Male and Female Wage Differentials: Theories and Empirical Results of Labor Market Discrimination

by

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I. Introduction

Throughout American History women have typically had a lower labor force participation rate than their male counterparts. Since World War II, the first large-scale variation of women's participation in the labor force, women have been increasing their segment of the Labor Force Participation Rate (LFPR) and are approaching that of males.

Though women have moved into the labor market in increasing numbers in recent years, descriptive evidence suggests that women earn less money than men. For example, in a paper titled Wages and Gender Composition: Why do Women's Jobs Pay Less?, wages between 1973-93 are examined and show that wage levels are substantially lower in predominantly female occupations (Macpherson and Hirsch, 1995). These wage differentials may reflect that women invest less in education and are more likely to be absent from the labor force, a topic discussed in an article titled: Effects of Intermittent Labor Force Attachment on Women's Earnings. (Jacobson and Levin, 1995) Human capital theory predicts that these gender differences in human capital are valid reasons for gender differences in pay. However, studies also find that women earn less than comparably skilled men. (Callan and Wren, 1994) This suggests a presence of gender discrimination in the labor market.

I study women's earnings compared to men's, controlling for human capital and other personal attributes. I run a regression of the log wage on age, marital status, urban or rural status and education levels. An initial regression examines the magnitude and significance of each variable, including a dummy variable for gender. The coefficient on the gender dummy indicates whether there are unexplained gender differences in wages of men and women are assumed to have a the same rate of return to personal attributes.

An important part of labor market discrimination, may arise from differences in the rate of return to personal attributes. To examine if the labor market compensates men and women differently, I use a method called the Oaxaca decomposition (Oaxaca, 1973). Separate regressions are run by gender and the wage differential is decomposed into two parts: explained and unexplained. The explained portion calculates how differences in the mean attributes explain a differential. For example if only 50% of men are college educated compared to 100% of women, then it is expected that men would make less than women by a factor of 0.5*(the estimated premium on a college education). The unexplained portion of the differential is calculated by multiplying the mean female value by the difference between male and female coefficients for each variable. The unexplained portion of the wage differential is considered the discrimination coefficient. By decomposing this differential, the analysis examines the extent to which the wage differential is due to unexplained differences in the rate of return to attributes.

The possible presence of gender discrimination is important. A gender differential implies that women will tend to under-invest in human capital because they earn a lower rate of return on their investment. Discrimination also creates a dead weight loss that is detrimental to society as a whole. By estimating the male-female wage differentials, the analysis provides a sense of the magnitude of labor market discrimination and the extent to which anti-discrimination programs are still required to eliminate gender discrimination.

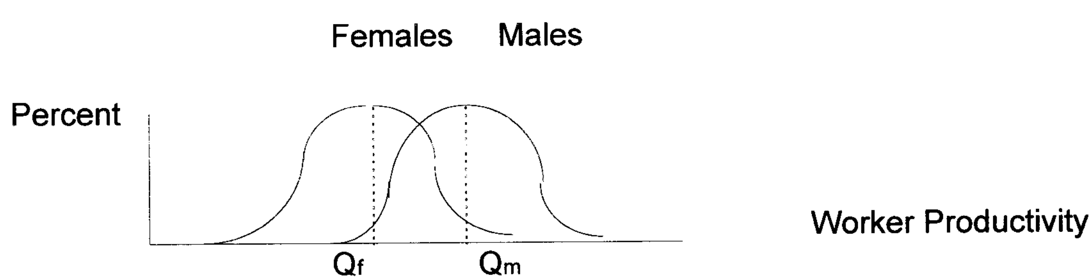
II. Literature Survey

This survey examines the three prevailing theories on labor market discrimination with regards to gender. I discuss three major theories, of labor market discrimination and supporting empirical evidence. The gender differential in incomes is a well documented topic in economics. One paper, using Norwegian data of 3500 employees estimates the wage differential. In the private sector, the gross wage differential is 23 percent (Barth and Mastekaasa, 1996). While there is little dispute that women on average make less than men, the causes of this wage differential are still not well understood. I consider each theory and its practical application to explain these differentials.

The first theory of discrimination is that of statistical discrimination. Statistical discrimination exists when an employer applies group characteristics to individual group members. An example is an employer in the process of hiring new laborers. There are certain characteristics that are very individual in nature and vary with each applicant such as education level, experience or exam placement scores. Other characteristics are very general and when used as a measure of worker ability, result in statistical discrimination. Gender or race are examples of these indices, which when used by employers to determine ability, give rise to statistical discrimination (Ainger and Cain, 1977; Phelps, 1972; Lundburg and Startz, 1983).

An example is a firm which has received a large pool of applications for a position they advertised in a local paper. Assume that the firm has only two characteristics by which to predict worker productivity: education and gender. If education were a perfect predictor of productivity, then the most educated of the applicant pool would be hired and comparably skilled men and women would make equal wages. However, if gender is also correlated with productivity, the firm will also use this characteristic to determine who the most productive workers are.

We see from illustration #1 that the mean productivity, in this



example, of females is less than men. Although some females are performing beyond the capability of the average male, it is still evident that the average male is more productive than the average female.

Women as a group may be less productive, because historically, women are less attached to the labor market than men. Thus, firms that provide specific training to their workers would find a female worker a relatively risky investment because these workers may leave before they recover the training costs.

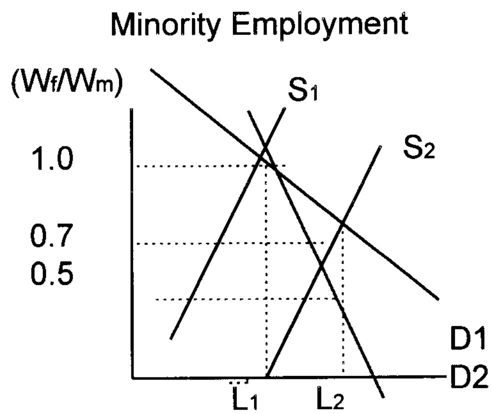
If employers find, that gender is correlated with productivity, then profit maximizing employers will look to this characteristic to make job hiring decisions. Since, in the example, the average productivity is lower, employers will systematically prefer males over females assuming their education is equal, thus leading to lower wages for comparably skilled females.

If we examine the implications of these hiring decisions we can see that an employer who hires only men appears to be a discriminating employer, but in reality is just behaving as a profit maximizing firm. The employer is hiring from the one group that, in general, will be more productive than the other group. Thus, a female worker may be denied employment because the firm, acting rationally and as a profit maximizer, recognizes women's attachment to the labor market as being less than men's. Statistical discrimination, therefore, can lead to unequal earnings between workers of identical qualifications based upon their group affiliation. In this case, differences will occur even in the absence of prejudice.

Simple prejudice, or a "taste for discrimination" is another form of discrimination that has been modeled. This prejudice may have three sources; employer, employee or customer. The first economist to examine prejudice was Gary Becker in 1957, in which he developed a theory on taste discrimination and a discrimination coefficient (Becker, 1971). Becker's taste for discrimination analysis has been revisited by numerous scholars including Arrow (1973) and Goldberg (1982).

According to Becker, an employer with a "taste for discrimination" is willing to pay a premium to hire white males. To illustrate this point, suppose that women make less than comparably skilled men and this information is known to all employers. A profit maximizing employer would hire exclusively females at wage W_f; however, an employer with biased preferences might act as if the actual cost of a females laborer is $W_f(1 + d_i)$, where d_i is the employees discrimination coefficient for females. This discrimination coefficient represents the disutility that the employer receives from hiring a female. The monetary measurement of this contact with females can be calculated as $W_f d_i$. We see that prejudice blinds the employer to the true monetary costs incurred in hiring female workers and he perceives the cost as being much higher.

Becker's model suggests that the size of the wage differential between majority and minority workers depends on two factors. The first factor is the size of the minority group. The intuition behind this fact is that if there is a small group of minorities, finding an employer who does not discriminate, or who has a discrimination coefficient = 0, is possible and all will find jobs where their wages equal those of the majority. If there are more minorities and hence their labor supply curve is to the right of the smaller group, then they will saturate the equal paying jobs and have to move into the jobs which have a positive discrimination coefficient.



As we can see in figure #2, when the labor supply curve shifts right, these minority workers must move into jobs with positive discrimination coefficients and earn less than their Value Marginal Product (VMP). The demand curve D2 yields the same predicted wage as D1 when there are S1 amount of minority workers, but yields a smaller relative wage when the supply of minority workers is S2. Thus, the bias of employers is greater in S2 than S1 and these employers require a lower minority wage in equilibrium to hire minority workers.

An alternative source of prejudice is the employee. An example is a male worker who is offered a wage W_m to work alongside a female worker. This male worker, however, receives disutility from working with women, and views his actual wage as $W_m(1\text{-}d)$. Therefore in this workers view, the integrated firm is actually offering less than an all male firm.

In other words, the firm would have to pay a compensating differential to attract male workers with biased preferences. Thus, it pays the firm to segregate its employees by gender. Unlike employer discrimination, employee discrimination does not generate a wage differential, rather it explains why sometimes it does not pay to "mix" workers of different genders. Also, employee discrimination does not affect the profitability of firms. We see that a firm who offers a job to a discriminating employee will actually hire only non-discriminating employees and thus they receive the maximum VMP for the wage they pay. Barry R. Chiswick, in a paper titled, "Racial Discrimination in the Labor Market: A Test of Alternative Hypotheses", made an important claim about employee discrimination. Because there is no advantage to pay more for one type of worker since the VMP for each is equal, he concluded that there are no market forces to diminish employee discrimination over time. (Chiswick, 1973)

The third potential source of taste discrimination comes from the customers of the firm who demand to buy goods or services from certain groups. Using Becker's discrimination coefficient we can say that consumers make their purchasing decisions based upon an adjusted price. Instead of considering the price of a good, p, the consumer sees the good's price to be $p(1+d)$. When consumers feel as if they are paying a higher price for a good, their utility per dollar drops and thus, they will buy from a firm that doesn't bring them disutility.

I work at a sporting goods store that sells ammunition for hunting rifles. At least once a day I hear a customer tell me that they are much happier to enter our relaxed downtown store to buy ammunition than go to a competing store which is much like entering a survivalist's bunker. Because customers view our employees as helpful and friendly, instead of soldiers of fortune, they are much happier to buy supplies from us where they will often pay more. As a result, if my résumé were to say that I was a militia man and trained assassin instead of a college student who enjoys skeet shooting, I probably would not have been hired.

This is an example of how the firm recognizes the customers' preferences and thus bases hiring decisions on those preferences, in an effort to profit maximize. The implications of these preferences are that, if a firm perceives that its customers prefer interacting with males, then less females will be hired and thus $W_m > W_f$.

One study done by Clark Nardinelli and Curtis Simon, looks at baseball cards of black and white players and compares their resale prices. Their findings are that, after controlling for position and performance, white player's cards were worth 10 to 13 percent more than those of black players. (Nardinelli; Simon, 1990) A historical example of this form of discrimination occurred in Tifton, Georgia where a drug store owner fired a black worker because he said that his customers objected to being served by a black. He was quoted as saying, "I have no prejudice at all, but it's hard for the small independent business to survive. You bend to what your customers say." (Atlanta Journal, 1987) Though customer discrimination is hard to measure, it is apparent that its presence in our society is viewed everywhere.

The last of the three forms of potential discrimination is labeled market power discrimination. The market power discrimination can be applied from either the demand side by monopsonistic firms, or on the supply side by labor unions. The principal is that neither the firm nor the union is simply a "wage taker" in the market, but rather both possess some forces to set the wage different from competitive forces.

In the case of monopsonistic discrimination, Joan Robinson developed an explanation for sex discrimination in wages. (Robinson, 1933) Her theory contends that two conditions must be satisfied for monopsonistic discrimination to take place. The first states that the firm's labor supply must be separable into distinct groups, such as male and female. The second condition is that the elasticity of the labor supply curve of one group must be different from the other.

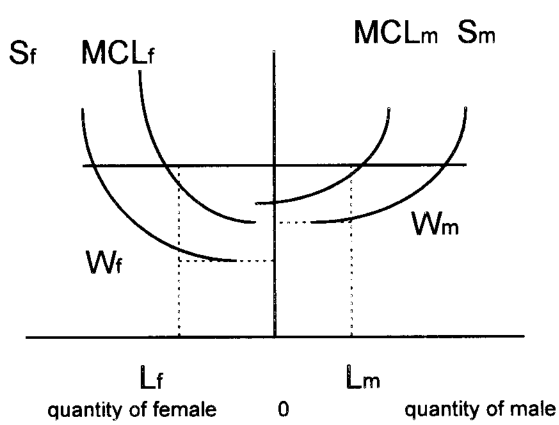


Figure #3 illustrates Robinson's theory on monopsony discrimination. The illustration shows male laborers on the right and women on the left. It is assumed that the monopsonist can hire either male or female workers and that they are equally productive, hence the flat MRP line. Note also, that the steeper labor supply curve for women implies a more inelastic supply function. To maximize profits, the monopsonist should hire workers from each group as long as their MRP is greater than or equal to their MCL. So the firm hires at point L_f and L_m, but pays the females less money than the men for equal work.

This is the outcome that Joan Robinson used to explain wage differentials in 1933. There are several assumptions that are crucial to this model, such as monopsony power and a very inelastic demand. Though these cases are not very common, they do occur. A good example is a married female professor in a town with one university. She is effectively faced with a monopsonistic labor market and has less opportunity to move then her married male colleagues due to society norms. (Settled families tend to move only for the male's career, not the females) Thus, we see the female professor tied to the local university where the university can take advantage of her greater inelasticity of supply by paying her a lower wage than they would pay equally productive men.

Other studies have been done more recently to quantify difference in pay between professional males and females. In a study of Ph.D's by Marianne Ferber and Betty Kordick, it was found that women had considerably less job mobility than men and that if they had been as mobile as men, ceteris parabis, their salaries would have been $673 to $905 higher (1984 dollars). (Ferber; Kordick, 1978)

We can conclude then, that although the exact assumptions of Joan Robinson's original model do no hold in general, that monopsonistic discrimination does in fact occur in some situations. Though it's difficult to detect and limited to few professions, the ramifications of monopsonistic discrimination are felt and are nonetheless worth considering.

The second part of market power discrimination comes from labor unions. Industrial unions tend to be in industries where the firm hires "off the street" and therefore, have been much more progressive on the issue of fair practices than have craft unions. Craft unions which include such industries as construction and longshoring, have built-in mechanisms which make excluding minorities much easier. Apprenticeship programs and hiring halls in these industries make it much easier for minorities to be excluded from these industries. F. Ray Marshall, in a paper titled, "The Negro and Organized Labor", discusses such factors that shape a union's racial policy and states that it is most often its organizational structure, (i.e. craft or industrial). Though discrimination in craft unions is much easier, it is also seen in industrial unions. The principal method in which discrimination is enacted is through the development of seniority systems that block the advancement of minority workers.

Though all of the forms of discrimination I have presented cannot always be applied to explain male and female wage differentials, they form the underlying structure that defines the principal discrimination theories. Each of these theories suggest that women earn less than their comparably skilled male counterparts. The empirical analysis in the paper exams the extent to which gender differences are present in wages.

III. Empirical Model

The variables that I have included in my model are factors that would cause differences in the natural log of an individual's wage. Gross income was divided by hours worked per year and then logged. The dependent variable is logged wage as a function of several factors assumed to affect wages. I have included nine independent variables in my model to predict income. I included a dummy variable that equals one for males and zero for females. The coefficient on this variable is expected to be positive showing a greater wage for males than for their comparably skilled female counterparts. I also included a variable for age, to capture the increased income as a person ages, and age squared, to explain decreasing returns to experience.

A dummy variable that equals one for married workers is included to examine whether stability and commitment associated with married workers increases income. Educational variables are also defined as dummies so that each increase in education level has its own wage premium. Specifically, dummy variables were included for: some high school, a high school diploma, some college, a bachelor's degree and post graduate degree.

Another variable included was a dummy that equals one if the person was from an urban household or a zero for rural. The logic behind this is that wages in urban centers tend to be larger than wages in rural areas and thus could explain differentials in the logged wage.

The wage equation can be expressed as:

log Y= $\beta0$ + $\beta1$Marriage + $\beta2$Gender + $\beta3$Age + $\beta4$Agesq + $\beta5$Somehigh +

(+) (+) (+) (-) (+)

$\beta6$Highschool + $\beta7$Somecollege + $\beta8$Bachelor + $\beta9$Postgraduate + $\beta10$Urban +ei

(+) (+) (+) (+) (+)

D1=0 if ever have been married

D2=1 if male

D10=1 if from urban household

The expectations of my model are that the coefficient on gender will be positive, implying that women make less than men. The coefficient on age should be positive, whereas it should be negative on age squared, explaining decreasing returns to age. Each of the dummy variables for education should have positive coefficients. The urban variable will be expected to be positive, predicting urban areas have higher wages than rural areas.

IV. Data

The data are cross sectional and includes those observations that have positive incomes and are less than the age of 65. I exclude non-workers for the obvious reason that they do not have a wage. After excluding those 65 and above and those without income I was left with 2219 cross sectional samples. The data and the regression statistics are summarized in tables 1 through 3. The data for this sample was randomly drawn from samples of the 1990 US census. The Data was downloaded from the WWW URL http://www.hist.umn.edu/~ipums/index.html. This page is maintained by the University of Minnesota Census History Department.

V. Empirical Results

Table 3, describes the initial regression summary and the statistics for the coefficients. The overall fit was reasonable with an adjusted R-square of .199, from table 2. The expected signs on the coefficients are in agreement with the products of the model. All were positive with the exception of the age squared term. To test the significance of each estimated coefficient, I set up the appropriate alternative and null hypotheses.

$H_o = \beta_1 X_1 = 0$

$H_a = \beta_1 X_1 \neq 0$

The critical t-value for 2219 samples and 10 explanatory variables at the 5% significance level equals 1.645. Using 1.645 as my critical t-value I rejected the null hypothesis and accepted the alternative for all estimated coefficients, with the exception of two. The t-stats for the dummy variables on a bachelors education and some high school are close to the critical value but are not greater, (1.097 and 1.550 respectively). Although the two do not show significance, I included them because their explanatory power makes theoretical sense and their signs were as expected. In general, because all signs prove to be as expected, and all but two coefficients show significance, I believe the model appears to be a good representation of determining factors of the log wage of a worker.

The initial regression included a dummy variable on gender. Proving this coefficient significant was an important piece of the original regression. The estimated coefficient on gender was .297 with a t-statistic of 9.349, from table 3. Due to this high t-stat I rejected the null and accepted the alternative hypothesis indicating that there was a significant wage differential between men and women. So, very convincingly the model predicted that men would earn more than women, assuming the same rate of return to personal attributes for men and women.

By using the Oaxaca decomposition we can actually calculate the differential without assuming the same rate of return and recognizing the differences in mean values of personal attributes between men and women. I sorted the data for men and women into two segments and ran regressions for each gender. Tables 4 and 6 show the regression statistics for males and tables 7 and 9 show the statistics for females. Using the data from these tables I calculated the Oaxaca decomposition for my data set.

My data set had a few characteristics that made this Oaxaca decomposition obtain results different from what I had expected. Women had more high school experience, more high school diplomas and more college experience than the men in my sample. Also, women showed a higher rate of return for a high school diploma, for post-graduate degrees, and for urban status. These factors all contributed to an indication, according to the decomposition, that the women of this data set should have actually made more than men.

The calculated wage differential, as discussed, has two aspects; explained and unexplained. This model predicts women should earn more than men and thus we conclude that the unexplained portion (discrimination) is actually more than the wage differential. Though this notion is different from theory and wage and education studies of the population in general, this was my calculated result. The explained difference equals -0.010439867, from table 10. The unexplained difference equals 0.229236655, calculating a total wage differential of 0.218796788. Table 10 shows my calculations using both methods of calculating the decomposition.

A few factors may have contributed to this result. There were two variables that were big factors to making the explained wage differential negative: some high school and some college. On the female regression these coefficients are not significant and therefore their beta is not a very reliable number. Thus, by calculating a differential where the women's mean value was greater for both variables (different from expected) plus making a calculation using non-significant coefficients, the resulting explanation may be tainted. So, the Oaxaca decomposition, although calculated correctly may be calculating numbers which aren't entirely accurate.

VI. Conclusion

The results from my research show that, for this sample of 2219 Americans, women earned significantly less than comparably skilled men. Undoubtedly there are some other variables beyond the scope of this paper that could have explained the differential even more. However, the differential estimated by the regression is large and predicts that women earned less than men.

The presence of a wage differential is consistent with the products of the several theories of discrimination in the paper. If women are not being paid what a comparably skilled male is, then there are many implications for our society as a whole. Firms could do better by hiring females at lower than market wages. Also, if women are not earning what they should, this represents a laborer earning less than their VMP. When workers earn this wage, a dead weight loss is created for society as a whole, and the economy would be better off if they were being paid their VMP.

Because women are being paid less, whether the differential is explained or not, women are not receiving the returns on education that men are. As discussed, this will prompt women to under-invest in education. If women are truly under-investing in education due to a discrimination coefficient bringing them less returns, then the implication is that the mean education of women will remain less than men's, and the differential will persist.

If the discrimination in the labor market is truly present, then the implications run deeper than what can be represented by a wage differential. It is possible that women are denied promotions, discriminated against in hiring practices and terminated easier than their comparably skilled male counterparts. Wages consider this in part, but the true effects of discrimination in the labor market can have much greater consequences. Women choosing not to participate in the labor market due to a discriminatory experience in the work place is also a possible implication of the wage differential as explained in several of the "feedback" hypotheses.

If the discrimination exists and is quantifiable by the wages of females compared the wages of comparably skilled males, then the implications of this are felt well beyond the payroll lines. The unseen and unquantifiable daily acts on a day to day basis could be great. Though economics can predict that there may be some sort of discrimination in the workplace, it is absolutely impossible to quantify the number of discriminatory acts that happen based upon gender. Therefore, we see that research in the field of wage differentials can serve as a good judge as to how laborers are being treated in everyday experiences in the labor force, not just on payday.

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Regression: Male and Female

Table 1

	Mean	Std. Deviation	N
LOGWAGE	2.0473	.8311	2219
ADJ.MAR	.7571	.4289	2219
ADJ.SEX	.5376	.4987	2219
AGE	37.55	11.75	2219
AGE2	1548.1298	947.8413	2219
BACHELOR	.2321	.4223	2219
HIGHSCHO	.8364	.3700	2219
POSTGRAD	8.472E-02	.2785	2219
SOMEHIGH	.9315	.2527	2219
SUMCOLLE	.3006	.4586	2219
URBAN	1.67	.47	2219

Regression: Male and Female

Table 2

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.450[a]	.203	.199	.7438

a. Predictors: (Constant), URBAN, HIGHSCHO, AGE, ADJ.SEX, POSTGRAD, ADJ.MAR, SUMCOLLE, SOMEHIGH, BA

Regression: Male and Female

Table 3[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.614	.195		-3.146	.002
	ADJ.MAR	8.941E-02	.045	.046	2.002	.045
	ADJ.SEX	.297	.032	.178	9.349	.000
	AGE	7.579E-02	.010	1.072	7.755	.000
	AGE2	-7.545E-04	.000	-.860	-6.414	.000
	BACHELOR	8.009E-02	.073	.041	1.094	.274
	HIGHSCHO	.250	.056	.111	4.464	.000
	POSTGRAD	.246	.068	.083	3.605	.000
	SOMEHIGH	.123	.079	.037	1.550	.121
	SUMCOLLE	.133	.064	.073	2.073	.038
	URBAN	.211	.034	.119	6.158	.000

a. Dependent Variable: LOGWAGE

Regression: Male

Table 4

	Mean	Std. Deviation	N
LOGWAGE	2.1797	.8260	1193
ADJ.MAR	.7561	.4296	1193
AGE	37.77	11.86	1193
AGE2	1567.3755	961.7081	1193
BACHELOR	.2355	.4245	1193
HIGHSCHO	.8164	.3873	1193
POSTGRAD	9.304E-02	.2906	1193
SOMEHIGH	.9145	.2797	1193
SUMCOLLE	.2992	.4581	1193
URBAN	1.66	.47	1193

Regression: Male

Table 5

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.503[a]	.253	.247	.7168

a. Predictors: (Constant), URBAN, HIGHSCHO, AGE, POSTGRAD, ADJ.MAR, SUMCOLLE, SOMEHIGH, BACHELOR,

Regression: Male

Table 6[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.691	.252		-2.735	.006
	ADJ.MAR	.196	.059	.102	3.302	.001
	AGE	9.645E-02	.013	1.384	7.463	.000
	AGE2	-9.707E-04	.000	-1.130	-6.287	.000
	BACHELOR	.129	.099	.066	1.294	.196
	HIGHSCHO	.259	.073	.122	3.567	.000
	POSTGRAD	.163	.088	.057	1.856	.064
	SOMEHIGH	.142	.097	.048	1.463	.144
	SUMCOLLE	.143	.087	.079	1.634	.103
	URBAN	.102	.045	.058	2.281	.023

a. Dependent Variable: LOGWAGE

Regression: Female

Table 7

	Mean	Std. Deviation	N
LOGWAGE	1.8932	.8107	1026
ADJ.MAR	.7583	.4283	1026
AGE	37.29	11.64	1026
AGE2	1525.7515	931.4256	1026
BACHELOR	.2281	.4198	1026
HIGHSCHO	.8596	.3475	1026
POSTGRAD	7.505E-02	.2636	1026
SOMEHIGH	.9513	.2154	1026
SUMCOLLE	.3021	.4594	1026
URBAN	1.69	.46	1026

Regression: Female

Table 8

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.362[a]	.131	.124	.7589

a. Predictors: (Constant), URBAN, SOMEHIGH, AGE, POSTGRAD, SUMCOLLE, ADJ.MAR, HIGHSCHO, BACHELOR.

Regression: Female

Table 9[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.236	.300		-.788	.431
	ADJ.MAR	-4.476E-02	.067	-.024	-.672	.502
	AGE	5.684E-02	.015	.816	3.871	.000
	AGE2	-5.685E-04	.000	-.653	-3.186	.001
	BACHELOR	3.169E-02	.106	.016	.298	.766
	HIGHSCHO	.261	.085	.112	3.059	.002
	POSTGRAD	.306	.106	.099	2.885	.004
	SOMEHIGH	4.865E-02	.134	.013	.364	.716
	SUMCOLLE	.116	.093	.066	1.249	.212
	URBAN	.341	.052	.195	6.582	.000

a. Dependent Variable: LOGWAGE

Table 10

Variables	BetaM	BetaF	MeanM	MeanF	BetaM-BetaF	MeanM-MeanF	(Bm-Bf)Meanf	Bm(MeanM-MeanF)
Marriage	0.196	4.48E-02	0.7561	0.7583	1.51E-01	-0.0022	0.114685292	-0.0004312
Age	9.65E-02	5.68E-02	37.77	37.29	3.97E-02	0.48	1.480413	0.0463392
Age2	-9.71E-04	-5.69E-04	1567.3755	1525.7515	-4.02E-04	41.624	-0.613657253	-0.040404417
Bachelor	0.129	3.17E-02	0.2355	0.2281	9.73E-02	0.0074	0.022196411	0.0009546
Highscho	0.259	0.261	0.8164	0.8596	-2.00E-03	-0.0432	-0.0017192	-0.0111888
Postgrad	0.163	0.306	9.34E-02	7.51E-02	-1.43E-01	0.01835	-0.01073215	0.00299105
Somehigh	0.142	4.87E-02	0.9145	0.9513	9.34E-02	-0.0368	0.088803855	-0.0052256
Sumcolle	0.143	0.116	0.2992	0.3021	2.70E-02	-0.0029	0.0081567	-0.0004147
Urban	0.102	0.341	1.66	1.69	-2.39E-01	-0.03	-0.40391	-0.00306
Constant	-0.691	-0.236			-4.55E-01	0	-4.55E-01	0
						Sum of:	Discrimination	Skills Differentials
							0.229236655	-0.010439867
						Sum of wages	0.218796788	
Variables	BetaM	BetaF	MeanM	MeanF	BetaM-BetaF	MeanM-MeanF	(Bm-Bf)MeanM	Bf(MeanM-MeanF)
Marriage	0.196	4.48E-02	0.7561	0.7583	1.51E-01	-0.0022	0.114352564	-9.8472E-05
Age	9.65E-02	5.68E-02	37.77	37.29	3.97E-02	0.48	1.499469	0.0272832
Age2	-9.71E-04	-5.69E-04	1567.3755	1525.7515	-4.02E-04	41.624	-0.630398426	-0.023663244
Bachelor	0.129	3.17E-02	0.2355	0.2281	9.73E-02	0.0074	0.022916505	0.000234506
Highscho	0.259	0.261	0.8164	0.8596	-2.00E-03	-0.0432	-0.0016328	-0.0112752
Postgrad	0.163	0.306	9.34E-02	7.51E-02	-1.43E-01	0.01835	-0.0133562	0.0056151
Somehigh	0.142	4.87E-02	0.9145	0.9513	9.34E-02	-0.0368	0.085368575	-0.00179032
Sumcolle	0.143	0.116	0.2992	0.3021	2.70E-02	-0.0029	0.0080784	-0.0003364
Urban	0.102	0.341	1.66	1.69	-2.39E-01	-0.03	-0.39674	-0.01023
Constant	-0.691	-0.236			-4.55E-01	0	-4.55E-01	0
						Sum of:	Discrimination	Skills Differentials
							0.233057618	-0.01426083
						Sum of wages	0.218796788	