0.060694***		
	(0.0575298)	(0.1449512)		(0.0120776)		
Both	0.3485879***	0.1504993**	0.0473681***	_		
Both	(0.0837318)	(0.0836521)	(0.0091105)			

As with our regression analysis we believe that our matching analysis using the whole sample provides valuable insights but does not yet provide our ultimate conclusion. If the existence

of a gender wage gap is a falsifiable hypothesis then this study has not yet made sufficient effort to falsify it. The matching model without industry or occupation variables offers at least a reasonable profile with respect to selection on observables. But this is only by transferring these variables to the "unobservable" category, with the resultant risk of bias on unobservables. That is, the degree of gender segregation by both industry and occupation in our sample is so high that it is doubtful that it is possible to select a control group of men which adequately match the women in the sample in terms of both industry and occupation. Gender segregation makes it very difficult to properly compare like with like - to be certain that women do indeed receive less pay for the same work.

Since we believe our results on matching with the full sample to be useful but not conclusive we adopted one further approach. Within the sample (see Appendix 1) there are only a few detailed industries which employ men and women in more or less equal proportions and for which there were in excess of 1000 observations. We selected three of these – banking, grocery stores and restaurants – for which we repeated the matching analysis at the industry level. Since we have concerns about using the full sample in the presence of gender segregation the intention was to improve the accuracy of matching by using (separately) three industries where we know men and women to be employed in significant numbers. The following section reports the results. Section 8 takes a similar approach but using a number of occupations selected for employing significant numbers of both sexes – see Appendix 2.

#### 7. Propensity Score Matching at the Industry Level

The results of the matching analysis (for each of the three selected industries) using gender as a single treatment are reported in Table 6.

Table 6: Propensity Score Matching Results for Selected Industries, outcome variable = log of hourly wages								
Kernel density matching, treatment = female, bootstrapped standard errors								
	Treated Controls Difference S.E. T-stat							
						Untreated	Treated	
						(male)	(female)	
Banking								
Unmatched	2.8973	3.3489	-0.4516	0.0321	-14.07	456	849	
ATT	2.8973	3.0702	-0.1729	0.0537	-3.22			
Grocery Stores								
Unmatched	2.3703	2.4979	-0.1276	0.0233	5.48	823	893	
ATT	2.3703	2.4834	-0.1131	0.0291	3.89			
Restaurants								
Unmatched	2.0932	2.2974	-0.2043	0.0157	-12.98	2,213	2,581	
ATT	2.0932	2.2882	-0.1950	0.0181	-10.79			

The variables used to create the propensity score were the same as for the full sample, except that sector dummy variables were no longer used. That is, the propensity score was created using *age*, *education years*, *hours worked*, *part-time*, *union membership*, *occupational category*, *ethnicity*, *region*, *married*, *parent* and *migrant*. Those variables not jointly significant in a trial run of the (probit) treatment model were eliminated from the version used to generate the propensity score.

The results suggest a statistically significant gender pay gap (at 99% confidence) for all three industries. The lowest estimate is for grocery stores – an estimated gender pay gap of about 11%. For banking the estimated gender pay gap was approximately 17% and for restaurants about 19%. Checks on the matching (diagrams only) are reported in Appendix 3. These suggest that, at industry level, matching of the control group (male) with the female group is much closer than for the full sample, although still not perfect in every respect. Using an industry which employs both men and women in similar proportions does improve the accuracy of matching.

The gender wage gap for both the banking and restaurants sectors are of a similar magnitude to estimates for the full sample. For these two the matching analysis at industry level does provide more statistically sound estimates and serves to re-enforce earlier conclusions. The reasons for the lower wage gap for grocery stores are not immediately obvious. The preponderance of small and, in particular, family firms might be one reason but the restaurants sector also shares these characteristics.

As with the full sample we also conducted IPWRA analysis for each of the three industries. Table 7 reports the results using gender and *young* (24 or under) as the two treatment variables. The results suggest an estimated gender wage gap of about 23-25% for banking, about 12% for grocery stores and around 21-22% for restaurants. The IPWRA analysis included the same variables as for the propensity score matching except that occupational dummies were excluded for computational reasons. In consequence, differences in the gender wage gap between the two estimators may be partly explained by the effects of the omission of occupational dummies. The results also suggest that young workers are paid less than older ones by an estimate of about 25-29% for banking, 20-37% for grocery stores and about 19% for restaurants.

Table 7: IPWRA Analysis for Selected Industries, treatments = (a) female and (b) young (24 or under)					
Outcome variable: log of hourly w	ages				
		Treatme	nt Group		
Control Group	None	Female	Young	Both	
Banking					
None		-0.2488845***	-0.2458963**	-0.3822232***	
None	-	(0.0366476)	(0.1102328)	(0.0555384)	
Fomala	0.2309572***		-0.234765**	-0.3964884***	
Female	(0.0361972)	-	(0.0928724)	(0.0416393)	
Young (24 or under)	0.2912628***	0.4214551***		-0.0909604	
foung (24 of under)	(0.0854079)	(0.1015625)	-	(0.0755514)	
Poth	0.7827763***	0.4139921***	0.1773528*		
Both	(0.1323177)	(0.0665209)	(0.0956104)	-	
Grocery Stores					
None		-0.1187162***	-0.1999603***	-0.2472074***	
None	-	(0.0243205)	(0.0364294)	(0.0370578)	
Female	0.1155783***		-0.2203828***	-0.2757366***	
	(0.0264012)	-	(0.0592837)	(0.0646771)	
Young (24 or under)	0.3700041***	0.1955258***		-0.0748831*	
foung (24 of under)	(0.0427763)	(0.039766)	-	(0.0389249)	
Deth	0.8775184***	0.5256967***	0.087469		
Both	(0.1896265)	(0.1592932)	(0.0536876)	-	
Restaurants					
Nene		-0.2223971***	-0.1856789***	-0.2750826***	
None	-	(0.0238335)	(0.0531225)	(0.062223)	
Famala	0.2057629***		0.0141359	-0.0472287	
Female	(0.0218401)	-	(0.0293309)	(0.0301994)	
Voung (24 or under)	0.1936046***	-0.0427095		-0.079008***	
roung (24 or under)	(0.0396057)	(0.0334089)	-	(0.0198733)	
Poth	0.3720949***	0.1674352***	0.076621**		
BOTU	(0.0323054)	(0.0321687)	(0.0207686)	-	

The results with both gender and part-time working as treatments are presented in Table 8. The results suggest a gender wage gap of between 27% and 30% in banking, 16-31% in grocery stores and about 25% for restaurants. Part-time workers in banking were estimated to receive between 62 and 67% lower hourly earnings in banking, 31-39% lower earnings in grocery stores and 35-38% lower hourly pay in restaurants.

Table 8: IPWRA Analysis for Selected Industries, treatments = (a) female and (b) part-time					
Outcome variable: log of hourly w	ages				
		Treatme	nt Group		
Control Group	None	Female	Part-time	Both	
Banking					
None		-0.30145***	-0.67663***	-0.60625***	
None	-	(0.03546)	(0.09576)	(0.05396)	
Fomalo	0.27193***		-0.40053***	-0.33646***	
Female	(0.03413)	-	(0.07028)	(0.03663)	
Dart time	0.61589***	0.38520***		0.0543	
Part-time	(0.03874)	(0.02239)	-	(0.04680)	
Poth	0.77547***	0.37721***	-0.09160		
Both	(0.05706)	(0.03890)	(0.06651)	-	
Grocery Stores					
Nene	-	-0.16172***	-0.31359***	-0.36529***	
None		(0.02939)	(0.03791)	(0.03074)	
Fomalo	0.16189***		-0.14438**	-0.20047***	
Female	(0.03061)	-	(0.05451)	(0.04403)	
Dart time	0.39218***	0.23252***		-0.02201	
Part-time	(0.03086)	(0.03129)	-	(0.02503)	
Poth	0.41870***	0.26556***	0.01746		
Both	(0.02674)	(0.02741)	(0.02290)	-	
Restaurants					
Nene		-0.26550***	-0.25299***	-0.37692***	
None	-	(0.02241)	(0.02113)	(0.01936)	
Fomalo	0.25531***		-0.03950*	-0.14468***	
Female	(0.02145)	-	(0.02400)	(0.0218)	
Dart time	0.34500***	0.0955***		-0.09049***	
rait-time	(0.0225)	(0.02490)	-	(0.01866)	
Both	0.44659***	0.20174***	0.08020***		
DUUI	(0.02093)	('0.02311)	(0.01807)	-	

#### 8. Propensity Score Matching at the Occupation Level

This section adopts an essentially similar approach to the industry level analysis but at the level of individual occupations. Like the industry level analysis occupations were not selected at random but specifically because they employ significant numbers of both men and women (see Appendix 2). That is, they are occupations which tend not to be gender segregated.

Table 9 presents the propensity score matching results for five different occupations. The control variables used to estimate the propensity score were essentially the same as for earlier analysis with one exception - dummy variables for sectors were used in place of the dummy variables for occupational categories used in the industry level analysis. This was intended to ensure that the control group shared a similar sectoral composition to the treated group.

Table 9: Propensity Score Matching Results for Selected Occupations, outcome variable = log of hourly wages							
Kernel density matching, treat	tment = female	, bootstrapped	l standard error	s			
	Treated	Controls	Difference	S.E.	T-stat	Observ	/ations
						Untreated	Treated
						(male)	(female)
Customer Representatives							
Unmatched	2.5956	2.6971	-0.1015	0.0292	3.48	403	821
ATT	2.5956	2.7164	-0.1208	0.0396	3.05		
Assemblers							
Unmatched	2.4611	2.6461	-0.1850	0.0357	5.18	358	257
ATT	2.4628	2.5875	-0.1247	0.0394	3.16		
Accountants							
Unmatched	3.1920	3.3776	-0.1856	0.0410	4.52	350	597
ATT	3.1920	3.3456	-0.1536	0.0490	3.13		
Lawyers							
Unmatched	3.5405	3.6506	-0.1102	0.0501	2.20	343	201
ATT	3.5383	3.7013	-0.1630	0.0558	2.92		
Janitors							
Unmatched	2.3765	2.5037	-0.1272	0.0254	5.00	961	414
ATT	2.3731	2.4572	-0.0841	0.0272	3.10		

For all five occupations a statistically significant (at 99% confidence) gender wage gap remains despite matching for a carefully selected control group and despite narrowing the comparison between male and female workers to a single occupation. That is, controlling for gender segregation does not eliminate a gender wage gap. The estimated wage gap for each occupation was:

- Customer representatives 12%
- Assemblers 12%
- Accountants 15%
- Lawyers 16%
- Janitors 8%

These estimates at the level of an individual occupation are lower than the comparable estimate for the gender wage gap for the full sample (16%) when industry and occupation

effects are ignored. But it is also clear that the gender wage gap is not eliminated by separately considering one of the few individual occupations which is not dominated by one gender. It is only possible to speculate the reasons for variation in the gender wage gap by occupation. It is worth noting that the two most highly educated occupations – lawyers and accountants – exhibited the highest wage gaps but the least skilled occupation (janitors) exhibited the lowest wage gap. Such evidence is consistent with Polachek's (1981) view of depreciation of human capital during absences from the work force.

As with earlier sections we extend the matching analysis to use the IPWRA estimator. Table 10 reports IPWRA results for each of the five selected occupations, using *female* and *young* as the two (0,1) treatment variables and the log of hourly earnings as the outcome. The results suggest a gender wage gap of around 12-14% for customer service representatives, between 12 and 16% for assemblers, about 18-20% for accountants, 11-13% for lawyers and between 7 and 10% for janitors. In all cases the gender wage gap is statistically significant at 99%, with one exception which is statistically significant at 95% confidence.

For each occupation Table 10 suggests that hourly earnings for young workers were statistically significantly less than for older ones. For customer service representatives the difference was about 35%, for assemblers about 14%, for accountants 29% and janitors 14%. Within our sample there were no lawyers aged 24 or under so the definition of "young" was changed to 32 or under. Lawyers in this category exhibited earnings approximately 10% less than older colleagues.

Table 10: IPWRA Analysis for Selecte	d Occupations, tr	eatments = (a) fen	nale and (b) young	(24 or under)
Outcome variable: log of hourly wag	ges			
		Treatme	nt Group	
Control Group	None	Female	Young	Both
<b>Customer Service Representatives</b>				
		-0.124793***	-0.3496312***	-0.4176019***
None	-	(0.0503465)	(0.0658485)	(0.1100788)
Formela	0.1443882***		-0.3240012***	-0.3594625***
Female	(0.034854)	-	(0.0597759)	(0.0772233)
Yours (24 on under)	0.4161964***	0.3039913***		-0.0131877
foung (24 or under)	(0.0433557)	(0.0290541)	-	(0.0431123)
Deth	0.6588445***	0.4420365***	0.0068195	
Βοτη	(0.1237194)	(0.0549305)	(0.0413747)	-
Assemblers				
N		-0.1205212***	-0.1412449**	-0.3189945***
None	-	(0.0409546)	(0.0599494)	(0.1014189)
5t.	0.1671849***		-0.0666222	-0.2366206***
Female	(0.0374647)	-	(0.0490757)	(0.0667401)
	0.3674162***	0.1690203***		-0.2054902**
Young (24 or under)	(0.0478571)	(0.042697)	-	(0.0962227)
_	0.2970866***	0.0932166**	0.1450502***	, , , , , , , , , , , , , , , , , , ,
Both	(0.0376251)	(0.0463679)	(0.052546)	-
Accountants	, , , , , , , , , , , , , , , , , , ,		,	
		-0.186109***	-0.2899971***	-0.4911419***
None	-	(0.0494381)	(0.0901414)	(0.1298124)
Female	0.2027532***		-0.2433694***	-0.4434765***
	(0.0379802)	-	(0.0888154)	(0.11202)
	0.28952***	0.103411	()	-0.1223937
Young (24 or under)	(0.0824908)	(0.0743557)	-	(0.1358909)
	0.2643761***	0.2028435***	0.1981847*	()
Both	(0.0391886)	(0.0603698)	(0.107261)	-
Lawvers	,		,	
		-0.1148562*	-0.1034099	-0.2558959**
None	-	(0.0617978)	(0.0765544)	(0.1002805)
	0.1330056**	,	-0.0899415	-0.2172641**
Female	(0.0528731)	-	(0.0730595)	(0.0965388)
	0.1944572***	0.0537724	. , ,	-0.1640895
Young <u>(32 or under)</u>	(0.0709555)	(0.0702609)	-	(0.1012082)
_	0.3041815***	0.2330991**	0.1816597*	, , , , , , , , , , , , , , , , , , ,
Both	(0.1087568)	(0.1000024)	(0.1002733)	-
Janitors				
		-0.0761538***	-0.1434114***	-0.1701779**
None	-	(0.0260189)	(0.0478079)	(0.0794163)
	0.1040407***	,	-0.0455125	-0.0757402
Female	(0.0252121)	-	(0.0512779)	(0.0791689)
	0.2295591***	0.0638495*	- /	-0.004467
Young (24 or under)	(0.0390682)	(0.0371308)	-	(0.0756111)
	0.3911997***	0.3723689***	-0.0134814	, <u> </u>
Both	(0.0782343)	(0.098374)	(0.0738851)	-

Tables 11 examines the treatment effects of *female* and *part-time* using IPWRA analysis for each of the same five occupations. For each of the five occupations there remains a statistically significant gender wage gap despite both the careful matching of control and treatment groups and despite narrowing of the sample to a single occupation in each case. The estimated gender wage gaps by occupation are:

- Customer service representatives about 14% to 15%
- Assemblers between 13% and 14%
- Accountants around 9%-10%
- Lawyers approximately 4%-6%
- Janitors between 13% and 15%

The results presented in Table 11 also show clearly that there is a substantial (and statistically significant at 99% confidence) gap in hourly wages between part-time and full-time worker in the same occupation. For each of the five occupations the gap between full-time and part-time hourly rates was estimated as:

- Customer service representatives about 35% to 40%
- Assemblers between 45% and 55%
- Accountants around 31%-35%
- Lawyers between 8% and 16%
- Janitors between 13% and 15%

From these results it is clear that part-time working has a substantial negative effect on hourly wages rates but this effect also varies considerably by occupation. The much higher prevalence of women in part-time work combined with the existence of a significant gap in hourly earnings between part-time and full-time workers makes an important contribution to the overall gender wage gap. It is also interesting to note that there is significant variation in the gap between full-time and part-time by occupation.

Table 11: IPWRA Analysis for Selected Occupations treatments = (a) female and (b) part-time employment				
Outcome variable: log of hourly w	ages			
		Treatme	nt Group	
Control Group	None	Female	Part-time	Both
Customer service representatives				
None		-0.1487057***	-0.3534196***	-0.3680808***
	-	(0.0396678)	(0.0472608)	(0.0347408)
Female	0.1414865***		-0.2845025***	-0.271185***
	(0.0336538)	-	(0.0420503)	(0.0275038)
Part-time	0.4027189***	0.295491***		0.012795
	(0.0586685)	(0.0545803)	-	(0.0439877)
Both	0.4302522***	0.3046563***	-0.0282729	
	(0.038757)	(0.0274633)	(0.0375144)	-
Assemblers				
None		-0.1401634***	-0.4519693***	-0.5399095***
	-	(0.0329684)	(0.1608717)	(0.133997)
Female	0.1327194***		-0.3444178**	-0.3788045***
	(0.0338971)	_	(0.16124)	(0.1324386)
Part-time	0.5508458***	0.4098758***	-	0.3262315
	(0.1005878)	(0.1111381)		(0.2822952)
Both	0.4616181***	0.3194279***	-0.0340648	_
	(0.0624531)	(0.075842)	(0.1700163)	
Accountants				
None	_	-0.094362**	0.3090078	-0.3023649***
		(0.0380756)	(0.3277291)	(0.0764005)
Female	0.1027392**	-	0.3047127	-0.2105931***
	(0.0417686)		(0.2877341)	(0.0658701)
Part-time	0.3477229**	0.2834063**	-	0.1237674
	(0.1433734)	(0.1096912)		(0.1591743)
Both	0.224411***	0.1711192**	0.4734096*	_
	(0.07523)	(0.0709356)	(0.2557447)	
Lawyers				
None	-	-0.0435249	0.0877164	-0.4759689***
		(0.0475804)	(0.3055808)	(0.1589755)
Female	0.062977	-	0.2463565	-0.3299125**
	(0.0496787)		(0.3169492)	(0.164113)
Part-time	-0.1594749	-0.2245749	-	-0.9445919***
	(0.1942277)	(0.2114903)		(0.3599515)
Both	0.556436***	0.514/488***	0.406542	-
	(0.0774624)	(0.0628055)	(0.3218023)	
Janitors		0 405 464 6888	0.0470000***	0.20020000***
None	-	-0.1354616***	-0.31/6832***	-0.2892986***
<b>5 1</b> .	0 4 405570***	(0.02/28/1)	(0.027802)	(0.0416898)
Female	0.14955/3***	-	-0.1526979***	-0.1455456***
Dent Marce	(0.028/1/4)	0 174077***	(0.0326459)	(0.0442963)
Part-time	0.3262411***	0.1/43//***	-	0.0226654
Deth	(0.02/9084)	(U.U324234)	0.0151070	(0.0444763)
BOLD	0.3213403***	0.141049/***	-0.0151978	-
Noto, sohust standard among and the	(0.0595824)	(0.0408576)	(0.0420962)	
Note: robust standard errors are in	i parentneses			

#### 9. Conclusions

That a crude gender wage gap exists in the US is neither hard to observe nor a surprise, given previous studies of the US and other countries. Like a number of previous studies of the US and other countries we find employment in the US to exhibit a high degree of gender segregation by both industry and by occupation. It is not just industries and occupations that tend to differ between men and women. Another important difference is that women represent a much higher proportion of the part-time labour force than do men.

Gender segregation at work and other differences such as part-time working make it very difficult to accurately compare women's pay with that of men. Heckman selection model estimates regressions with a large number of control variables suggest that a statistically significant gender wage gap exists but the limitations of the estimators in this context are well known. Following a number of authors we used a propensity score matching (PSM) approach and, again, find a statistically significant gender wage gap.

The study also used the PSM approach to estimate the gender wage gap for various categories of workers, already identified in the literature as contributing to the gender wage gap. In particular (as with previous studies) the gender wage gap was found to be much reduced (but still statistically significant) for young workers. For the sample of part-time workers the gender wage gap was even more reduced. This provides an important clue for further research and suggest that the interactions between age, parenthood, marriage and part-time working offer the most likely explanations of a persistent gender wage gap.

Although a matching approach should provide a much more accurate comparison between male and female wages we still have concerns about its adequacy when applied to the full sample. A reasonably matched control group can be selected if industry and occupation are ignored but if they are included, as they must be, it is difficult to obtain an adequate control group. Put simply, gender segregation in particular, means that many women and many men are undertaking different roles which are not easy to directly compare.

Our approach to address this problem is, firstly, to pick three industries in which both men and women are employed in similar numbers and for which there were sufficient observations. This does provide much more accurate selection of a control group than with the overall sample. The results still suggest a statistically significant (at 99%) gender wage gap for each of the three industries. This gender wage gap persists despite increasingly thorough attempts to control for wage differences arising from age, education, ethnic background, industry, occupation, part-time working, region and other factors.

Finally, we conduct a similar analysis for five different occupations, each of which was selected for having significant numbers of each gender in the same occupation. For all of the five occupations we found robust evidence of a gender pay gap. Taking the study overall we conclude that we were unable to falsify the proposition that women are paid less for undertaking essentially the same work as men. That is, the crude gender pay gap can be reduced (and hence explained) but not eliminated by taking into account a wide range of factors such as part-time working, education, age and, most importantly, gender segregation.

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#### **Conflict of Interest:**

The authors declare that they have no conflict of interest.

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Appendix 1: Share of Females in Employment and Mean Hourly Wages by Industry, sorted by mean wage.				
Code	Industry Description	Observations	% female	Mean wage
3370	Communications, and audio and video equipment manufacturing	78	28.21%	58.11
2070	Petroleum refining	93	16.13%	51.91
3365	Computer and peripheral equipment manufacturing	164	34.15%	50.77
0390	Metal ore mining	35	8.57%	49.20
0470	Nonmetallic mineral mining and guarrying	66	7.58%	48.07
2090	Miscellaneous petroleum and coal products	12	16.67%	40.62
6490	Software publishers	44	38.64%	39.72
6970	Securities, commodities, funds, trusts, and other financial investments	624	44.23%	37.28
7380	Computer systems design and related services	1125	30.22%	36.52
1390	Tobacco manufacturing	4	75.00%	36.09
2290	Industrial and miscellaneous chemicals	280	22 50%	35.84
2170	Resin synthetic rubber and fibers and filaments manufacturing	119	27 73%	35.01
7460	Scientific research and development services	363	42 98%	34.95
9590	National security and international affairs	539	39 52%	34.55
6080		212	8 96%	22 72
6570	Motion nictures and video industries	165	20 20%	33.72
3590	Aerospace product and parts manufacturing	105	39.39%	22 52
0670	Water steam air conditioning and irrigation systems	120	20.90%	22.61
7000		130	21.74%	32.01
7290	Monagement, exignified and technical consulting conices	507	27.00%	32.57
7390	Interret publishing and bracksating and web search partols	583	40.31%	31.92
0072	Dedie and television broadcasting and cable subscription programming	21	38.10%	31.92
0070	Radio and television broadcasting and cable subscription programming	358	33.80%	31.79
2190		261	47.51%	31.55
6070	Air transportation	318	36.48%	31.01
/3/0	Specialized design services	111	50.45%	30.95
8390	Vocational rehabilitation services	103	59.22%	30.81
7490	Other professional, scientific, and technical services	137	55.47%	30.79
9180		51	45.10%	30.67
3990	Not specified manufacturing industries	101	29.70%	30.26
7270		854	62.06%	30.20
9380	Public finance activities	242	66.12%	29.83
8560		288	41.32%	29.54
6780		27	55.56%	29.46
9570	Administration of economic programs and space research	444	44.59%	29.28
0590	Electric and gas, and other combinations	60	28.33%	29.23
0570	Electric power generation, transmission, and distribution	457	21.23%	29.23
6290	Services incidental to transportation	416	21.63%	29.20
6480	Periodical, book, and directory publishers	149	53.69%	28.82
3580	Aircraft and parts manufacturing	276	19.57%	28.57
0690	Not specified utilities	20	30.00%	28.55
9490	Administration of environmental quality and housing programs	260	45.38%	28.53
0380	Coal mining	137	5.84%	28.42
9470	Justice, public order, and safety activities	1810	34.70%	28.37
3380	Navigational, measuring, electromedical, and control instruments	145	35.86%	28.23
6680	Wired telecommunications carriers	371	33.15%	28.17
6990	Insurance carriers and related activities	1503	64.60%	28.15
3390	Electronic component and product manufacturing, n.e.c.	392	34.18%	27.94
0580	Natural gas distribution	67	31.34%	27.87
4380	Drugs, sundries, and chemical and allied products merchant wholesalers	146	48.63%	27.76
7280	Accounting, tax preparation, bookkeeping, and payroll services	501	65.87%	27.72
3890	Furniture and related product manufacturing	268	25.37%	27.39
4170	Professional and commercial equipment and supplies merchant wholesale	209	37.80%	27.02
3980	Miscellaneous manufacturing, n.e.c.	282	37.23%	27.01
6890	Nondepository credit and related activities	486	58.02%	26.75
9190	Business, professional, political, and similar organizations	95	56.84%	26.62
3095	Commercial and service industry machinery manufacturing	48	33.33%	26.53
7470	Advertising, public relations, and related services	266	51.50%	26.46

Appendix 1 (continued)				
Code	Industry Description	Observations	% female	Mean wage
4195	Household appliances and electrical and electronic goods merchant whole	128	28.13%	26.40
5590	Electronic shopping	73	52.05%	26.35
0190	Forestry, except logging	28	35.71%	26.24
6690	Other telecommunications services	334	35.63%	26.21
6695	Data processing hosting and related services	66	50.00%	26.21
7970	Colleges universities and professional schools including junior colleges	2560	50.00%	26.21
6870	Banking and related activities	2309	55.10%	20.09
0070		1355	05.31%	26.07
2470	Administration of human resource programs	14	35.71%	20.02
9480		684	/0.32%	25.94
4180	Metals and minerals, except petroleum, merchant wholesalers	33	18.18%	25.86
0000		//	80.52%	25.43
8190	Hospitals	4137	76.99%	25.28
6270	Pipeline transportation	57	26.32%	25.06
4490	Petroleum and petroleum products merchant wholesalers	123	24.39%	24.92
7190	Commercial, industrial, and other intangible assets rental and leasing	62	19.35%	24.90
7970	Offices of physicians	818	83.01%	24.64
7860	Elementary and secondary schools	5988	75.80%	24.57
3960	Medical equipment and supplies manufacturing	389	48.07%	24.57
1370	Beverage manufacturing	139	21.58%	24.52
1070	Animal food, grain, and oilseed milling	121	30.58%	24.45
8180	Other health care services	1303	70.91%	24.39
9390	Other general government and support	81	43.21%	24.35
7070	Real estate	1088	53 77%	24.33
6090	Water transportation	13	20.93%	24.33
4270	Machineny equipment and supplies merchant wholesalers	216	20.55%	24.31
7000	Pusiness, technical, and trade schools and training	210	23.01/6	24.17
7000	Management of companies and enterprises	00	58.82%	24.07
7570		11/	49.57%	23.95
0680		74	17.57%	23.90
6170	Truck transportation	918	13.07%	23.82
9170	services	489	68.71%	23.80
3470	Household appliance manufacturing	39	30.77%	23.66
3490	Electrical lighting and electrical equipment manufacturing, and other	168	29.76%	23.65
3970	Sporting and athletic goods, and doll, toy and game manufacturing	54	29.63%	23.59
0370	Oil and gas extraction	49	16.33%	23.46
8090	Outpatient care centers	833	78.63%	23.43
2970	Ordnance	46	36.96%	23.41
3680	Ship and boat building	120	12.50%	23.39
4890	Lawn and garden equipment and supplies stores	183	38.25%	23.28
0490	Support activities for mining	395	13.92%	23.12
7980	Offices of dentists	484	91.12%	23.11
2270	Paint, coating, and adhesive manufacturing	42	23.81%	23.02
6370	Postal Service	467	41.33%	22.97
9370	Executive offices and legislative bodies	708	51.84%	22.95
4265	wholesalers	82	19 51%	22.78
4560	Alcoholic beverages merchant wholesalers	91	18 68%	22.76
0480	Not specified type of mining	15	13 33%	22.74
1870	Pulp, paper, and paperboard mills	13	17.46%	22.50
2280	Soon cleaning compound and cosmotics manufacturing	92	17.40%	22.51
2200		03	53.01%	22.34
2070	Agricultural chemical manufacturing	3CT	10.13%	22.34
2180		21	28.5/%	22.28
/6/0		150	56.67%	22.26
4570	Farm supplies merchant wholesalers	47	27.66%	22.25
3190	Machinery manufacturing, n.e.c.	367	22.34%	22.23
7780	Other administrative and other support services	147	38.78%	22.11
3080	Construction, and mining and oil and gas field machinery manufacturing	83	15.66%	21.79
3180	Engine, turbine, and power transmission equipment manufacturing	35	25.71%	21.75
3570	Motor vehicles and motor vehicle equipment manufacturing	535	27.66%	21.62
0770	Construction	4236	10.98%	21.62

Appendix	Appendix 1 (continued)				
Code	Industry Description	Observations	% female	Mean wage	
3670	Railroad rolling stock manufacturing	14	28.57%	21.60	
4290	Miscellaneous durable goods merchant wholesalers	61	40.98%	21.50	
8370	Individual and family services	940	79.15%	21.47	
8570	Museums, art galleries, historical sites, and similar institutions	232	50.86%	21.38	
3170	Metalworking machinery manufacturing	104	16.35%	21.37	
4090	l umber and other construction materials merchant wholesalers	79	16 46%	21.30	
2570	Cement concrete lime and gypsum product manufacturing	93	9.68%	21.30	
5070	Pharmacies and drug stores	527	66 22%	21.23	
2790	Cutlery and hand tool manufacturing	20	25.00%	21.22	
5591		20	25.00%	21.14	
4370	Paper and paper products merchant wholesalers	30	38.46%	21.03	
4795	Flactronics stores	281	32 03%	21.04	
4470	Greenv and related product morehant wholesalers	471	25.05%	20.32	
2000	Not appointed metal industrias	4/1	23.03%	20.80	
7900	Other schools and instruction, and educational support conices	225	55.55%	20.80	
8870		172	12 70%	20.74	
5600		1/2	12.79%	20.58	
2400		59	55.93%	20.48	
2490	Glass and glass product manufacturing	80	20.00%	20.46	
2690	Nonferrous metal, except aluminum, production and processing	25	8.00%	20.27	
1090	Fruit and vegetable preserving and speciality food manufacturing	96	43.75%	20.01	
4585	Wholesale electronic markets and agents and brokers	32	46.88%	20.00	
4390	Apparel, piece goods, and notions merchant wholesalers	49	55.10%	19.97	
2480	Clay building material and refractories manufacturing	18	16.67%	19.97	
8790	Electronic and precision equipment repair and maintenance	67	11.94%	19.89	
9160	Religious organizations	697	51.22%	19.80	
2590	Miscellaneous nonmetallic mineral product manufacturing	34	23.53%	19.79	
2370	Plastics product manufacturing	160	31.25%	19.79	
4080	Furniture and home furnishing merchant wholesalers	36	38.89%	19.64	
1890	Miscellaneous paper and pulp products	64	35.94%	19.62	
2380	Tire manufacturing	35	8.57%	19.58	
2980	Miscellaneous fabricated metal products manufacturing	167	23.35%	19.56	
6470	Newspaper publishers	179	43.02%	19.49	
1990	Printing and related support activities	338	36.39%	19.45	
6380	Couriers and messengers	388	21.13%	19.41	
6880	Savings institutions, including credit unions	185	72.97%	19.37	
2770	Foundries	68	17.65%	19.36	
3780	Veneer, plywood, and engineered wood products	16	6.25%	19.36	
4670	Automobile dealers	702	20.37%	19.32	
4580	Miscellaneous nondurable goods merchant wholesalers	88	42.05%	19.13	
1170	Dairy product manufacturing	130	24.62%	19.02	
4070	Motor vehicle and motor vehicle parts and supplies merchant wholesalers	101	26.73%	19.02	
8380	Community food and housing, and emergency services	79	72.15%	19.01	
6770	Libraries and archives	160	87.50%	18.90	
2780	Metal forgings and stampings	31	19.35%	18.87	
7480	Veterinary services	185	79.46%	18.86	
6180	Bus service and urban transit	332	40.06%	18.84	
1280	Seafood and other miscellaneous foods, n.e.c.	133	39.85%	18.81	
3690	Other transportation equipment manufacturing	16	18.75%	18.76	
3070	Agricultural implement manufacturing	113	20.35%	18.66	
2870	Structural metals, and boiler, tank, and shipping container manufacturing	176	13.64%	18.65	
2880	Machine shops; turned product; screw. nut. and bolt manufacturing	184	9.78%	18.56	
4590	Not specified wholesale trade	27	33.33%	18.52	
0280	Fishing, hunting, and trapping	23	8.70%	18.44	
4680	Other motor vehicle dealers	65	18.46%	18.44	
2390	Rubber product, except tire, manufacturing	49	32.65%	18.43	
7180	Other consumer goods rental	50	16.00%	18,37	
1480	Fabric mills, except knitting mills	62	40.32%	18 36	
9080	Funeral homes, and cemeteries and crematories	67	31.34%	18.30	

Appendix	Appendix 1 (continued)				
Code	Industry Description	Observations	% female	Mean wage	
0170	Crop production	350	21.71%	18.28	
8590	Other amusement, gambling, and recreation industries	1006	48.01%	18.18	
1770	Footwear manufacturing	28	53.57%	18.14	
8880	Personal and household goods repair and maintenance	54	16.67%	18.13	
7790	Waste management and remediation services	263	15.21%	17.89	
1290	Not specified food industries	33	48.48%	17.86	
5592	Mail-order houses	52	71.15%	17.83	
7590	Business support services	467	64.24%	17.79	
2680	Aluminum production and processing	45	24.44%	17.71	
1880	Paperboard container manufacturing	60	20.00%	17.68	
1670	Knitting fabric mills, and apparel knitting mills	7	85.71%	17.65	
5670	Vending machine operators	21	33.33%	17.61	
7080	Automotive equipment rental and leasing	97	26.80%	17.59	
5680	Fuel dealers	76	31.58%	17.58	
5190	Jewelry, luggage, and leather goods stores	103	71.84%	17.49	
5080	Health and personal care, except drug, stores	162	70.37%	17.46	
4980	Specialty food stores	148	52.70%	17.31	
4480	Farm product raw material merchant wholesalers	53	32.08%	17.29	
7580	Employment services	528	54.36%	17.25	
8770	Automotive repair and maintenance	556	10.79%	17.19	
5480	Office supplies and stationery stores	105	45.71%	17.10	
5790	Not specified retail trade	133	58.65%	17.09	
4770	Furniture and home furnishings stores	298	38.93%	17.07	
9090	Other personal services	149	63.76%	17.00	
4780	Household appliance stores	33	18.18%	16.99	
8070	Offices of optometrists	64	87.50%	16.86	
6590	Sound recording industries	10	40.00%	16.68	
1080	Sugar and confectionery products	62	35.48%	16.63	
4870	Building material and supplies dealers	549	30.60%	16.54	
6390	Warehousing and storage	211	24.64%	16.43	
4280	Recyclable material merchant wholesalers	51	9.80%	16.35	
7990	Offices of chiropractors	59	86.44%	16.31	
8990	Nail salons and other personal care services	156	78.85%	16.28	
7680	Investigation and security services	485	23.92%	16.27	
3770	Sawmills and wood preservation	79	12.66%	16.21	
5580	Miscellaneous retail stores	241	55.60%	16.20	
8670	Recreational vehicle parks and camps, and rooming and boarding houses	41	53.66%	16.17	
1680	Cut and sew apparel manufacturing	130	61.54%	16.16	
3290	Not specified machinery manufacturing	5	20.00%	16.16	
4990	Beer, wine, and liquor stores	66	36.36%	15.95	
0270	Logging	52	9.62%	15.88	
8270	Nursing care facilities (skilled nursing facilities)	1204	86.13%	15.69	
1270	Bakeries and tortilla manufacturing, except retail bakeries	103	38.83%	15.54	
1490	Textile and fabric finishing and coating mills	11	27.27%	15.49	
3790	Prefabricated wood buildings and mobile homes	16	12.50%	15.47	
6190	Taxi and limousine service	96	20.83%	15.43	
2890	Coating, engraving, heat treating and allied activities	35	25.71%	15.39	
3875	Miscellaneous wood products	117	14.53%	15.36	
5295	Musical instrument and supplies stores	31	32.26%	15.36	
6280	Scenic and sightseeing transportation	19	42.11%	15.32	
0290	Support activities for agriculture and forestry	77	40.26%	15.20	
8290	Residential care facilities, except skilled nursing facilities	509	71.51%	15.11	
4690	Automotive parts, accessories, and tire stores	297	16.84%	15.09	
8780	Car washes	71	8.45%	15.04	
8170	Home health care services	548	89.78%	14.77	
1570	Carpet and rug mills	22	45.45%	14.54	
8660	Traveler accommodation	904	56.53%	14.39	
1180	Animal slaughtering and processing	373	37.80%	14.37	

Appendix	(1 (continued)			
Code	Industry Description	Observations	% female	Mean wage
5390	Miscellaneous general merchandise stores	323	61.30%	14.27
4880	Hardware stores	188	34.57%	14.08
8470	Child day care services	717	94.84%	13.92
7770	Landscaping services	406	11.08%	13.74
1190	Retail bakeries	118	61.02%	13.58
5470	Retail florists	42	71.43%	13.50
5180	Shoe stores	93	55.91%	13.46
5570	Gift, novelty, and souvenir shops	86	82.56%	13.46
5275	Sporting goods, and hobby and toy stores	280	41.79%	13.41
5380	Department stores and discount stores	1407	61.90%	13.35
4970	Grocery stores	1797	51.53%	13.25
8580	Bowling centers	32	43.75%	13.23
1590	Textile product mills, except carpet and rug	50	64.00%	13.15
1470	Fiber, yarn, and thread mills	4	50.00%	13.13
5170	Clothing stores	611	79.05%	12.95
8980	Beauty salons	350	91.43%	12.93
5490	Used merchandise stores	112	66.07%	12.93
0180	Animal production and aquaculture	307	18.89%	12.81
7690	Services to buildings and dwellings	597	49.08%	12.59
5090	Gasoline stations	297	57.91%	12.47
7170	Video tape and disk rental	9	55.56%	12.41
8970	Barber shops	31	45.16%	12.29
9070	Drycleaning and laundry services	196	63.27%	12.27
5280	Sewing, needlework, and piece goods stores	29	79.31%	12.17
9290	Private households	430	87.44%	12.08
1790	Leather tanning and finishing and other allied products manufacturing	14	28.57%	11.87
5370	Book stores and news dealers	83	59.04%	11.57
8680	Restaurants and other food services	4920	54.07%	10.57
8690	Drinking places, alcoholic beverages	133	52.63%	10.38
8890	Footwear and leather goods repair	2	50.00%	8.41
1690	Apparel accessories and other apparel manufacturing	1	0.00%	8.00

Appendix 2: Share of Females in Employment and Mean Hourly Wages by Occupation, sorted by mean wage.				
Code	Industry Description	Observations	% female	Mean wage
2920	Television, video, and motion picture camera operators and editors	18	5.56%	173.63
9650	Pumping station operators	23	0.00%	96.38
2700	Actors	12	50.00%	89.02
9410	Transportation inspectors	19	10.53%	85.42
9200	Locomotive engineers and operators	40	0.00%	72.96
4340	Animal trainers	10	80.00%	72.53
3256	Nurse anesthetists	19	52.63%	62.27
3010	Dentists	43	25.58%	59.02
3257	Nurse midwives	2	100.00%	52.70
1220	Operations research analysts	96	47.92%	51.13
0110	Computer and information systems managers	346	23.99%	51.10
0010	Chief executives	686	24.93%	50.89
1210	Mathematicians	5	20.00%	46.92
0850	Personal financial advisors	185	35.14%	46.67
1660	Life scientists, all other	2	50.00%	46.46
3820	Detectives and criminal investigators	86	22.09%	45.85
2025	Miscellaneous community and social service specialists, including	69	65.22%	45.48
3050	Pharmacists	173	57.23%	44.48
3258	Nurse practitioners	75	93.33%	43.31
2100	Lawyers	565	36.81%	43.27
2840	Technical writers	43	60.47%	42.87
1840	Urban and regional planners	22	36.36%	42.53
1020	Software developers, applications and systems software	637	23.39%	42.33
4465	Morticians, undertakers, and funeral directors	16	25.00%	42.15
0300	Architectural and engineering managers	70	8.57%	42.04
1860	Miscellaneous social scientists and related workers	46	50.00%	41.98
1106	Computer network architects	58	15.52%	41.93
9030	Aircraft pilots and flight engineers	82	7.32%	41.34
0930	Tax examiners and collectors, and revenue agents	50	54.00%	41.10
1700	Astronomers and physicists	14	28.57%	40.85
3060	Physicians and surgeons	456	38.60%	40.64
1010	Computer programmers	284	22.89%	40.32
1200	Actuaries	14	35.71%	39.96
4965	Sales and related workers, all other	107	48.60%	39.63
3040	Optometrists	8	12.50%	39.37
0230	Education administrators	592	66.05%	39.04
1320	Aerospace engineers	94	14.89%	38.89
3250	Veterinarians	38	52.63%	38.71
1800	Economists	23	39.13%	38.38
1230	Statisticians	34	50.00%	38.33
2105	Judicial law clerks	4	75.00%	37.87
1520	Petroleum engineers	16	6.25%	37.77
1410	Electrical and electronics engineers	193	8.29%	37.77
3245	Therapists, all other	79	81.01%	37.43
0800	Accountants and auditors	968	63.22%	37.40
1400	Computer hardware engineers	43	4.65%	37.33
1420	Environmental engineers	34	14.71%	37.23
0840	Financial analysts	28	42.86%	37.09
0725	Meeting, convention, and event planners	65	80.00%	37.05
1530	Engineers, all other	219	10.05%	37.05
3110	Physician assistants	65	70.77%	37.01
0430	Managers, all other	1643	39.68%	37.01
0050	Marketing and sales managers	584	49.49%	36.98
3235	Exercise physiologists	2	50.00%	36.78
1510	Nuclear engineers	10	20.00%	36.50
1350	Chemical engineers	44	13.64%	36.45
1360	Civil engineers	233	12.45%	36.09
3850	Police and sheriffs patrol officers	424	11.08%	36.01
9040	Air traffic controllers and airfield operations specialists	36	13.89%	35.92
1006	Computer systems analysts	279	41.94%	35.73

Appendix 2 (continued)					
Code	Industry Description	Observations	% female	Mean wage	
0136	Human resources managers	161	75.78%	35.70	
6840	Mining machine operators	64	3.13%	35.30	
1460	Mechanical engineers	171	4.68%	35.02	
0425	Emergency management directors	7	28.57%	35.02	
0820	Budget analysts	42	52.38%	34.95	
0360	Natural sciences managers	10	80.00%	34.85	
1300	Architects, except naval	80	26.25%	34.74	
1005	Computer and information research scientists	14	42.86%	34.64	
0710	Management analysts	348	44.25%	34.64	
1760	Physical scientists, all other	107	45.79%	34.56	
1500	Mining and geological engineers, including mining safety engineers	9	22.22%	33.87	
0420	Social and community service managers	244	70.90%	33.72	
0350	Medical and health services managers	383	73.63%	33.55	
0120	Financial managers	698	58.02%	33.52	
2200	Postsecondary teachers	937	50.05%	33.30	
1610	Biological scientists	81	49.38%	33.20	
1740	Environmental scientists and geoscientists	64	28.13%	33.16	
1430	Industrial engineers, including health and safety	120	17.50%	33.11	
0060	Public relations and fundraising managers	53	66.04%	33.10	
4920	Real estate brokers and sales agents	262	59.92%	33.00	
0150	Purchasing managers	131	49.62%	32.83	
1060	Database administrators	70	38.57%	32.61	
0040	Advertising and promotions managers	45	48.89%	32.27	
1007	Information security analysts	31	16.13%	32.15	
0100	Administrative services managers	94	42.55%	32.14	
1820	Psychologists	91	73.63%	32.02	
0565	Compliance officers	150	44.67%	31.95	
4820	Securities, commodities, and financial services sales agents	140	34.29%	31.95	
1440	Marine engineers and naval architects	6	0.00%	31.76	
4930	Sales engineers	19	21.05%	31.47	
8840	Semiconductor processors	3	0.00%	31.37	
1105	Network and computer systems administrators	150	22.67%	31.30	
3150	Occupational therapists	66	90.91%	31.25	
1720	Chemists and materials scientists	56	39.29%	31.20	
9340	Bridge and lock tenders	4	0.00%	31.15	
3140	Audiologists	8	100.00%	30.93	
0900	Financial examiners	13	38.46%	30.78	
3160	Physical therapists	126	74.60%	30.66	
0220	Construction managers	310	10.00%	30.65	
0650	Training and development specialists	89	58.43%	30.59	
0020	General and operations managers	698	32.38%	30.50	
1450	Materials engineers	27	7.41%	30.30	
0735	Market research analysts and marketing specialists	105	53.33%	30.15	
0135	Compensation and benefits managers	9	66.67%	30.06	
2320	Secondary school teachers	799	59.20%	29.94	
0740	Business operations specialists, all other	165	59.39%	29.90	
1/10	Aunospheric and space scientists	5	20.00%	29.86	
1240	Inscenarieous mathematical science occupations	3	33.33%	29.81	
2/10	Producers and directors	81	45.68%	29.71	
1040	Computer support appointies	21	33.33%	29.56	
1050	Computer support specialists	301	27.57%	29.43	
3310		97	98.97%	29.34	
0140	Other education training and libran workers	147	19.05%	29.24	
2000	Decision de la constant de	/6	67.11%	28.87	
3255	Registered fullses	1836	91.67%	28.67	
3230	Speech-language pathologists	/6	97.37%	28.61	
0137	Fraining and development managers	28	46.43%	28.58	
1310	Surveyors, cartographers, and protogrammetrists	35	17.14%	28.53	
2825	Public relations specialists	107	65.42%	28.31	
1340		/	28.5/%	28.23	

Code	Industry Description	Observations	% female	Mean wage
5500	Cargo and freight agents	4	0.00%	27.82
0830	Credit analysts	20	70.00%	27.00
1030		20	70.00%	27.80
1030	Credit equipalem and lean officers	92	27.17%	27.79
0910		219	57.99%	27.77
0700	Logisticians	67	32.84%	27.74
3200	Radiation therapists	9	77.78%	27.69
1600	Agricultural and food scientists	37	29.73%	27.69
2960	Media and communication equipment workers, all other	2	50.00%	27.54
3710	First-line supervisors of police and detectives	68	13.24%	27.54
2340	Other teachers and instructors	446	65 25%	27 51
0860	Insurance underwriters	72	72 61%	27.01
1915		72	73.01%	27.44
2720	Suivey researchers	5	00.00%	27.44
3720	First-line supervisors of life lighting and prevention workers	31	3.23%	27.39
4850	Sales representatives, wholesale and manufacturing	753	27.09%	27.21
9330	Ship engineers	4	0.00%	27.11
2310	Elementary and middle school teachers	2048	81.59%	27.03
6910	Roof bolters, mining	9	0.00%	26.88
0950	Financial specialists, all other	38	57.89%	26.81
1107	Computer occupations, all other	215	19.53%	26.63
0630	Human resources workers	380	76 32%	26 59
9050	Flight attendants	500	90.00%	26.55
0000		55	12.64%	20.47
0600		66	13.64%	26.46
6700	Lievator installers and repairers	19	10.53%	26.29
4810	Insurance sales agents	273	48.72%	26.29
9000	Supervisors of transportation and material moving workers	141	29.08%	26.25
0410	Property, real estate, and community association managers	272	58.09%	26.23
7100	Electrical and electronics repairers, industrial and utility	11	0.00%	26.22
1650	Medical scientists	89	52.81%	26.17
2810	News analysts, reporters and correspondents	42	35 71%	26.06
0540	Claims adjusters appraisers examiners and investigators	207	61 94%	26.00
0310	Shin and host cantains and operators	207	01.04/0	20.05
2600	Artista and roletad workers	15	0.00%	26.01
2000		53	58.49%	25.98
2720	Athletes, coaches, umpires, and related workers	150	40.67%	25.91
3220	Respiratory therapists	73	67.12%	25.86
1930	Geological and petroleum technicians	13	23.08%	25.61
2330	Special education teachers	263	87.07%	25.59
1550	Engineering technicians, except drafters	252	15.48%	25.51
4710	First-line supervisors of non-retail sales workers	477	29.56%	25.44
9730	Mine shuttle car operators	1	0.00%	25.40
7410	Electrical power-line installers and repairers	86	1 16%	25 33
3320	Diagnostic related technologists and technicians	220	70.87%	25.35
1010	Sales representatives services all other	230	22.07%	25.25
4840	Componentian honofite, and job analysis analysis	2/6	32.9/%	25.24
0040		49	81.63%	25.22
1540		93	18.28%	25.19
7700	First-line supervisors of production and operating workers	487	19.10%	25.19
8150	Heat treating equipment setters, operators, and tenders, metal and	2	0.00%	25.18
1920	Chemical technicians	55	47.27%	25.00
7000	First-line supervisors of mechanics, installers, and repairers	196	8.16%	24.92
1560	Surveying and mapping technicians	38	13.16%	24.82
2830	Editors	110	56 36%	24.81
E1E0	Procurement clerks	15	66.67%	24.01
0500	Agents and husiness managers of artists, notfermore, and athletes	15	27 500/	24.00
0000	Designers	24	37.50%	24.79
2630		352	48.86%	24.71
6200	First-line supervisors of construction trades and extraction workers	356	3.37%	24.66
8160	Layout workers, metal and plastic	6	33.33%	24.59
0530	Purchasing agents, except wholesale, retail, and farm products	148	56.08%	24.54
0160	Transportation, storage, and distribution managers	170	12.35%	24.51
2015	Probation officers and correctional treatment specialists	64	50.00%	24.46
3700	First-line supervisors of correctional officers	20	40,00%	24.43
	Derrick rotany drill and service unit operators oil gas, and mining	20	0.00%	24.20
6800		77	1 / 1 8 / 70	

Appendix 2 (continued)				
Code	Industry Description	Observations	% female	Mean wage
3000	Chiropractors	5	20.00%	24.28
0810	Appraisers and assessors of real estate	39	43.59%	24.19
8620	Water and wastewater treatment plant and system operators	52	7.69%	24.17
2400	Archivists, curators, and museum technicians	39	51.28%	24.16
2040	Clergy	278	22.30%	24.05
2010	Social workers	495	84.24%	24.02
7140	Aircraft mechanics and service technicians	96	1.04%	23.97
6500	Reinforcing iron and rebar workers	6	0.00%	23.93
3540	Other healthcare practitioners and technical occupations	44	43 18%	23.91
6355	Electricians	403	2 48%	23.87
3030	Dietitians and nutritionists	59	91 53%	23.87
0340	Lodging managers	55	57 41%	23.86
9240	Railroad conductors and vardmasters	42	2 38%	23.80
2850	Writers and authors	74	60.81%	23.85
3500	Licensed practical and licensed vocational nurses	375	89.60%	23.01
2900	Broadcast and sound engineering technicians and radio operators	575	11 54%	23.74
7420	Telecommunications line installers and renairers	120	6 20%	23.00
6520	Sheet metal workers	60	1 459/	23.39
7960	Drilling and boring machine tool setters operators and tenders metal	2	1.45%	23.56
2160	Miscellaneous legal support workers	122	75.100/	23.50
2800		133	75.19%	23.49
2000		32	9.38%	23.46
2740	Advertising sales agents	6	66.67%	23.41
4800	Adventising sales agents	133	48.87%	23.41
9420		8	0.00%	23.17
1040		50	22.00%	23.16
1940		2	0.00%	23.14
1900	Agricultural and lood science technicians	20	70.00%	23.09
3300		206	/4.2/%	23.04
2140	Paralegals and related workers	260	85.77%	22.98
2750	Musicians, singers, and related workers	62	48.39%	22.96
7020	Radio and telecommunications equipment installers and repairers	100	10.00%	22.93
6440		284	1.76%	22.89
2000		473	71.88%	22.75
7330		312	3.53%	22.72
0940	Tax preparers	52	59.62%	22.70
7430		42	7.14%	22.61
8350		31	70.97%	22.58
2430		158	87.34%	22.53
0520	wholesale and retail buyers, except farm products	102	50.98%	22.35
3830	Fish and game wardens	3	33.33%	22.25
5540		99	48.48%	22.14
9500		3	33.33%	22.13
7540	Locksmiths and sate repairers	11	9.09%	22.12
7030	Avonics technicians	8	12.50%	22.12
6660	Construction and building inspectors	43	4.65%	22.11
0330	Gaming managers	23	43.48%	22.09
7320	Home appliance repairers	23	4.35%	22.04
7130	Security and fire alarm systems installers	28	0.00%	22.00
5165	Financial clerks, all other	51	80.39%	21.93
7110	Electronic equipment installers and repairers, motor vehicles	9	0.00%	21.92
8630	Miscellaneous plant and system operators	30	13.33%	21.90
1910	Biological technicians	14	50.00%	21.88
7520	Commercial divers	2	0.00%	21.86
5550	Postal service mail carriers	195	35.90%	21.76
7220	Heavy vehicle and mobile equipment service technicians and mechanics	141	1.42%	21.74
8610	Stationary engineers and boiler operators	71	1.41%	21.58
6530	Structural iron and steel workers	35	0.00%	21.56
6740	Rail-track laying and maintenance equipment operators	8	0.00%	21.55
5000	First-line supervisors of office and administrative support workers	890	69.78%	21.54
0726	Fundraisers	57	73.68%	21.49
5250	Eligibility interviewers, government programs	62	75.81%	21.48

Appendix	Appendix 2 (continued)					
Code	Industry Description	Observations	% female	Mean wage		
2910	Photographers	35	65.71%	21.43		
1950	Social science research assistants	3	33.33%	21.36		
7360	Millwrights	39	5.13%	21.27		
1830	Sociologists	1	100.00%	21.26		
7050	Electrical and electronics installers and repairers, transportation	2	0.00%	21.25		
2860	Miscellaneous media and communication workers	36	63.89%	21.17		
5220	Court, municipal, and license clerks	54	87.04%	21.14		
7010	Computer, automated teller, and office machine repairers	147	12.93%	21.13		
4210	First-line supervisors of landscaping, lawn service, and groundskeeping	64	6.25%	21.09		
3730	First-line supervisors of protective service workers, all other	66	27.27%	20.88		
3740	Firefighters	172	5.81%	20.83		
3210	Recreational therapists	8	87 50%	20.83		
3750	Fire inspectors	14	7 14%	20.82		
6820	Earth drillers, except oil and gas	20	5.00%	20.02		
3610	Occupational therapy assistants and aides	12	91 67%	20.70		
7315	Heating, air conditioning, and refrigeration mechanics and installers	19/	1 55%	20.75		
6210	Boilermakers	8	0.00%	20.55		
5020	Statistical assistants	12	53.85%	20.57		
2440	Library technicians	24	87 35%	20.31		
6010	Agricultural inspectors	12	A6 15%	20.49		
8130	Tool and die makers	13	40.13%	20.43		
7160	Automotive glass installers and repairers	42	2.36%	20.42		
5020	Communications equipment operators all other	13	7.69%	20.41		
5030	Operating engineers and other construction equipment operators	4	50.00%	20.38		
3400	Emergeney medical technicians and parametics	258	0.78%	20.35		
5400		100	34.00%	20.33		
5230	Dreefreeders and easy markers	33	81.82%	20.29		
5910	Province and copy markers	6	83.33%	20.17		
5940		362	/5.14%	20.09		
6220	Brickmasons, blockmasons, and stonemasons	59	1.69%	20.09		
3535	Disastehese	91	63.74%	20.03		
5520	Dispatchers	149	56.38%	20.01		
6930	Helpers—extraction workers	3	0.00%	20.00		
6250	Cement masons, concrete finishers, and terrazzo workers	33	0.00%	19.96		
5800	Computer operators	65	47.69%	19.87		
1965	Miscellaneous life, physical, and social science technicians	108	42.59%	19.87		
8730	Furnace, kiln, oven, drier, and kettle operators and tenders	7	14.29%	19.86		
5420	Information and record clerks, all other	80	87.50%	19.83		
6940	Other extraction workers	62	1.61%	19.80		
3910	Private detectives and investigators	52	50.00%	19.69		
5600	Production, planning, and expediting clerks	183	62.84%	19.65		
0205	Farmers, ranchers, and other agricultural managers	84	15.48%	19.59		
6730	Highway maintenance workers	74	0.00%	19.58		
3260	Health diagnosing and treating practitioners, all other	7	57.14%	19.58		
7210	Bus and truck mechanics and diesel engine specialists	188	0.53%	19.53		
6460	Plasterers and stucco masons	10	0.00%	19.48		
6750	Septic tank servicers and sewer pipe cleaners	6	0.00%	19.48		
6260	Construction laborers	590	2.37%	19.46		
7630	Other installation, maintenance, and repair workers	112	4.46%	19.40		
7340	Maintenance and repair workers, general	264	2.27%	19.35		
4620	Recreation and fitness workers	188	66.49%	19.24		
2050	Directors, religious activities and education	26	65.38%	19.19		
6240	Carpet, floor, and tile installers and finishers	61	1.64%	19.11		
8030	Machinists	261	4.60%	19.05		
5410	Reservation and transportation ticket agents and travel clerks	82	63.41%	19.02		
3655	Miscellaneous healthcare support occupations, including medical	119	78.15%	19.01		
6400	Insulation workers	30	3.33%	18.97		
5560	Postal service mail sorters, processors, and processing machine	44	47.73%	18.95		
5700	Secretaries and administrative assistants	1908	95.81%	18.91		
9230	Railroad brake, signal, and switch operators	2	0.00%	18.91		
4300	First-line supervisors of gaming workers	59	42.37%	18.89		
7900	Computer control programmers and operators	47	4.26%	18.89		
0325	Funeral service managers	8	37.50%	18.89		

Appendix 2 (continued)				
Code	Industry Description	Observations	% female	Mean wage
8120	Multiple machine tool setters, operators, and tenders, metal and plastic	4	0.00%	18.88
3510	Medical records and health information technicians	67	97.01%	18.87
6920	Roustabouts, oil and gas	13	0.00%	18.85
0510	Buyers and purchasing agents, farm products	6	0.00%	18.82
8740	Inspectors, testers, sorters, samplers, and weighers	432	33.33%	18.81
8910	Etchers and engravers	6	33.33%	18.73
8940	Tire builders	8	12.50%	18.66
7740	Structural metal fabricators and fitters	19	0.00%	18.64
8040	Metal furnace operators, tenders, pourers, and casters	7	14.29%	18.62
3800	Bailiffs, correctional officers, and jailers	270	26.67%	18.61
4830	Travel agents	36	77.78%	18.58
4700	First-line supervisors of retail sales workers	1651	49.67%	18.48
2060	Religious workers, all other	54	62.96%	18.43
5820	Word processors and typists	74	91.89%	18.36
6230	Carpenters	569	2.28%	18.33
3900	Animal control workers	6	33.33%	18.30
3520	Opticians, dispensing	29	68.97%	18.28
5200	Brokerage clerks	8	50.00%	18.26
0310	Food service managers	487	53.59%	18.19
9130	Driver/sales workers and truck drivers	1752	4.91%	18.10
3420	Health practitioner support technologists and technicians	348	83.33%	18.06
9560	Hoist and winch operators	3	0.00%	18.04
5630	Weighers, measurers, checkers, and samplers, recordkeeping	40	45.00%	18.01
5140	Payroll and timekeeping clerks	125	90.40%	18.00
8500	Cabinetmakers and bench carpenters	34	5.88%	17.96
7200	Automotive service technicians and mechanics	446	1.35%	17.86
8140	Welding, soldering, and brazing workers	335	6.87%	17.74
8750	Jewelers and precious stone and metal workers	18	66.67%	17.70
9510	Crane and tower operators	40	2.50%	17.70
5120	Bookkeeping, accounting, and auditing cierks	809	90.85%	17.62
7730	Engine and other machine assemblers	11	18.18%	17.60
4950	Door-to-door sales workers, news and street vendors, and related	60	38.33%	17.56
2016		97	80.41%	17.54
6720	New accounts clocks	23	17.39%	17.54
7120	Electronic home entertainment equipment installers and repairers	1/	70.59%	17.52
9520	Dredge excavating and loading machine operators	24	0.00%	17.47
8760	Medical dental and onbthalmic laboratory technicians	25	4.55%	17.47
7350	Maintenance workers, machinery	17	11 76%	17.43
2300	Preschool and kindergarten teachers	/32	98.61%	17.41
3630	Massage therapists	432 54	88 80%	17.38
5210	Correspondence clerks	54	50.00%	17.37
6830	Explosives workers, ordnance handling experts, and blasters	8	0.00%	17.33
8930	Paper goods machine setters, operators, and tenders	22	27 27%	17.31
5330	Loan interviewers and clerks	71	90 14%	17.30
5510	Couriers and messengers	136	20.59%	17.23
6710	Fence erectors	19	0.00%	17.26
5530	Meter readers, utilities	16	18.75%	17.15
3620	Physical therapist assistants and aides	46	65.22%	17.12
6130	Logging workers	34	2.94%	17.11
6360	Glaziers	24	0.00%	17.02
8810	Painting workers	70	8.57%	17.00
8210	Tool grinders, filers, and sharpeners	1	0.00%	17.00
5020	Telephone operators	30	73.33%	16.96
9750	Material moving workers, all other	32	15.63%	16.92
6330	Drywall installers, ceiling tile installers, and tapers	65	1.54%	16.91
4320	First-line supervisors of personal service workers	52	63.46%	16.90
9260	Subway, streetcar, and other rail transportation workers	10	20.00%	16.89
7150	Automotive body and related repairers	80	1.25%	16.83
7940	Rolling machine setters, operators, and tenders, metal and plastic	8	25.00%	16.82
5860	Office clerks, general	681	85.61%	16.82

Appendix	2 (continued)			
Code	Industry Description	Observations	% female	Mean wage
5840	Insurance claims and policy processing clerks	165	81.21%	16.79
5110	Billing and posting clerks	288	88.89%	16.66
5360	Human resources assistants, except payroll and timekeeping	32	81.25%	16.62
6420	Painters, construction and maintenance	207	6.28%	16.56
5310	Interviewers, except eligibility and loan	110	86.36%	16.50
8250	Prepress technicians and workers	24	54.17%	16.47
7300	Control and valve installers and repairers	13	0.00%	16.47
9300	Sailors and marine oilers	11	0.00%	16.45
4200	First-line supervisors of housekeeping and janitorial workers	133	39.85%	16 44
7040	Electric motor, power tool, and related repairers	18	5.56%	16.41
4520	Miscellaneous personal appearance workers	122	85 25%	16.32
6765	Miscellaneous construction and related workers	17	0.00%	16.19
3640	Dental assistants	200	98 50%	16.13
8255	Printing press operators	140	22.86%	16.13
6300	Paving surfacing and tamping equipment operators	9	11 11%	16.15
5240	Customer service representatives	1258	67 57%	16.05
7600	Signal and track switch repairers	2250	0.00%	15.04
7920	Extruding and drawing machine setters operators and tenders metal	2	0.00%	15.94
7560	Rinners	3	0.00%	15.88
5910	Data entry keyers	104	0.00%	15.65
5010	Bill and account collectors	194	71 229/	15.70
5100 8065	Draduction workers, all other	139	71.22%	15.78
7440		533	27.02%	15.74
7440	Cutting purphing and proce machine actions and tenders	2	0.00%	15.73
7950	Colling, pulling, and pless machine setters, operators, and renders,	56	7.14%	15.65
7510	Coin, vending, and amusement machine servicers and repairers	20	15.00%	15.64
4240	Pest control workers	30	6.67%	15.61
8100	Molders and molding machine setters, operators, and tenders, metal and	25	24.00%	15.55
3860		3	0.00%	15.49
9140	Taxi drivers and chauffeurs	152	16.45%	15.48
3649		73	80.82%	15.48
8650	Crushing, grinding, polishing, mixing, and blending workers	59	20.34%	15.46
6515	Roofers	100	2.00%	15.37
9120	Bus drivers	368	39.95%	15.36
2760	Entertainers and performers, sports and related workers, all other	13	53.85%	15.27
2540	Teacher assistants	678	91.74%	15.24
4760	Retail salespersons	2005	51.82%	15.24
3945	Transportation security screeners	19	63.16%	15.24
7240	Small engine mechanics	25	0.00%	15.23
3930	Security guards and gaming surveillance officers	603	19.40%	15.18
8860	Cleaning, washing, and metal pickling equipment operators and tenders	5	20.00%	15.12
8020	Milling and planing machine setters, operators, and tenders, metal and	3	0.00%	15.00
3647	Pharmacy aides	29	75.86%	14.99
5260	File Clerks	224	84.82%	14.95
5130	Gaming cage workers	7	100.00%	14.93
4750	Parts salespersons	84	9.52%	14.82
4000	Chefs and head cooks	220	21.82%	14.82
5010	Switchboard operators, including answering service	27	81.48%	14.80
9600	Industrial truck and tractor operators	311	6.75%	14.77
5350	Order clerks	82	67.07%	14.75
8200	Plating and coating machine setters, operators, and tenders, metal and	9	22.22%	14.68
7850	Food cooking machine operators and tenders	17	23.53%	14.62
5610	Shipping, receiving, and traffic clerks	343	30.90%	14.59
9740	Tank car, truck, and ship loaders	2	0.00%	14.58
8720	Extruding, forming, pressing, and compacting machine setters,	24	20.83%	14.56
7720	Electrical, electronics, and electromechanical assemblers	102	48.04%	14.49
8530	Sawing machine setters, operators, and tenders, wood	20	0.00%	14.42
9720	Refuse and recyclable material collectors	56	8.93%	14.41
8220	Metal workers and plastic workers, all other	221	20.81%	14.31
8450	Upholsterers	14	21.43%	14.28
6600	Helpers, construction trades	34	8.82%	14.26

Appendix 2 (continued)						
Code	Industry Description	Observations	% female	Mean wage		
7750	Miscellaneous assemblers and fabricators	515	40.19%	14.22		
4740	Counter and rental clerks	75	41.33%	14.19		
8550	Woodworkers, all other	11	0.00%	14.18		
8540	Woodworking machine setters, operators, and tenders, except sawing	16	0.00%	14.18		
8460	Textile, apparel, and furnishings workers, all other	15	46.67%	14.10		
4530	Baggage porters, bellhops, and concierges	38	15.79%	14.09		
8000	Grinding, lapping, polishing, and buffing machine tool setters, operators,	33	12.12%	14.03		
3840	Parking enforcement workers	3	0.00%	14.00		
8950	Helpers—production workers	32	31.25%	13.99		
8710	Cutting workers	52	23.08%	13.97		
5400	Receptionists and information clerks	862	91.65%	13.89		
9415	Transportation attendants, except flight attendants	28	64.29%	13.87		
8920	Molders, shapers, and casters, except metal and plastic	15	33.33%	13.86		
7710	Aircraft structure, surfaces, rigging, and systems assemblers	5	60.00%	13.78		
6540	Solar photovoltaic installers	2	0.00%	13.75		
7810	Butchers and other meat, poultry, and fish processing workers	224	25.00%	13.73		
8256	Print binding and finishing workers	7	57.14%	13.69		
7610	Helpers-installation, maintenance, and repair workers	18	11.11%	13.67		
3646	Medical transcriptionists	44	93.18%	13.66		
6100	Fishers and related fishing workers	15	0.00%	13.64		
4460	Embalmers and funeral attendants	11	27.27%	13.57		
9610	Cleaners of vehicles and equipment	172	16.86%	13.54		
7855	Food processing workers, all other	79	37.97%	13.54		
4220	Janitors and building cleaners	1411	30.05%	13.45		
4900	Models, demonstrators, and product promoters	49	79.59%	13.38		
9620	Laborers and freight, stock, and material movers, hand	1123	18.52%	13.38		
3645	Medical assistants	245	95.10%	13.35		
6430	Paperhangers	2	100.00%	13.31		
8010	Lathe and turning machine tool setters, operators, and tenders, metal	4	25.00%	13.29		
5320	Library assistants, cierical	79	84.81%	13.27		
6005	First-line supervisors of farming, fishing, and forestry workers	32	9.38%	13.24		
4050	Combined tood preparation and serving workers, including tast tood	200	66.00%	13.21		
8850	Adhesive bonding machine operators and tenders	6	66.67%	13.15		
4640	Residential advisors	44	65.91%	13.15		
9150		38	7.89%	13.14		
5160	Ferring machine actions anotation, and tenders, metal and plastic	262	88.55%	13.13		
7930	Forging machine setters, operators, and tenders, metar and plastic	2	50.00%	13.13		
4010	Food balchillakers	/1	49.30%	12.97		
4010	Caming services workers	303	62.05%	12.93		
4400		82	45.12%	12.92		
5900		32	65.63%	12.91		
7550	Manufactured building and mobile home installers	286	94.06%	12.80		
5850	Mail clerks and mail machine operators, excent postal service	3	0.00%	12.83		
4350	Nonfarm animal caretakers	40	52.17%	12.83		
5620	Stock clerks and order fillers	020	78.82%	12.79		
4250	Grounds maintenance workers	500	34.73%	12.77		
8800	Packaging and filling machine operators and tenders	102	56 57%	12.75		
9110	Ambulance drivers and attendants, except emergency medical	198	40.00%	12.75		
8340	Shoe machine operators and tenders	8	87 50%	12.72		
3940	Crossing guards	42	69.05%	12.00		
9630	Machine feeders and offbearers	20	35.00%	12.00		
3955	Lifequards and other recreational, and all other protective service workers	74	54 05%	12.57		
7800	Bakers	105	55.24%	12.42		
4420	Ushers, lobby attendants, and ticket takers	24	33.33%	12.40		
4940	Telemarketers	82	63 41%	12.38		
3600	Nursing, psychiatric, and home health aides	1290	87.75%	12.31		
9360	Automotive and watercraft service attendants	58	24.14%	12.28		
7260	Miscellaneous vehicle and mobile equipment mechanics, installers, and	42	0.00%	12.23		
6120	Forest and conservation workers	9	22.22%	12.21		
4600	Childcare workers	574	93.73%	12.04		
8060	Model makers and patternmakers, metal and plastic	3	0.00%	11.99		
8510	Furniture finishers	- 5	20.00%	11.95		
4500	Barbers	26	34.62%	11.83		
8420	Textile winding, twisting, and drawing out machine setters, operators,	11	54.55%	11.81		
9640	Packers and packagers, hand	240	55.83%	11.80		
7830	Food and tobacco roasting, baking, and drying machine operators and	4	50.00%	11.73		

Appendix 2 (continued)						
Code	Industry Description	Observations	% female	Mean wage		
5300	Hotel, motel, and resort desk clerks	103	67.96%	11.64		
6040	Graders and sorters, agricultural products	76	59.21%	11.58		
6050	Miscellaneous agricultural workers	456	16.45%	11.50		
3648	Veterinary assistants and laboratory animal caretakers	36	75.00%	11.43		
4430	Miscellaneous entertainment attendants and related workers	113	46.90%	11.26		
4610	Personal care aides	683	83.60%	11.20		
8320	Sewing machine operators	83	72.29%	10.91		
8830	Photographic process workers and processing machine operators	27	59.26%	10.90		
4230	Maids and housekeeping cleaners	811	88.90%	10.80		
9350	Parking lot attendants	35	8.57%	10.79		
4160	Food preparation and serving related workers, all other	1	0.00%	10.75		
4120	Food servers, nonrestaurant	124	66.94%	10.71		
8300	Laundry and dry-cleaning workers	123	60.98%	10.66		
8330	Shoe and leather workers and repairers	4	50.00%	10.58		
4650	Personal care and service workers, all other	52	53.85%	10.52		
8520	Model makers and patternmakers, wood	1	0.00%	10.50		
4540	Tour and travel guides	18	61.11%	10.44		
4020	Cooks	1230	41.54%	10.44		
4720	Cashiers	1964	73.98%	9.91		
8310	Pressers, textile, garment, and related materials	35	82.86%	9.87		
8400	Textile cutting machine setters, operators, and tenders	5	40.00%	9.84		
4030	Food preparation workers	532	62.97%	9.74		
4040	Bartenders	268	54.85%	9.51		
4130	Dining room and cafeteria attendants and bartender helpers	236	52.12%	9.25		
4140	Dishwashers	185	20.54%	9.19		
6110	Hunters and trappers	1	0.00%	9.00		
4150	Hosts and hostesses, restaurant, lounge, and coffee shop	148	87.16%	8.90		
4410	Motion picture projectionists	5	40.00%	8.73		
4060	Counter attendants, cafeteria, food concession, and coffee shop	147	73.47%	8.62		
4110	Waiters and waitresses	1386	71.21%	8.50		
8440	Fabric and apparel patternmakers	2	100.00%	8.25		
8360	Textile bleaching and dyeing machine operators and tenders	2	0.00%	8.00		
6020	Animal breeders	3	33.33%	6.47		

# **APPENDIX 3: MATCHING CHECKS – BIAS ON OBSERVABLES (COMMON SUPPORT)**



Full Sample with Industry and Occupation Dummies

Full Sample without Industry and Occupation Dummies



#### Parents



#### **Non-parents**



#### Married



#### Unmarried



Young (24 or under):



Older (25 or over):



#### Part-time



#### Full-time:



#### Banking:



#### **Grocery Stores:**



#### **Restaurants:**



#### Customer Service Representatives;



#### Assemblers:



#### Accountants:



#### Lawyers:



#### Janitors:

