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Towards a Broader Explanation of Male-Female Wage Differences

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Abstract: Most analyses of wage discrimination have followed the traditional Blinder-Oaxaca decomposition of wage differences into endowment and discrimination components. This approach has neglected the possibility of wage discrimination at point of entry to the labour market and also the issue of selectivity bias. Using some recently developed techniques of Neumann and Oaxaca this paper decomposes male-female wage differences taking account of discrimination in terms of access to the labour market and also selectivity bias. It finds considerable evidence of discrimination at point of entry but that discrimination owing to selectivity bias is minimal.

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Towards a Broader Explanation of Male-Female Wage Differences

1. Introduction

The decomposition of wage differentials between various categories of workers (e.g. male-female, black-white) into that part due to differences in endowments of human capital and that part due to differences in returns to endowments (usually called discrimination) has become a standard exercise since the seminal contributions of Blinder (1973) and Oaxaca (1973). One criticism which can be levelled at this approach (henceforth called B-O) is that it only measures discrimination *in the labour market*. If there is differential access to those endowments which are rewarded in the labour market, e.g. males have easier access to higher education than females, or indeed if, ceteris paribus, males have a higher probability of employment than females, then the standard B-O approach will understate the degree of discrimination present. A comprehensive analysis of discrimination involves explaining not just observed wage differences but also a whole lifetime sequence of choices and decisions.

Such a task is obviously beyond the scope of this paper (and arguably beyond the scope of any study). So in this paper we limit ourselves to extending the measure of discrimination to also include the issue of employment. In the spirit of the B-O decomposition we break down the probabilities of employment for men and women into differences in endowments and differences in returns to these endowments, using a technique introduced by Even and Macpherson (1990). We then present the standard B-O decomposition but including a term which corrects for selectivity bias. In turn this term can be decomposed into that part due to endowments and that part due to discrimination following Neuman and Oaxaca (1998). While we will see that the decomposition of this term is not entirely straightforward, we believe that overall we will have obtained a more comprehensive explanation of the differing labour market experiences of males and females, incorporating differences not just in wages but also in employment.

The layout of this paper is as follows: in section 2 we present results for the standard B-O procedure. In section 3 we apply a decomposition to the probability of employment.

Section 4 then presents a decomposition of wages correcting for selectivity and including the decomposition of this term, while section 5 provides some concluding comments.

2. The Standard Blinder-Oaxaca Decomposition

The standard B-O decomposition follows from a wage equation of the following type:

$$Y_i = X_i' b_i + e_i$$

where Y_i refers to the log of the wage for males (females), X_i is a vector of determinants of market wages (e.g. age, education etc.), b_i is the associated parameter vector and e_i is an error term following a normal distribution (0, σ_ε). The standard B-O decomposition then breaks down the difference between male and female wages in the following way:

$$\overline{Y}_m - \overline{Y}_f = \overline{X}_f'(\hat{b}_m - \hat{b}_f) + (\overline{X}_m - \overline{X}_f)'\hat{b}_m$$

where $\overline{Y}_i$ is the predicted mean (log) wage , $\overline{X}_i'$ is the mean vector of wage determining variables and $\hat{b}_i$ is the vector of estimated returns to the wage determinants. Thus the first term on the right-hand side above is viewed as the discrimination component of the wage difference while the second term is that due to differences in endowments of human capital. Decompositions of the above type will be sensitive to whichever group's wage structure is assumed to be the norm. This is a standard index number issue and in this paper we will select the wage structure of the dominant group (i.e. the male wage structure) as the norm.[2]

Before presenting estimates of the above equation we will first present some summary statistics of our data. Our data set is the *Family Resources Survey (FRS) 1995*. The FRS is a continuous survey of household characteristics and living standards, which covers about 25,000 households in Great Britain. It contains extensive information about a variety of issues relating to the family, including information upon various labour market and human capital indicators. We restrict our sample to married couples aged less than 65, and excluding the self-employed. This gives a sample consisting of 8747 couples. While the confining of our sample to married couples is obviously restrictive in some senses, from the point if view of measuring male-female wage discrimination it

[2] See Oaxaca and Ransom (1994) for a discussion of this issue.

may be helpful. The inclusion of married couples only may control for some degree of unobserved heterogeneity in the population, although it means of course that our analysis will not pick up discrimination against, for example, single women.

In table 1 we present summary statistics for the variables of relevance for the wage equation, with standard deviations in brackets. We note a male wage premium of around 40%. Human capital characteristics are broadly similar, but men are on average about 1.5 years older. The breakdown by occupation shows fairly significant differences with much higher proportions of men in the managerial, craft and plant categories while women dominate in the clerical and "other" categories.

In table 2 we present results from a wage equation estimated over the human capital variables in table 1 (the omitted occupational category is "other"). The coefficients are of the expected sign and using the information in tables 1 and 2 we can perform the decomposition in equation 2. The results of this are shown in table 3. Thus proportionately about 16% of the observed wage difference is accounted for by differences in endowments and the remaining 84% is attributed to discrimination.

We will now extend this analysis to take account of differing probabilities of employment and also the inclusion into the wage equation of a term correcting for selection.

3. Decomposition of Employment Probabilities

As stated above, one of the criticisms of the standard B-O approach is that it only examines discrimination which occurs *in the labour market*. If we believe that discrimination also applies in terms of access to the labour market, then this must be taken account of when trying to build up a more complete picture of labour market discrimination. Thus suppose that in addition to our wage equation we also have an equation which determines employment:

$$Y_i^* = Z_i'g + u_i$$

where Y_i^* is a latent variable associated with being employed, Z_i' is a vector of variables determining employment with g the associated parameter vector and u_i is an error term following a normal distribution (0, s_u), whose correlation with the error term in the wage equation is r. Thus the probability of being employed is given by

$$\Pr(Y_i^* > 0) = \Pr(u_i > -Z_i'g) = \Phi(Z_i'g)$$

where $\Phi(.)$ is the standard normal C.D.F., with the variance of u_i normalised to one. Suppose the average predicted employment probabilities for men and women are given by $\overline{P}_m$ and $\overline{P}_f$ respectively., where $\overline{P}(Z_i'\hat{g}) = (1/n)\sum_{i=1}^{n}\Phi(Z_i'\hat{g})$ Then this difference in employment probabilities can be decomposed as follows: the total gap in male and female employment probabilities is given by

$$\overline{P}_m - \overline{P}_f = \overline{P}(Z_m'\hat{g}_m) - \overline{P}(Z_f'\hat{g}_f)$$

In turn this is composed of the explained gap i.e. that portion of the gap due to differences in characteristics:

$$EXP = \overline{P}(Z_m'\hat{g}_m) - \overline{P}(Z_f'\hat{g}_m)$$

plus the portion which is unexplained by characteristics, but is due to differences in returns:

$$UNEXP = \overline{P}(Z_f'\hat{g}_m) - \overline{P}(Z_f'\hat{g}_f)$$

In turn, following Even and Macpherson (1990) the contribution of the explained gap due to the *r*th explanatory variable is defined as:

$$EXP_r = [\overline{P}(Z_m'\hat{g}_m) - \overline{P}(Z_f\hat{g}_m)]\left[\frac{(\vec{Z}_{mr} - \overline{Z}_{fr}).\hat{g}_{mr}}{(\overline{Z}_m - \overline{Z}_f)\hat{g}_m}\right]$$

In table 4 we present the results from a probit estimation for employment and then in tables 5 and 6 we present the decompositions outlined above. We see that our decomposition suggests that there is substantial discrimination at point of entry to the labour market, so much so that it accounts for over 100% of the difference in the participation rates for men and women. On the basis of characteristics alone, then women should have *higher* participation rates than men by about 20%, but this explained part of the difference is swamped by the unexplained portion.[3]

[3] Note that as well as discrimination in terms of labour market access *per se*, there may be discrimination in terms of access to different occupations. The modelling of this is a topic for future research, but see Reilly (1991) for an application to Irish data.

While the global explained difference between employment probabilities for men and women is relatively small at around 20%, there is huge variation in the contribution of different characteristics in terms of accounting for this difference. Including age and age squared as capturing the same variable, then the largest contribution to the explained difference is the interaction term between age and education, which accounts for over 100% of this difference. Health and health interacted with age accounts for about 53% of the difference, while age contributes –41%. Recall that this precise breakdown is sensitive to our choice of males as the reference group but nevertheless it illustrates how relatively small global figures can conceal large differences in terms of the various contributory factors. From a policy point of view it also suggests that, for example, any attempt to close this explained gap between males and females would need to be carefully targeted at the appropriate characteristic.

4. <u>Discrimination with Selectivity Corrected Wage Equations</u>

So far we have examined the standard B-O decomposition which examines discrimination in the labour market only, and discrimination which occurs in terms of entering the labour market. However, it may well be the case that the sample of men (and women) working will not be a random sample, but instead may suffer from *selection bias*. Thus if the unobservables which influence entry to the labour market are correlated with unobservable factors influencing wages then there is a relationship between the process determining labour market participation and the process determining wages. If in turn these unobservable factors are correlated with observable factors in the wage equation, then failure to take account of this will yield biased wage equation coefficients.[4] The standard way of dealing with this issue is to append an extra term to the standard wage equation, the inverse Mills ratio (IMR). As Neuman and Oaxaca (1998) show, this term in turn can be decomposed, which will give us a measure of wage discrimination which takes account of selection bias.

Combining our wage equation and our equation determining employment we have the expected wage of a worker observed to be in employment given by

$$E(Y_i \mid Y_i^* > 0) = X_i' b + E(e_i \mid u_i > -Z_i' g)$$

$$= X_i'b + q\,l_i$$

where $q = r\,s_e$, $l_{ii} = f(Z_i'g)\,/\,\Phi(Z_i'g)$ and $\phi(.)$ is the standard normal density function. Given this revised expression for the wage equation we now require an amended decomposition, which incorporates the additional selectivity term.

$$\overline{Y}_m - \overline{Y}_f = \overline{X}_f'(\hat{b}_m - \hat{b}_f) + (\overline{X}_m - \overline{X}_f)'\hat{b}_m + (\hat{q}_m\hat{l}_m - \hat{q}_f\hat{l}_f)$$

where $\hat{q}$ is an estimate of $r\,s_e$ and $\hat{l}$ is an estimate of the mean IMR. The incorporation of the final term above into the decomposition raises the question of whether it too can be decomposed into characteristics and discrimination components. How exactly to go about this is not an entirely straightforward issue. Here, we follow the approach of Neuman and Oaxaca (1998) and examine a number of different ways of proceeding with this decomposition and also provide empirical evidence as to the importance of this issue.

The first question that must be addressed is how to measure the mean of the IMR, since the IMR is a nonlinear function of the index function $Z'g$. Probably the easiest approach to take is to measure the central tendency of λ as $\hat{l} = \sum_{i=1}^{n} l_i \,/\, n$, which has the advantage of being consistent with the Heckman two-step estimation procedure, in the sense that its use ensures that the predicted value of Y will be the sample mean value. We now turn to the problem of how to decompose the term $\hat{q}_m\hat{l}_m - \hat{q}_f\hat{l}_f$. One approach is that of Reimers (1983). She simply takes this term onto the left-hand side of the overall decomposition, so that the right-hand side contains the familiar terms for differences in characteristics and discrimination i.e.

$$(\overline{Y}_m - \overline{Y}_f) - (\hat{q}_m\hat{l}_m - \hat{q}_f\hat{l}_f) = \overline{X}_f'(\hat{b}_m - \hat{b}_f) + (\overline{X}_m - \overline{X}_f)'\hat{b}_m$$

However the problem with this approach is that it essentially sidesteps the issue. It presents a decomposition of the *selectivity adjusted* wage difference as opposed to a decomposition of the *observed* wage difference.

Neumann and Oaxaca (1998) introduced the following decomposition of the conditional mean error term for the wage equations for men and women:

$$\overline{E}(e_m | u_m > -Z_m'\hat{g}_m) - \overline{E}(e_f | u_f > -Z_f'\hat{g}_f) = \hat{q}_m\hat{l}_m - \hat{q}_f\hat{l}_f$$

[4] See Vella (1998) for a recent discussion.

$$= \hat{q}_m(\hat{l}_f^0 - \hat{l}_f) + \hat{q}_m(\hat{l}_m - \hat{l}_f^0) + (\hat{q}_m - \hat{q}_f)\hat{l}_f$$

where $\hat{l}_f^0 = \sum_i^{N_f} \hat{l}_{if}^0 / N_f$ and $\hat{l}_{if}^0 = f(Z'_{if}\hat{g}_m) / \Phi(Z'_{if}\hat{g}_m)$. Thus here $\hat{l}_f^0$ is the mean value of the IMR if females faced the same selection equation that men faced. The term $\hat{q}_m(\hat{l}_f^0 - \hat{l}_f)$ measures the effects of gender differences in the parameters of the probit selectivity equation on the male/female wage differential. The effects of gender differences in the characteristics which determine selectivity into employment are given by $\hat{q}_m(\hat{l}_m - \hat{l}_f^0)$. Finally the effects of gender difference in the wage response to the probability of employment are given by $(\hat{q}_m - \hat{q}_f)\hat{l}_f$. Equivalently this last term captures the wage differential effects of gender differences in the correlation between unobservables in the selection equation and unobservables in the wage equation plus gender differences in wage variability.

Having completed the decomposition of the IMR term it now remains to allocate the components to discrimination and characteristics. There seems little doubt that the first term referred to above, $\hat{q}_m(\hat{l}_f^0 - \hat{l}_f)$, should be allocated to characteristics, nor that the second term, $\hat{q}_m(\hat{l}_m - \hat{l}_f^0)$, should be allocated to discrimination. Thus the crucial decision is how to interpret the last term, $(\hat{q}_m - \hat{q}_f)\hat{l}_f$. The allocation of this term to discrimination could be regarded as taking the broadest interpretation of discrimination. Such an interpretation implies that gender differences in the correlation between the selectivity equation error term and the wage equation error term result from labour market discrimination, not to mention assigning gender differences in the standard deviation of the wage equation error term to discrimination also (we label this interpretation 1). While this may appear to imply an implausibly broad view of discrimination, it may also be difficult to argue that these differences should be put down to differences in characteristics (we label this interpretation 2). Alternatively, rather than assign $(\hat{q}_m - \hat{q}_f)\hat{l}_f$ to either characteristics or discrimination we could simply regard it as a separate selectivity term in the decomposition (we label this interpretation 3).

In table 7 we present estimates of the wage equation with the IMR added and in table 8 we present the relevant parameters for the decomposition of the selectivity term. It can be seen that the terms arising from the decomposition of the selectivity term are small in magnitude compared to the terms arising from the standard B-O decomposition in the absence of the correction for selectivity. Correspondingly, the addition of these terms makes little difference to the decomposition of the wage difference between characteristics and discrimination. This arises from the small size of the $\hat{q}_i$ terms, reflecting the fact that there appears to be little or no evidence of selectivity bias in our wage equations.

Finally, in table 9 we present the decomposition of the wage differential for all three interpretations of the selectivity term as well as the traditional B-O decomposition. As is apparent from tables 7 and 8, the inclusion of the selectivity term and its decomposition has virtually no effect on the allocation of the wage differential to characteristics and discrimination. Indeed, given that the "ambiguous" term in the decomposition, $(\hat{q}_m - \hat{q}_f)\,\hat{l}_f$, is negative, we have the curious situation that interpretation 1, the broadest definition of discrimination, is that which accords the lowest weight to discrimination in terms of explaining the wage differential. But overall, it is fair to say that the inclusion of the selectivity term is of little relevance for the decomposition of the wage differential into characteristics and discrimination, for this data set at least.[5]

5. Conclusion

In this short paper we have tried to extend the traditional Blinder-Oaxaca decomposition of wage differences to take account of (a) discrimination at point of entry to the labour market and (b) the possibility of selection bias. Our results show that in a global sense factor (a) appears to be of considerable importance. Also while the explained portion of the gap in participation rates is relatively small, this hides quite large effects of individual components of endowments on wage differences. Our results also show that factor (b) is of little empirical importance, reflecting the absence of selectivity bias in our estimated wage equations. We emphasise however that these results are likely

[5] Neumann and Oaxaca (1998) find that its inclusion makes a substantial differences for their estimates.

to be quite specific to our data set and that it would be unwise to presume that they can be generalised to other cases. The importance of these issues in terms of wage decompositions is a question which ultimately must be empirically determined on a case-by-case basis.*

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Table 1: Summary Statistics for Wage and Human Capital Variables for those working (standard dev. in brackets)

	Male	**Female**
Participation	0.769 (0.42)	0.631 (0.48)
Weekly Hours Worked	42.487 (9.85)	28.388 (11.92)
Weekly Wage (log)	2.091 (0.58)	1.684 (0.56)
Age	42.436 (10.09)	40.901 (9.78)
Years Full-time Education	16.976 (2.55)	16.958 (2.25)
Non-White	0.044 (0.21)	0.036 (0.19)
Health Problem	0.131 (0.34)	0.121 (0.33)
Managerial	0.225	0.078
Professional	0.125	0.111
Associated	0.079	0.107
Clerical	0.064	0.274
Craft	0.186	0.024
Personal	0.067	0.143
Sales	0.038	0.103
Plant	0.150	0.045
Other	0.066	0.115

Table 2: Wage Equation, Dep. Var.=Log Wage

	Male (N=6728)	**Female (N=5522)**
Age	0.069 (0.005)	0.035 (0.005)
Age^2	-0.0007 (0.00005)	-0.0004 (0.00006)
Years Full-time Education	0.047 (0.003)	0.046 (0.003)
Non-White	-0.288 (0.028)	-0.035 (0.032)
Health Problem	-0.076 (0.017)	-0.019 (0.018)
Managerial	0.706 (0.026)	0.656 (0.028
Professional	0.600 (0.030)	0.856 (0.030)
Associated	0.582 (0.031)	0.661 (0.026)
Clerical	0.237 (0.032)	0.382 (0.021)
Craft	0.263 (0.026)	0.080 (0.042)
Personal	0.201 (0.032)	0.109 (0.023)
Sales	0.313 (0.037)	0.060 (0.025)
Plant	0.105 (0.027)	0.171 (0.032)
Constant	-0.567 (0.111)	-0.189 (0.115)

Table 3: Standard B-O Decomposition of Wages

$\log w_m - \log w_f$	0.4063
$\bar{X}_f'(\hat{b}_m - \hat{b}_f)$	0.3393 (83.5%)
$(\bar{X}_m - \bar{X}_f)'\hat{b}_m$	0.0670 (16.5%)

Table 4: Probit Estimation for Employment

	Male (N=8741)	**Female (N=8741)**
Age	0.205 (0.018)	0.211 (0.017)
Age^2	-0.002 (0.0001)	-0.002 (0.0001)
Education	0.139 (0.032)	0.131 (0.028)
Non-White	-0.637 (0.068)	-0.710 (0.062)
Own-Health	-0.741 (0.170)	0.012 (0.163)
Spouse Health	-0.207 (0.041)	-0.243 (0.035)
Age*Health	-0.007 (0.003)	-0.014 (0.003)
Age*Education	-0.002 (0.001)	-0.002 (0.001)
Constant	-4.082 (0.623)	-5.100 (0.561)

Table 5: Decomposition of Probabilities

$\bar{P}_m - \bar{P}_f$	0.138
$\bar{P}(Z_m'\hat{g}_m) - \bar{P}(Z_f'\hat{g}_m)$	-.028 (-20.5%)
$\bar{P}(Z_f'\hat{g}_m) - \bar{P}(Z_f'\hat{g}_f)$	0.166 (120.5%)

Table 6: Contribution of *r*th Characteristic to Difference in Employment Probabilities

$\overline{P}(Z'_m\hat{g}_m) - \overline{P}(Z'_f\hat{g}_m)$	-.028
Age	0.158 (-556.1%)
Age^2	-0.146 (515.2%)
Education	0.002 (-6.6%)
Non-White	0.0002 (-7.6%)
Own Health	-0.009 (33.6%)
Spouse's Health	0.003 (-9.4%)
Age*Health	-0.005 (19.1%)
Age*Education	-0.030 (105.0%)

Table 7: Selectivity Corrected Wage Equation

	Male (N=6728)	**Female (N=5522)**
Age	0.0706 (.0055)	0.0382 (.0061)
Age^2	-0.0008 (.0001)	-0.0004 (.0001)
Years Full-time Education	0.0471 (.0028)	0.0469 (.0036)
Non-White	-0.2934 (.0299)	-0.0483 (.0354)
Health Problem	-0.0868 (.0261)	-0.0308 (.0226)
Managerial	0.7065 (.0261)	0.6558 (.0279)
Professional	0.5999 (.0297)	0.8562 (.0292)
Associated	0.5818 (.0308)	0.661 (.0258)
Clerical	0.2374 (.0320)	0.3819 (.0208)
Craft	0.2629 (.0261)	0.0805 (.0416)
Personal	0.2013 (.0315)	0.1087 (.0232)
Sales	0.3133 (.0371)	0.0602 (.0252)
Plant	0.1052 (.0269)	0.1710 (.0324)
λ	0.0213 (.0385)	0.0320 (.0381)
Constant	-0.6037 (.1295)	-0.2805 (.1581)

Table 8: Estimates of Average Lambdas and Associated Coefficients

$\log w_m - \log w_f$	0.4063
$\hat{l}_m$	0.4038
$\hat{l}_f$	0.6145
$\hat{l}_f^0$	0.3543
$\hat{q}_m$	0.0213
$\hat{q}_f$	0.0320
$(\overline{X}_m - \overline{X}_f)'\hat{b}_m$	0.0664
$\hat{q}_m(\hat{l}_m - \hat{l}_f^0)$	0.0011
$(\hat{q}_m - \hat{q}_f)\hat{l}_f$	-0.0066
$\overline{X}_f'(\hat{b}_m - \hat{b}_f)$	0.3509
$\hat{q}_m(\hat{l}_f^0 - \hat{l}_f)$	-0.0055

Table 9: Decomposition of Wage Differentials with Selectivity Correction

		Contribution of		
	$\log w_m - \log w_f$	Characteristics	Discrimination	Selectivity
Standard B-O	0.4063	0.0670 (16.5%)	0.3393 (83.5%)	0.0000 (0.0%)
Interpretation 1		0.0675 (16.6%)	0.3388 (83.4%)	0.0000 (0.0%)
Interpretation 2		0.0620 (15.3%)	0.3443 (84.7%)	0.0000 (0.0%)
Interpretation 3		0.0675 (16.6%)	0.3443 (84.7%)	-0.0055 (-1.3%)

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